REMOTE SENSING APPLICATIONS TO WATER RESOURCES

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Remote sensing has emerged as a major tool in studying and analyzing the complex water resource systems. With the advent of earth observation satellites, better understanding of the land surface conditions has become possible which is essential for several applications in hydrology, meteorology and agronomy. This article highlights various applications of remote sensing to water resources such as hydrology, watershed management, flood plain management, drought monitoring, irrigation management, irrigated crop yield assessment among others. It also includes micro-wave remote sensing applications to water resources with the availability of Synthetic Aperture Radar (SAR) data of European Satellites. Geographic Information System (GIS) has further improved the utility of remotely sensed data by linking the spatial database with temporal database at different locations. A discussion on GIS applications to water resources is also presented. Global Positioning System (GPS) has helped in collecting precise 'ground truth' for better utilization of remotely sensed data (Precision agriculture etc.) A brief introduction to GPS with its adaptability to water resources management is presented. Various remote sensing missions and their capabilities are briefly presented with special emphasis on Indian remote sensing (IRS) satellites and the future plans with specific missions for better utilization of earth resources. A state-of-the-art review of research in remote sensing applications to water resources is presented.

1 Introduction

Remote sensing is the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a sensor that is not in direct contact with the target of investigation. Remote sensing (RS) studies include data collected with measurements on the ground (hand-held, truck-mounted, etc.) and from a variety of airborne and spaceborne platforms (e.g. satellites) Satellites may be in geo-synchronous orbit or sun- synchronous orbit. A variety of sensors, which measure reflective, thermal, and dielectric properties of the earth's surface are available [28]. Both active sensors, which send a pulse (in microwave, thermal range etc.) and measure the return pulse and passive sensors, which measure emissions or reflectance from natural sources (e.g. solar energy), are used. Sensors used for water resources applications cover a broad range of the electromagnetic spectrum. RS techniques indirectly measure hydrological variables. So the electromagnetic variables measured by RS techniques have to be related to the hydrological variables empirically or with transfer functions.

Remote sensing can play useful role in harnessing available water resources wealth. There are several areas in the field of water resources wherein RS proves useful for effective applications – particularly in surveying and inventorying. The International Satellite Land-Surface Climatology Project (ISLSCP) encourages scientists to use remote sensing data to better understand natural processes on the global land surface [88]. Large-scale field experiments have been conducted to validate remote sensing algorithms for estimating surface parameters and fluxes such as evapotranspiration [112]. There is ample scope for the application of remote sensing in the assessment of various components of hydrologic cycle, quantification of these components in various environs and the fluxes of water through these environs. Some of the fields include hydrologic studies, river morphology, reservoir dynamics and sedimentation, watershed conservation, command area planning and management, flood estimation and forecasting, ground water studies, water quality and environmental protection. Remote sensing application in hydrology is briefly reviewed by Schultz [84]. A review of remote sensing applications to ground water studies is presented by Meijerink [52]. An exhaustive list of various applications to water resources, wherein RS may substitute or complement or supplement the conventional methods, is given by Balakrishnan [2]. A state-of-the-art review on satellite remote sensing applications in irrigation management is given by Bastiaanssen [5]. This article presents an overview of the applications of remote sensing to various aspects of water resources. Narayanan [62] presented number of articles popularizing the use of remote sensing in various fields. Joseph [42] and Kalyanaraman [43] presented the past, present and future of Indian remote sensing missions and their capabilities. More information about Indian space program can be found at http://www.isro.org/.

2 Hydrological Studies

Hydrological processes are highly dynamic phenomena which vary both in time as well as space. Conventional measurements of these hydrological processes are accomplished by in-situ or point measurements. These are then interpolated or extrapolated to get the aerial estimates. The advent of RS technology has opened new vistas for the study of various components of hydrologic cycle.

Some examples of parameters, used in hydrological modeling, which have been derived from satellite data with sample references are presented in Table 1.

Table 1. Parameters in hydrology and water resources currently obtainable from satellite remote sensing data (modified from [47])

Parameter	Satellite/ Sensor	Wavelength or Frequency	Spatial Resol-ution	Coverage	Sample references
Snow area	NOAA	0.62, 10.8 mm Bands 1, 4	1 km	2 per day	[45, 12]
Snow Depth	GOES	0.65 mm	2 km	2 per hour	[22, 14]
	Nimbus 7	37 GHz	30 km	-do-	
Snow water equivalent	SSM/I	19.3, 37 GHz	25 km	2 per day	[92, 107]
	MOS-1-MSR	23, 31 GHz	23-32 km	-do-	
Changes in snowmelt	ERS-1	5.3 GHz C-band SAR	30 m	35 days	[21]
Surface Temperature	NOAA	10.80 mm Band 4	1 km	2 per day	[23]
Evapotrans-piration	NOAA	0.62, 0.91, 10.8,12.0 mm	1 km	2 per day	[71]
	GOES	0.64,11.5 mm	2-8 km	2 per hour	[11]
Precipitation	Meteosat	0.65 mm	3 km	2 per hour	[70]
Land cover/ Land use	Landsat 5 MSS	0.55, 0.65, 0.75, 0.95 μm	80 m	8-16 days	[46, 111]
Vegetation	NOAA	0.62, 0.91 μm	1 km	2 per day	[1]
	IRS 1C/1D (WIFS)	0.92, 0.67 μm	188 m	5 days	[48]
Suspended Sediment/	Landsat 5 MSS	0.55, 0.65, 0.75, 0.95 μm	80 m	8-16 days	[78]
Algal growth	IRS P4 OCM		360 m	2 days	[44]
Spring runoff	Nimbus 5	19 GHz	30 km	2 per hour	[109]
Changes in soil moisture	JERS-1	1 GHz L-band SAR	30 m	35 days	[69]
Groundwater	Landsat	0.95 μm	80 m	8-16 days	[10]
Water depth	Landsat	0.48, 0.56, 0.66 μm	30 m	8-16 days	[33]
Oceanography	IRS P4 OCM	412,443,490,520 555,670,765 nm	360 m	2 days	[43]
	MSMR	6.6, 10.65, 18, 21 GHz		2 days	

There are three broad categories for using remote sensing in hydrological studies [80].

- Simple qualitative observations/ assessments are made. e.g. A visual observation of a photo that water from industrial effluent into a stream has a different colour than the stream water, suggesting a site for collection of a sample.
- Information on geometric form, dimensions, patterns, geographic location and distribution are derived for features such as land cover categories that influence runoff, evapotranspiration and soil moisture.
- Development of correlation between the remotely sensed observations and the corresponding point measurements on the ground for estimation of a hydrologic parameter. Examples include the estimation of rainfall, soil moisture, snow depth, sediment load etc.

2.1 *Rainfall Estimation and Monitoring*

Conventional means of rainfall monitoring using a network of rain gauges has limitations due to their sparse density more so in remote areas as well as over oceans. Radar is an active microwave remote sensing system operating in the 1 mm – 1 m region of electromagnetic spectrum (EMS) In a radar system, a pulse of electromagnetic energy is transmitted as a beam, which is partially reflected by cloud or rainfall, back to the radar. Radar has the unique capability to observe the areal distributions of rainfall and provide real-time estimates of rainfall intensities. Operational use of ground based radar for rainfall monitoring is limited due to smaller range and being costly. With the advent of satellites, it has become possible to obtain spatially continuous and homogeneous data over large areas including oceans in real-time. The use of satellite data for estimating rainfall is mainly based on relating brightness of clouds observed in imagery to rainfall intensities.

Various aspects of rainfall hydrometeorology amenable to improved analysis using satellite data are [3]: (i) Delineating the boundaries of areas likely to get rain, (ii) Assessing basin rainfall totals over time, (iii) Assessing extreme events of rainfall, (iv) Assessing the climatology of rainfall distributions and (v) forecasting of rainfall especially in regions with sparse data.

The wavelengths most commonly used for rainfall studies are [4]:

- Visible (VIS) : 0.5 – 0.7 μm
- Infrared (IR) : 3.5 – 4.2 μm and 10.5 – 12.5 μm and
- Microwave (MW): 0.81 to 1.55 cm

Most of the meteorological satellites currently used for precipitation estimation are either geostationary or polar-orbiting satellites. Geostationary satellites (e.g. NOAA, GOES, GMS, Meteosat, INSAT) typically carry infrared (IR) and visible (VIS) imagers with spatial resolution from 1-4 km. A geostationary satellite

positioned over equator can provide high frequency (hourly or better) images of a portion of the tropics and middle latitudes, while a polar orbiting satellite provides roughly twice-daily coverage of the entire globe. Polar orbiters also fly in a low earth orbit, which is more suitable for the deployment of microwave imagers on account of the later's coarse resolution. High quality microwave imagery was made available after the launch of SSM/I (Special Sensor Microwave Imagery) with spatial resolution in the order of 10 km. SSM/I data is found more reliable for rainfall estimation. However it suffers from two limitations viz., coarse temporal resolution and coarse spatial resolution. The geometrical effects of three-dimensional rain clouds on radiances observed by an oblique viewing radiometer such as SSM/I have been examined and were found to be considerable [31].

There are a good number of satellite rainfall estimation algorithms documented in the literature. For example, 55 algorithms were evaluated in the Third Algorithm Intercomparison Project (AIP-3) of the Global Precipitation Climatology Project (GPCP) including 16 VIS/IR, 29 MW and 10 mixed IR/MW algorithms. Petty and Krajewski [68] presented a review of some of the important algorithms.

Cloud indexing method [30] is normally used to estimate daily rainfall over an area through statistical averaging of cloud-rainfall relationships. In this approach three most important types of clouds viz., cumulonimbus, cumulocongestus and nimbostratus are considered. This method is widely used in support of broad scale hydrology.

To meet the growing need for stably calibrated, long, time series data sets for global climate change, a number of organized scientific programs or projects are actively promoting the development, validation and/or access to the user community of satellite-derived precipitation products. Pathfinder precipitation products produced from SSM/I data using GSCAT algorithm are available freely from Distributed Active Archive Center (DAAC) of NAA, USA (http://daac.gsfc.nasa.gov) National Climate Data Center (NCDC) is currently producing rainfall products and distributing for both 1^0 and 2.5^0 grids (http://www.ncdc.noaa.gov) from a combination of archived microwave and infrared satellite data, surface rain gauge data and numerical forecast model output.

2.2 *Snow Mechanics, Mapping and Monitoring*

Snow in hydrology is a renewable resource and is one of the most complicated parameters to be measured. In India during summer months rivers rising in the Himalayas are substantially fed by snowmelt runoff. Periodic snow cover monitoring is essential for assessing the snowmelt runoff likely to occur. Conventional methods have serious limitations in the study of dynamic processes like snow and its monitoring complicated by inaccessibility. Considering the vastness of snow clad watersheds, aerial surveys are expensive and of little use. Satellite remote sensing has a vital role to play to obtain near real-time snow cover area (SCA) maps with good accuracy. Depletion curves of SCAs indicate the gradual areal diminishment of the seasonal snow cover during the snowmelt season. The typical shape of depletion curves can be approximated by the equation [2].

$$S = 100/(1+e^{bn})$$

where S is SCA in % obtained from satellite imagery, b is a coefficient and n is the number of days before (-) and after (+) the date at which S=50%.

The snow extent over the globe has become available on daily basis since 1972 from National Oceanic and Atmospheric Administration – Advanced Very High Resolution Radiometer (NOAA-AVHRR) satellite, assuming no cloud interference at 1.1 km spatial resolution. Passive microwave observations of snow cover extent are assured every 1-2 days from SSM/I due to cloud penetration capability but the spatial resolution is coarse (about 25 km)

US National Weather Service (NWS) distributes products of periodic river basin snow cover extent maps (http://www.nohrsc.nws.gov) from NOAA-AVHRR and Geostationary Operational Environmental Satellite (GOES) Some good examples of operational applications of such snow extent data are already there in India. Initially Ramamoorthi [73, 74] started to use NOAA-AVHRR data in a simple regression approach for empirical forecasts of seasonal snow melt runoff in the Sutlej river basin (43,230 km^2) and both the forecasts were extended to other basins. Ramamoorthi [74] also used satellite data as input to a snowmelt runoff model (SRM) for short term forecasts. Kumar *et al.* [49] further developed the idea for use in operational forecasts of daily and weekly snowmelt runoff in the Beas (5,144 km^2) and Prabati (1,154 km^2) river basins in India. Another type of application to operational snow hydrology is production of monthly hemispherical snow maps from GOES and NOAA-AVHRR data for climatological applications. EOS Multifrequency Passive Microwave Radiometer (MPMR) scheduled to be launched in 2000 can obtain 8 km resolution by using a much larger antenna than currently used for SSM/I. A detailed review of applications space borne remote sensing for snow hydrology is given by Rango [76].

2.3 *Rainfall-Runoff Studies*

Runoff in the form of water volume flowing through a river cross-section during a specified time interval cannot be measured on the basis of remote sensing data alone. This may evolve in future, if it becomes possible to measure the width and depth of a river cross section with the aid of remotely sensed data and flow velocities by ultrasonic or laser methods. At present RS data is indirectly used to determine runoff with the aid of hydrologic models. RS data is used either as model input or for the determination of model parameters or both. Most existing models do not incorporate the use of RS capabilities. Therefore it is necessary to develop structures of hydrological models which are amenable to the spatial and temporal resolution provided by RS data. Areal distribution of information from RS data can

be better utilized by the application of distributed deterministic models. The spatial resolution of a model structure and the spatial resolution of its input data should have some correlation. For example, it makes no sense to structure a model in space according to the IRS 1-C PAN pixel size of 5m and use as its input precipitation data from one gauge for an area of several thousand square kilometers. Further, there has to be a reasonable correlation between the applied resolution to time and to space. For example, if only monthly runoff values are being used, there is no need to seek for a high spatial resolution data (say IRS LISS II with a spatial resolution of 36.25 m) Peck et al [66] identified 13 variables which can be obtained using remotely sensed data with some degree of success. They also presented a review of the existing hydrologic models with regard to their adaptability to remote sensing data. Similar studies were also presented in Balakrishnan [2] and Schultz [85].

Non-linear regression models based on RS and ground truth data were used for runoff modeling. A detailed sensitivity analysis for river basins in tropical West Africa was carried out by Papadakis *et al.* [65] to obtain information on the resolution required for the modeling effort in time, space and spectral channels. Meteosat data from European geostationary satellite with a high temporal resolution of 30 min and spatial resolution of 5 km was used for modeling monthly runoff for a large catchment area. The model functions in two consecutive steps: (i) Estimation of monthly precipitation values with the aid of Meteosat IR data and (ii) transformation of the monthly rainfall volumes into the corresponding runoff volumes with the aid of rainfall/ runoff model. For the three available spectral channels of Meteosat (IR, Visible and Water Vapor) it was shown that only IR information is relevant. Following a modified Arkin method [24], a monthly cloud cover index (CCI) is estimated indicating all pixels having a temperature in the IR channel below a specified threshold value. This threshold value varies from region to region. Monthly precipitation values are then obtained from daily CCI values as a nonlinear function of CCI [65]. Monthly runoff computed on the basis of rainfall estimated with the help of satellite imagery compared well with the observed runoff.

There have been many efforts to improve the performance of existing hydrological models by the use of RS data for improved parameter estimation. A very well received approach is for the improvement of the Soil Conservation Service (SCS) runoff Curve Number (CN) model [103]. Various SCS models allow computation of direct runoff volumes Q, in terms of land use and soil type without requiring hydrological data for calibration. The volume of direct runoff is given by the equation:

$$Q = \frac{(P - I_a)^2}{(P - I_a) + S}$$

where P is volume of rainfall, I_a is initial abstraction and S is retention parameter.

In SCS model, $I_a=0.2\ S$. Thus Q becomes a function of rainfall and S only. In practice a runoff curve number, CN, is defined as transformation of S according to the relationship, CN = 1000/ (S+10) The CN depends on the hydrological soil group and land use description. Conventionally, the curve numbers are given in tables. The introduction of RS data allowed a better estimation of the land use and thus a more reliable estimation of the relevant curve number. Two approaches have been used for estimating CN using remotely sensed data. In one approach land cover information was obtained using RS data which was then combined with general soil data to estimate the CN. Ragan and Jackson [72] used Landsat multi spectral data and this approach for runoff estimation. The other approach made use of Landsat average watershed reflectance ratios of spectral bands 0.5-0.6 μm and 0.8-1.1 μm to directly compute the CN without using ancillary soil data [9]. Remote sensing data can be a valuable tool in runoff prediction especially in areas experiencing rapid land use changes. Satish Chandra *et al.* [82] used Landsat imagery and aerial photographs to derive land use and vegetal cover data for Upper Yamuna basin and then obtained morphometric and relief characteristics of the basin. These were in turn used to derive runoff coefficients for various land uses for use in simulation of runoff, employing rational formula.

3 Watershed planning and management

Proper planning and management is essential for conservation of water and land resources for optimum productivity. Remote sensing via aerial and space borne sensors can be effectively used for watershed characterization and assessing watershed priority evaluation problems, potentials and management requirements and periodic monitoring. Various physiographic measurements which could be obtained from remotely sensed data include watershed area, size and shape, topography, drainage pattern and landforms. Spectral bands in the wavelengths 0.6-0.7 μm and 0.8-1.1 μm have been found to be useful for physiographic mapping of drainage basins. Stereoscopic attribute of aerial photographs permits quantitative assessment of landforms and evaluation of basin topography that can be used to develop or update the topo maps. Remote sensing due to its more current nature can provide better and more reliable information for quantitative analysis of drainage networks. Near Infra Red (NIR - 0.8-1.1 μm) band reveals the contrast between land and water features and is best suited for mapping large streams where as the visible red band (0.6-0.7 μm) facilitates differentiation among land, vegetated and non-vegetated features and is most useful for drainage network delineation [81]. The information on drainage network/ pattern is largely a reflection of the lithology and structure of the basin, stream orders, stream length, stream frequency, bifurcation ratio, stream sinuosity, drainage density and linear aspects of channel systems and can be obtained using RS data.

The most complex hydrological models are water balance models since they simulate all components in a water balance on and below the earth's surface and also in the atmosphere to a certain extent. Hydrological processes to be modeled in time and space in a water balance model include (1) precipitation, which usually serves as model input, (2) evapotranspiration, (3) runoff (surface and sub-surface), (4) storage change in the unsaturated zone and (5) ground water flow. Remote sensing data come into the water balance model at several levels [85]:

- Precipitation may be estimated from weather radar or from satellite imagery.
- Evapotranspiration models use leaf area index (LAI) data or NDVI (Normalized Differential Vegetation Index) for consideration of the transpiration of plants. These may be derived from Landsat, IRS or NOAA-AVHRR data [19, 114].
- Interception model also uses LAI or NDVI [20].
- Soil storage component uses land use classification from RS data [86].

Airborne laser altimeters provide quick and accurate measurements for evaluating changes in land surface features and is an effective tool to understand watershed properties. Airborne laser measurements can be used to measure directly topography, stream channel cross sections, gully cross sections, soil surface roughness and vegetation canopy height, cover and distribution [77].

Watershed degradation of soil and land resources could be mapped and monitored via remote sensing for reclamative measures. The mapping of soil degradation involving salinity/ alkalinity, water logging, erosion, desertification, shifting cultivation, excessive permeability, wetlands etc are successfully done in various regions using satellite imagery. Multitemporality (repetitive coverage) of satellite data is very much useful for change detection studies such as growth of desertification, flood damage area and encroachment of ravines on agricultural lands.

Remote sensor data also facilitates identification and classification of existing and potential erosion-prone areas for taking reclamation/ preventive measures. Effect of various watershed characteristics on soil erosion can be evaluated using aerial and satellite data. Many methods of erosion detection and measurement can be based on RS. Tueller and Booth [102] listed the following as erosion features identifiable from RS data:

- Erosion potential associated with changes in vegetation and litter
- Changes in soil type and soil colour
- Occurrence of dendritic soil patterns
- Occurrence of sand dunes
- Definition between bare soil or rock and
- Vegetal cover.

Spanner *et al.* [94] demonstrated the potential of using various data sources, through a data base approach, to map potential soil loss using Universal Soil Loss Equation (USLE) The data sources among others include Landsat MSS data, digitized USDA

SCS soil maps, digitized NOAA precipitation isopluvial maps and USGS digital elevation model topographic data.

4 Irrigation management

Irrigation is the largest consumer of fresh water. Seckler *et al.* [87] estimated that 70% of all water used each year produces 30 to 40% of world's food crops on 17% of all arable land. As water scarcity becomes more acute and competition for fresh water intensifies, better irrigation management will be required to achieve greater efficiency in the use of this valuable resource. Achieving food security through irrigation while combating water logging and salinization, to ensure sustainable agriculture requires quantitative and repetitive analysis of the irrigation processes. Distinct spatial variations in soil properties, soil moisture status, cropping conditions and micro-meteorology occur within an irrigation scheme. Although information on irrigation practices can be acquired by conventional survey methods, they have subjective character and usually differ from survey to survey. Consequently, remote sensing from space, which can regularly provide objective information on the agricultural and hydrological conditions of irrigated area, has a great potential for enhancing the management of irrigation systems. Studies have established that the presence of crops can be determined and several biophysical parameters can be measured with an accuracy of over 80% using RS data. In addition, RS data facilitates the construction of long time series (covering as much as 20 years) for investigation of changes in irrigation conditions. Many publications [5, 54, 99, 105] present the state-of-the-art of remote sensing applications in irrigation management. Molden et al [56] presented various indicators for comparing performance of irrigated agricultural systems. Bastiaanssen [5] categorized remote sensing publications, which explicitly refer to irrigation management. These categories include irrigated area, land use, crop water needs, use and stress, crop yield, soil salinity, water logging and reservoir mapping. Earlier works mainly included soil salinity mapping, land use and the quantification of area under irrigation. Recent works included crop classifications and crop yield estimation due to improved sensors onboard Landsat, SPOT and IRS yielding higher spatial resolution [59].

Thematic land classes can be derived digitally by grouping pixels, having similar spectral signatures, from measurements of individual bands throughout the EMR spectrum. Usually this classification is made using the visible, near-infrared and middle infrared parts of the spectrum. *Supervised classification* approach is the most common methodology for forming classes based on similar spectral reflectance [89]. In this approach, pixels are assigned to classes (i.e., training classes) verified on the ground (ground truth) in selected areas. These training sets represent a small percentage of an image. Then maximum likelihood criterion based on *a priori* probabilities [97], is used for classifying the entire image. Alternative criteria for classifying the images are based on minimum Euclidean distance to

mean and Mahalanobis distance. *Unsupervised classification* algorithm clusters pixels multispectrally into classes through the use of standard statistical approaches such as the centroid and ward methods and does not rely on assigned classes from field visits. Cluster analysis technique also has some advantages. Huumeman and Broekema [38] presented an approach for classification of multi sensor data using a combination of image analysis techniques. A well-known phenomenon in pixel based image classification is the 'mixed' pixel, which comprise of a heterogeneous land surface i.e., two or more objects occur within a single pixel [5]. In agricultural areas, crop variety, seeding date and supply of fertilizer are often unevenly distributed among and within the crop fields. Due to this, the spectral reflectance of a given crop may contain a wide scatter [51]. *Fuzzy classification*, with more continuous land cover classes, has been developed to account for variations in natural conditions [108]. Fuzzy classifications are based on the relative strength of a class membership that a pixel has, relative to all defined classes and it does not require any assumption about the statistical distribution of the data. Neural network classifier [8, 34] also helps in thematic classification of an image for different crops.

4.1 *Spectral Vegetation Indices*

A vegetation index is a common spectral index that identifies the presence of chlorophyll. The index is based on reflectance in the red spectral region, R (0.62 to 0.70 μm) and a portion (0.7-1.1 μm) of the near infrared spectral region, NIR. Chlorophyll has a relative low reflectance in the red band (strong absorption) and a relatively high reflectance in the NIR band. Multiple combinations of red and NIR band data have been formulated and various crop parameters identified from vegetation indices using biophysics. Normalized Difference Vegetation Index (NDVI) is given by (NIR-R)/(NIR+R) SAVI (Soil adjusted vegetation index), TSAVI (Transformed soil adjusted vegetation index) and WDVI (Weighted difference vegetation index) indices are the improved indices by reformulation to minimize the back scattering of canopy-transmitted, soil-reflected radiation in partial canopies. Introduction of GEMI (Global environment monitoring index) and ARVI (Atmospherically resistant vegetation index) made it easier to quantify the time series of vegetation indices, despite continual change in atmospheric conditions and aerosol effects. Rondeaux *et al.* [79] reviewed the merits of most of the classical and upgraded vegetation indices recommended for application in agronomy.

4.2 *Irrigated Area Assessment*

Identification of irrigated area and separation from non-irrigated areas using remote sensing has started from early 80s. Thiruvengadachari *et al.* [101] estimated the irrigated area from IRS LISS II data and it was noticed that the estimated area has far exceeded the authorized area for irrigation, highlighting violations both in cropped area and cropping pattern. Visser [106] tested different methods to distinguish irrigated from non-irrigated areas. He found that supervised classification procedures performed (average accuracy of 92.5%) better than a multiplier of reflectance ratios in Landsat Thematic Mapper (TM) bands 3, 4 and 5 (90% accuracy) and than principal component analysis (85%) Nageswara Rao and Mohan Kumar [61] described the classification of irrigated crops through various vegetation indices (NDWI, NDVI and GVI) derived from Landsat TM and suggested that NDWI is better suited for identifying irrigated crops. Hussin and Shaker [37] classified the main land-use types in Sumatra, Indonesia using Landsat MSS and TM data combined with radar measurements from the European Remote Sensing Satellite (ERS-1 SAR) The spatial resolution of ERS-1 SAR (Synthetic Aperture Radar) was 12.5 m with a swath width of 100 km and a wavelength of 5.3 GHz or 5.6 cm (C-band) The multisensor spectral classification of TM and SAR data gave less satisfactory results, due to the speckle noise of SAR data, although paddy fields could be identified better. Paddy fields appeared very dark on the radar image, which is quite useful for delineating irrigated rice basins when the skies are cloudy. Texture labeling and texture spectrum analysis of ERS-1 SAR data was carried out by Nagesh Kumar *et al.* [60] to delineate irrigated area when the data from optical sensors was not available due to cloud cover.

Identification of different crop types by pattern recognition from multispectral high resolution satellite images is a classic remote sensing research problem in agriculture. Research on this issue seems to be continuously improving with better spectral and spatial resolution capabilities and sophisticated classification algorithms. Menenti *et al.* [53] adopted a multi-index, mutli temporal crop classification procedure, based on time composites of vegetation index and designed a transformed vegetation index (TVI), which expresses the density of full ground cover. They then combined TVI with the sample ratio to identify the cropping patterns in the irrigated plains of Italy. Use of TVI values allowed them to correct for variations in crop development due to differences in planting dates, irrigation water supply and farmers' practices. Jayasekera and Walker [41] applied a hybrid classification procedure in the densely vegetated Gal Oya irrigation project in Sri Lanka. They used principal component analysis and unsupervised classification of Landsat MSS bands and identified five categories of paddy practices, which differed in plant vigor, canopy density, and depth of standing water. Pedley and Curran [67] used SPOT-XS data for a field-by-field classification in South Yorkshire, U.K. The accuracy for 12 land cover classes was 46% at pixel scale and 55% at field scale. The best accuracy (62%) was achieved by using measures of prior probabilities and texture within a pre-field format. Thiruvengadachari *et al.* [101] used IRS LISS I image for irrigated crop classification in Bhadra reservoir command, Karnataka, India both by visual and digital interpretations and also evaluated the performance of the irrigation system.

In Netherlands, Schotten *et al.* [83] used eight ERS-1 SAR precision images with a 12.5 m resolution to identify potatoes, sugarbeats, winter wheat, maize,

spring barley, winter rape, beans, onions, peas, grass, lucerne and orchards with a field based maximum likelihood classifier. The images were captured during the growing season between May 12 and November 3. Field size varied from 1 to 20 hectares and an overall classification accuracy of 80% could be obtained after an extensive ground survey. A SPOT-XS image with a 20 m resolution was used to fix the geometry of the agricultural fields prior to the classification procedure.

RADARSAT Scan SAR (Synthetic Aperture Radar) data of different dates were used to analyze the signature of rice crop in West Bengal, India [64]. The analysis showed that the lowland practice of cultivation gives distinct signature to rice due to the initial water background with relatively stable back scatter. Around 94% classification accuracy was achieved using two date data. The 300 km swath with 50 m resolution of ScanSAR was found cost effective for large area crop monitoring.

IRS-P3 Modular Optoelectronic Scanner (MOS-B) spectrometer data over parts of Northern India was evaluated by Singh *et al.* [91] for Wheat crop monitoring involving (a) sub pixel Wheat fractional area estimation using spectral mixing approach and (b) growth assessment by red edge shift at different phenological stages. Results obtained were compared with those obtained using IRS WiFS (Wide Field Scanner)

Accuracy levels attained in crop classification with the help of different sets of satellite images was summarized by [5].

Biophysical parameters are important for irrigation management because they reflect water and production issues. They include fractional vegetation cover and leaf area index (LAI) for vegetation development, surface roughness, surface emissivity, surface temperature, surface resistance, crop coefficients and transpiration coefficients for crop evapotranspiration and crop yield estimation. Bastiaanssen [5] described these parameters in detail along with their estimation based on remotely sensed data. Remote sensing applications for evapotranspiration monitoring over land surface is presented by Kustas and Norman [50].

5 Drought management

Agricultural drought assessment can be made with the help of spectral vegetation indices explained in the previous section. In a well executed project (ongoing) viz., 'National Agricultural Drought Assessment and Monitoring System', Dept of Space, India, is providing biweekly drought bulletins (June to December) for 246 districts in ten different states of India. The drought assessment is based on a comparative evaluation of satellite observed green vegetation cover (both area and greenness) of a district in any specific time period, with that of similar period in previous years. NDVI images derived from NOAA AVHRR data are used for this purpose. This nation wide early warning service has been found to be useful for providing first alert of drought conditions [98]. At present IRS 1D WiFS data with higher spatial resolution is being used for the same purpose.

6 Soil moisture estimation

As soil moisture controls the water balance in the crop root zone and also in the estimation of surface runoff, many attempts were made to retrieve soil moisture data from airborne and space borne multi spectral remote sensors. Bastiaanssen [5] presented a review of studies on soil moisture estimation based on remote sensing. Recent attempts to convert thermal infrared measurements into soil moisture maps are based on surface roughness [6] or use of the evaporative fraction to assimilate soil moisture in soil-vegetaion-atmosphere-transfer (SVAT) models [104]. Major contrast between the dielectric constants of water (~80) and dry soil (~3.5) produces very different propagation characteristics of the electromagnetic wave in soils having different moisture levels. For describing the soil moisture under given conditions, wave lengths between 0.3 cm (100 GHz) and 30 cm (1 GHz) are the most effective. Microwave radiometry reflects the moisture conditions in the top 10 cm of soil. The use of microwave emission is perturbed by surface roughness, attenuation and microwave emission by canopies and to a lesser degree by soil texture. Njoku and Entekhabi [63] presented the potentials of passive microwave technology for soil moisture estimation. Airborne microwave radiometry with spatial resolutions of a few meters, has shown greater success [15] compared to space borne passive microwave with very course spatial resolution. Radar instruments, which are active microwave sensors, are being used more frequently due to their improved spatial resolution [40]. Musiake *et al.* [58] conducted comparative study between microwave radars on board ERS (C-band) and JERS (L-band) for determining the soil moisture in agricultural fields and found good correlation (0.93) between the two radiometers. Engman and Chauhan [27] prepared a summary of the applications using microwave remote sensing, including radiometry, to detect soil moisture.

7 Soil salinity

Rising water tables, due to recharge from irrigation canals and watered fields, due to naturally poor groundwater quality or due to rock weathering, may cause soil salinity problems. In irrigated areas, the features, indicating salinity in increasing order, are stunted crop growth, poor and patchy germination, crop stress, death of crop, encroachment of halophytic species, bare soils with efflorescence and salt crust development. Visible reflectance of leaves from plants growing on such salt-affected soils is lower prior to plant maturation and higher there after. Steven *et al.* [96] showed that indices nearer to middle infrared indices are proper indicators of chlorosis occurring in stressed crops (normalized difference of TM bands 4 and 5) This index is immune to color variations and provides an indication of leaf water potential. Bastiaanssen [5] presented a review of different sensor applications for soil salinity detection and concluded that Landsat TM bands 5 and 7 are frequently used to detect soil salinity and drainage anomalies. Chaturvedi *et al.* [16] and Singh

and Srivastav [90] used microwave brightness and thermal infrared temperatures synergistically for the identification of salt affected areas. Interpretation of microwave data was done by means of a two layer model with fresh and saline groundwater. Larger wavelengths (L-band, P-band) are capable of penetrating the soil and retrieving information from a soil layer rather than just from the soil surface. Combined remote sensing and geographic information system (GIS) with ancillary information on soil types, digital elevation data etc will yield better results for mapping soil salinity.

A general guideline for the use of remote sensing in irrigation management in terms of classifying cropping patterns, crop communities, land cover and land use cannot be given. However, a set of potentially successful components can be suggested [5].

- Ground truth on crop types across the entire classification domain
- Multitemporal, high resolution images
- At least 15 pixels per field
- Hybrid classifications based on both unsupervised and supervised classifications
- GIS-based aerial and contextual classifiers
- Spectral bands in the near-infrared, middle-infrared and microwave spectral range
- Definition of fuzzy classes for conditions with variable cultivation practices.

The potential usefulness of selected remote sensing applications for day-to-day and season-to season management of water resources in large irrigation schemes is summarized in Table 2, adopted from Bastiaanssen [5].

Wolters *et al.* [113] mentioned that satellite remote sensing cannot be effectively utilized for the day-to-day operation of irrigation system due to low frequency of high resolution images which are not compatible with the flexibility that canal operations require. But with the recent satellite missions (e.g. IRS 1C, WIFS), images can be acquired at higher frequency. Sriramany and Murthy [95] demonstrated the capability of remote sensing for mitigating crop stress or water logging in Greater Mae Klong System in Thailand.

Table 2. Irrigation Management Information that can be derived from Remote sensing

Parameter	Need for field data	Preferred Principle
Precipitation	High	Cold cloud duration and rain gauge network
Surface runoff	High	Curve number method
River discharge	High	Polarization differences, altimetry
Potential evapotranspiration	Low	1. Two-step Penman-Monteith equation with crop coefficient 2. Two-step Penman-Monteith equation 3. Radiation type of expression
Potential transpiration	Low	Transpiration coefficients
Potential evaporation	Low	Difference between Potential evapotranspiration and Potential transpiration
Actual evapotranspiration	Low	SEBAL algorithm
Actual transpiration	Moderate	LAI, transpiration coefficient and SAR
Actual evaporation	Moderate	Difference between actual evapotranspiration and actual transpiration
Crop stress indicators	Low	Water deficit index
Crop yield	Moderate	NDVI at heading stage
Relative yield	Low	Time-integrated relative transpiration
Topsoil moisture	Moderate	C-band, L-band microwave
Root-zone moisture	High	Inverse surface resistance and LAI
Soil salinity	High	Visible, near infrared, thermal infrared, microwave synergy
Salt minerals	High	Hyperspectrometry

In Crop Acreage and Production Estimation (CAPE) project under Remote Sensing Applications Mission (RSAM) in India, the acreage and production estimates [93] for wheat, rice, groundnut and sorghum were studied over a large area of 70.3 million hectares covering 21.4% of the geographical area of the country.

Application of remote sensing in irrigation management should be worked out through a two-way structure of demonstration and implementation. Demonstration projects should be initiated by international organizations (such as FAO, UN) The aim should be to reduce the gap between the information which remote sensing is technically capable of producing and the information needed for managing irrigation water for improving crop productivity. Elements that are successfully evaluated in the demonstration phase should be transferred to the implementation phase in close coordination with professionals. Also training of technicians and researchers on water related remote sensing issues is essential to achieve tangible results.

8 Reservoir sedimentation

Generally, suspended sediment causes the most serious pollution of water bodies. This not only reduces the reservoir storage and its life but also restricts the use of water for the intended multiple purposes. Remote sensing data is an important source in monitoring sedimentation of lakes and reservoirs through repetitive coverage. Quantifiable relationships between suspended sediment and remotely sensed data have been established. Remote sensing can be used in the following ways to monitor reservoir sedimentation [2].

- Inventorying the watershed runoff potential for taking steps to minimize sediment in the runoff and maximize clear water recharge.
- Identification and delineation of flood front during a storm event and establishing correlation between flood front extent and storm magnitude to predict future impact
- Mathematical modeling of sedimentation by correlating reflectance values with sedimentation rate.

Some of the variables used in hydrodynamic models of sedimentation can be measured using air and space borne sensors. They include near surface turbidity, Sechhi disc transparency, suspended solids concentration, surface temperature, flow velocity and surface area. Remotely sensed data generally represent fine materials, as large particles get deposited in the delta. These fine particles play an important role in biological and chemical dynamics of water bodies. Landsat MSS digital data has provided significant insight into analysis and understanding of near surface turbidity characteristics [110]. According to Moore [57], (i) turbid water is more reflective than clear water at all visible and NIR wavelengths, (ii) the remote signal from turbid water represents only near surface conditions and (iii) measured reflectance is dependent on the wave length used, size and shape of the particles present and their reflectance, absorption and refraction characteristics. Ratios of MSS bands, band 4/ band 1, band 3/ band 1 and band 2/ band 1 were found suitable for estimation of suspended sediments of high, high to low and low concentrations respectively. Spectral mixture analysis was used to estimate the concentration of suspended sediments in surface waters in Amazon basin wetlands by Mertes *et al.*, [55]. Surface concentration of suspended sediment load was estimated for many reservoirs and lakes in India by Chakraborti et al [13].

A comparative study of suspended sediment concentration potential derived from four band (100-300 nm) Landsat MSS, five broad band (40-300 nm) Landsat TM and eight narrow band (20-40 nm) IRS-P4 OCM spectral bands with that of the conventional (NIR-Red and NIR+Red) indices was made by Kaur and Rabindranathan [44]. A specific numerical index is proposed based on broad/ narrow n-wave band data from Landsat MSS/TM or IRS-P4 OCM spectral data. Prediction accuracies were observed to be the highest with the proposed index calculated from narrow OCM-P4 spectral data.

9 Flood monitoring and flood plain monitoring

Floods are regular phenomena in many parts of the world including India. Flood damage surveys are essential not only to assess the extent and severity of damage caused by the floods periodically in river valleys but also for economic evaluation of flood control measures. Moreover timeliness of information is crucial for tackling events like flood. Conventional methods have serious limitations in this aspect. Remote sensing facilitates the flood surveys by providing the much needed information on flood inundated areas, river course and its spill channels, spurs and embankments affected/ threatened etc so that appropriate flood relief and mitigation measures can be planned and executed in time. Through proper selection of platform and sensor, remote sensing can offer a quick and reasonably accurate means of surveying the spatial extent and assessment of flood damage. The effectiveness of existing flood control works in containing the flood can be assessed and vulnerable reaches identified for strengthening. New structures can be planned wherever necessary. Near real time monitoring of number of flood events of Indian rivers viz., Brahmaputra, Ganga, Kosi, Jhelum and Godavari has demonstrated that valuable information can be provided regarding flood affected areas for planning flood relief activities [75]. Availability of microwave data (ERS-1 SAR) has helped mapping flood inundation even during cloud covered periods [32].

10 Geographic information system

Geographic Information System (GIS) technology provides tools for effective and efficient storage and manipulation of remotely sensed information and other spatial and non-spatial information [29]. The strength of GIS comes from its ability to analyze data representing a particular point, line, or polygon. All features of the landscape can be reduced to one of these three spatial data categories. Water bodies, Soil type and cropped areas are all examples of features that are represented as polygons (areas) in a GIS database. Canal networks, roads and rivers are all lines, and features such as point elevation, precipitation data from a rain gauge are points in GIS. Some possible layers in GIS are shown in Figure 1.

Remote sensing images, effectively integrated within a GIS, can be used to facilitate measurement, mapping, monitoring and modeling activities [25]. Building a GIS database includes import or entry of data from different sources and digitizing data from different source documents. Data themes can range from hydrological (e.g. runoff) and climatological (e.g. temperature, precipitation) to data from both point and areal measurements.

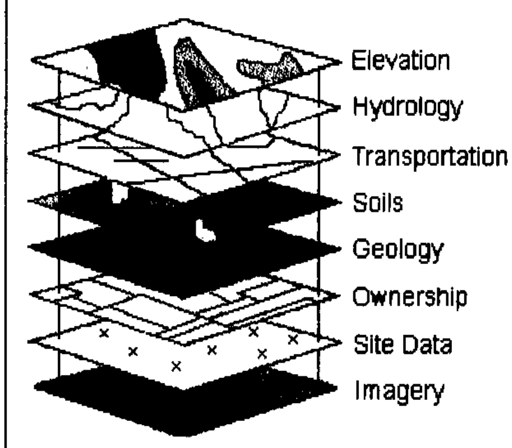

Figure 1. Typical GIS Data Layers

GIS analyses allow the user to perform a wide variety of investigations such as

- Proximity analyses, neighborhood operations (e.g. identifying objects within a certain neighborhood fulfilling specific criteria)
- Determine the relationships between data sets within such a neighborhood
- Temporal operations and analyses
- Generation of new information by combining several data layers and attributes (e.g. by splitting or aggregating etc)

DeVantier and Feldman [18] presented a review of use of GIS, Digital Terrain Modelling (DTM) and remote sensing data in hydrologic modeling. Baumgartner *et al.* [7] showed the advantages of integrated use of remote sensing, GIS, DBMS (Database Management Systems) and hydrological models.

11 Global positioning system

Global Positioning System (GPS) is a Satellite Navigation System funded by and controlled by the U. S. Department of Defense [17, 35]. The nominal GPS Operational Constellation consists of 24 satellites, which orbit the earth in 12 hours [36]. This constellation provides the user with five to eight Satellites visible from any particular point on the earth at any given time. GPS provides specially coded satellite signals, which can be processed in a GPS receiver, enabling the receiver to compute position (latitude and longitude), velocity and time. Four GPS satellite signals are used to compute positions in three dimensions. Earlier precise signal (encrypted signal) from GPS was available only for U.S. defense purposes. Recently GPS signal is made public for precise location [39]. Differential positioning (DGPS) involves determination of the relative coordinates of one or more receivers with respect to the position of a receiver located at a known position referred to as the Base (Monitor reference station)

GPS has an effective role in utilization of remote sensing and GIS in water resources. Some of its utilities are as follows.

- Ground truth collection for better classification of the satellite imagery. For example, different crop types can be located on the field with GPS during ground truth collection and they can be effectively transferred to the satellite imagery as training tests for classification of the entire image of an irrigated area into different crop types.
- Ground truth collection to verify the interpreted results from a remote sensing imagery.
- Point elevation information from GPS survey for improving the existing contour map, DEM model or any other topo information.
- Transfer of any point source information (e.g. rain gauge data) to the precise location in a satellite imagery or GIS layer.

12 Future scope

Impact of remote sensing on hydrology will be significant in future for several reasons.

- It has the ability to provide spatial data rather than point data
- It has the potential to provide measurements of hydrological variables which are not available through traditional techniques, such as soil moisture, snow water content
- It has the ability to provide long-term globe-wide data for remote and generally inaccessible regions of the Earth at regular intervals.

Most of the advances in using remote sensing for hydrology have come from new areas of hydrological analysis where existing methods were unsatisfactory and areas where sufficient data was non existent. These areas include General Circulation Model (GCM), land parameterizations, snow hydrology and measurement of soil moisture [26].

In the near future, more complex multi spectral, multi temporal and multi variate data sets of different origins will be available from different satellite platforms. The needs for long term monitoring of the hydrologic cycle are a high temporal (12 hours) and a moderate spatial (100-250 m) resolution as well as

consistent data systems (sensors) and data sets. The imaging spectrometer – especially the moderate (MODIS by NASA) or medium (MERIS by ESA) resolutions systems – will improve the collection of remote sensing data. In addition to a high temporal and moderate spatial resolution, these systems offer an excellent spectral resolution, which improves the utility in hydrological applications.

Future Indian remote sensing (IRS) missions include [43]:

- CARTOSAT-1 which is meant as a mapping mission for cartographic applications, will carry two panchromatic cameras, one looking in the aft direction and the other in Fore direction in order to provide stereo pair images during the same satellite pass. The spatial resolution contemplated is 2.5 m with a height resolution more than 5 m.
- OCEANSAT satellite carrying a scatterometer, thermal infrared sensor, an altimeter and an ocean color monitor (OCM similar to that in IRS-P4)
- CLIMATSAT satellite with a payload of microwave radiometer, humidity sounder and a radiation budget monitor. The satellite will provide scientific data pertaining to the tropical regions viz., data on water vapor, ice in clouds, cloud liquid water using microwave radiometers at frequencies 10, 18, 23, 37, 85 and 157 GHz and humidity profiler around 183 GHz in 6 channels to get the vertical humidity profile. In addition, a radiation budget monitor operating from wave length of 0.2 μm will provide data for total radiation budgeting.

All these missions will provide vital information for hydrologic budgeting, analysis and various applications in water resources.

For comparison of global data sets, where satellite remote sensing plays a vital role, procedures for geo-coding (including digital elevation models for a three dimensional correction), calibration, normalization and atmospheric correction, must be standardized.

The processing algorithms have to be adapted for more synthetic, integrative and automated analyses including contextual pixel analysis. In addition, digital photogrammetry, computer science and digital cartography should be integrated. Future interpretation systems (expert systems and Fuzzy systems) based on artificial intelligence with *a priori* expert knowledge stored in a database can then utilise the integrated findings to get at more enlightened decisions.

13 Conclusions

Remote sensing applications in different fields of water resources discussed in detail reveal the strong potential of use of remote sensing for water resources planning and management.

Studies have suggested that the use of remote sensing data in hydrology and water resources could yield very high benefit/cost ratios from savings in flood damage and in improved planning of irrigation and hydro electric production. Such applications are well suited for hydrologic modeling.

Active microwave remote sensing data from satellites offers the potential of (almost) all-weather application due to their penetration capabilities through clouds and shadows when compared to the optical sensors. However, the necessary algorithms are not universally applicable.

The current usage of remote sensed data in hydrologic modeling is relatively low. One reason is, most hydrological models in operational use are not designed to use spatially distributed data which is a prerequisite to the sensible use of remotely sensed data. Research is needed into the development of generalized algorithms and into the design of hydrological models more suited to the routine use of remotely sensed data. Another reason for the low usage of remotely sensed data in hydrological modeling is the lack of appropriate education and training. Operational agencies and consultants predominantly use traditional techniques. Potential users should be properly trained and appraised about the advantages of use of remote sensing.

Satellite remote sensing can also be an appropriate tool to help alleviate some of the hydrometric data collection and management problems facing many developing countries.

Progress in water resources research depends on the availability of adequate data for model development and validation. Remote sensing plays a vital role in this process and can address successfully some of the previously intractable problems. For the water resources applications, proper image processing of remotely sensed data and spatio-temporal analyses with GIS and a complete integration of image processing, GIS and GPS are necessary.

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