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Use of Remote Sensing for Parameterisation of Hydrological Models

N. Patidar[1], Ashok K. Keshari[2]
[1]PhD Scholar, [2]Professor, Department of Civil Engineering, Indian Institute of Technology, Delhi, India
Email: niteshpatidar88@gmail.com, akeshari@civil.iitd.ac.in

Abstract: With the advancement of earth observing satellites, remote sensing has become an important tool in monitoring and managing natural resources.Substantial research has been carried out in the field of hydrology to obtain wide range of information from remote sensing data. In particular, use of remote sensing data in estimating evapotranspiration, snow cover mapping, and flood-plain mapping, monitoring of sediment and water pollution and estimating soil moisture have been topics of intense interest during the past three decades. In the present paper, various remote sensing approaches to extract information for hydrological modelling are examined. Discussions are focused on the remote sensing data, land use and land cover (LULC) classification techniques and retrieval of leaf area index and surface albedo.The literature reviewsuggested that major approaches during the past decade include LULC classification using traditional pixel based approaches for hydrological modelling. In addition to this, there has been a lag between the development of techniques of land surface parameter determination from remote sensing and application of these techniques in hydrological modelling.

Key words: Hydrological modelling, land use and land cover, leaf area index and surface albedo.

1. Introduction

In the earlier days, estimations of the hydrological components such as runoff, evapotranspiration, soil moisture and groundwater with their spatial variability were challenging. With the advancement of the remote sensing technology, satellite-based remote sensing methods are now being widely used to capture the spatial variation in the hydrological variables. Remote sensing is the science of obtaining information about an object, area or phenomenon without any physical contact with the target. In remote sensing, the information is obtained through sensors which measure the Electromagnetic Radiation (EMR) reflected or emitted from the object. The EMR used in remote sensing is divided into different bands. The most import regions of the EMR in satellite remote sensing include visible (0.4–0.7 μm), infrared (0.7–100 μm) and microwave regions (0.1–100 cm). The visible and infrared bands are typically used in hydrology for snow cover mapping, water quality estimation, evapotranspiration estimation and land cover mapping. The microwave portion of EMR typically used for soil moisture and snow studies (Schmugge et al. 2002).

The remote sensing has been recognised as a useful tool in acquiring information in many fields of resources monitoring and management. Substantial research has been carried out in the field of hydrology to obtain wide range of information from remote sensing data. In particular, use of remote sensing data in estimating evapotranspiration, snow cover mapping, flood-plain mapping, monitoring of sediment and water pollution and estimating soil moisture have been topics of intense interest during the past three decades(Ahmad et al. 2010; Yang et al. 2013; Rittger et al. 2013; Bhavsar 1984; Jordan et al. 2014; Syvitski et al. 2012). Moreover, the recent advancement in remote sensing technology triggered the use of space inputs for the assessment of groundwater (Soni & Syed 2015) and streamflow (Hirpa et al. 2013). A major focus of remote sensing research in hydrology has been to develop approaches for,i) direct estimation of hydrological variables include evapotranspiration, soil moisture and snow cover, and ii) indirect estimation of these variables with the aid of hydrological models(Schultz 1996; Schmugge et al. 2002). The first method requires only the remotely sensed data for estimating hydrological components, whereas the second method utilizes remotely sensed data to parameterize hydrological models.The objective of this review is to address various techniques developed and remote sensing data requirements for estimating hydrological components.

2. Model parameter determination using remote sensing information

Estimation of runoff from RS data with the aid of hydrological model has become a common practice in hydrology. RS data have been typically utilized for hydrological model parameterization and as a model input. RS data particularly optical imagery have been widely employed to define vegetation and soil parameters(Dadhwal et al. 2010; Iroumé & Palacios 2013; Wagner et al. 2013; Raje & Krishnan 2012; Dams et al. 2013). RS based data precipitation, temperature and soil moisture etc. have been used as model inputs(Blyth 1993; Elga et al. 2015). The following section describes different RS data available and techniques to utilize RS data for hydrological modelling.

2.1 Remote sensing data

The various RS data are available which can be utilized to parameterize hydrological models. Selection of these data are subjected to spatial scale and purpose of the study. The RS data are typically used in the form of images to extract the land surface information to parameterize hydrological models. Based on spatial resolution, RS imagery can be broadly classified into high resolution (< 10 m), medium resolution (10-100 m) and coarse resolution (> 100 m; Weng 2012). Spatial resolution of the data defines the level of spatial detail depicted, and it is often related to the size of the smallest possible feature that can be detected from a RS image.The high resolution imagery are more appropriate when small features are of interest, whereas the coarse resolution imagery are suitable for larger coverage. The most widely used RS imagery in hydrological modelling is from Landsat satellite (e.g., Jordan et al. 2014; Carlson & Arthur

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2000; Chen et al. 2005). Due to continuous availability from 1972 to present, the Landsat imagery gained more attention as compared to other RSimagery.With the launch of high resolution satellites, such as IKONOS (launched 1999), QuickBird (2001), and OrbView (2003), great efforts have been made in the applications of these remote sensing images toextract land surface information. However application of theses imagery in hydrology is limited.

2.2 Land use and land cover extraction

Land Use Land Cover (LULC)information is needed for most of the hydrological models to define vegetation parameters. The extraction of LULC information from RS imagery is the most time and cost effective way, and therefore, is the most common practice in hydrological modelling. For LULC mapping multispectral RS images are typically utilized. The RS imagery are classified into LULC classes of interest using animage classification technique. A variety of image classification techniques have been developed, such as Maximum Likelihood (ML), Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Fuzzy Logic (FL), Spectral Unmixing (SU) and Object Based Image Analysis (OBIA).Selection of image processing method is the important step to get reliable information about LULC.Thepixel based ML classifier is the most popular classifier for LULC classificationfor hydrological modelling (e.g., Szuster et al. 2011; Sun et al. 2009; Aboel Ghar et al. 2004; Wagner et al. 2013).The ML classifier is a parametric classifier, relies on multivariate normality assumption. However, selection of training samples that satisfy the normality assumption is a challenging task (Myint & Lam 2005), and therefore, modern statistical learning classifiers such as ANN, RF and SVM can outperform the traditional ML classifier. Tang et al., (2012) compared five different classifier, including ML classifier, DT classifier, bagging classifier, RF and SVM classifier. They found that SVM is the most robust classier. Another challenge in RS image classification is the mixed pixel problem which arises due to high spatial heterogeneity. The mixed pixel problem can affect the classification accuracy significantly, particularly when medium (10-100 m) or coarse (> 100 m) resolution RS images are used(Weng 2012). In general, the mixed pixel problem is more noticeable in urban areas due to high spatial heterogeneity of urban composition(Wu 2004).Therefore, great efforts have been made to handle mixed pixels in RS image classificationthrough developingsub-pixel classification techniques. In sub-pixel classification, each pixel is assigned a class membership of each LULC type rather than a single class label (Wang 1990).A variety of sub-classification techniques have been developed, including fuzzy set theory, Dempster-Shafer theory, certainty factor (Bloch 1996),spectral mixture analysis (Ridd 1995; Roberts et al. 1998), neural network (Mannan & Ray 2003), and fuzzy support vector machine (Lin & Wang 2002). Because of its effectiveness in handling mixed pixel problem and easy implementation, spectral mixture analysis has been the most widely used techniques for urban LULC classification in recent years(Yang et al. 2010; Wu & Murray 2003; Kumar et al. 2015; Powell et al. 2007; Wu 2004; Somers et al. 2011; Okujeni et al. 2013).However, these spectral mixture analysis based applications share a common problem, that is, impervious surface tends to be overestimated in theareas with small amounts of impervious surface, but is underestimated in the areas with large amounts of impervious surface. The similarity in spectral properties among non-photosynthetic vegetation, soil, and various impervious surface materials makes it difficult to distinguish impervious from pervious materials. In addition, shadows caused by tall buildings and large tree crowns in the urban areas may lead to underestimation of impervious surface area with high resolution imagery. The advanced statistical learning techniques, including artificial neural network and support vector machines started to gain popularity in sub-pixel LULC mapping(Weng 2012). Application of these advanced sub-pixel classification techniques is very limited in hydrological modelling(Chormanski et al. 2008; Dams et al. 2013). The selection of the classification technique is of critical importance for the outcome of hydrological models. Ampe et al. (2012) evaluated the impact of classification methods, including pixel based mahalanobis distance classifierand multi-scale region-based classifier onhydrological model performance. Theydemonstrated that the uncertainty in LULC classification can significantly affect hydrological model performance. Dams et al. (2013) suggested that, sub-pixel classification techniquesare better than pixel based classification techniques for hydrological modelling of urban catchments.

2.3 Derivation of albedo values

Land surface albedo is defined as that fraction of the incident solar radiation in the 0.4-2.5 µmspectrum domain which is reflected by the land surface.Surface albedo is a key parameter in hydrological models for energy budget calculations. It is an important parameter in understanding soil-water-plat-atmosphere relationships(Bonan 2008), affecting evapotranspiration, thus ultimately impacting hydrological cycle. Due to spatio-temporal variations in land surface and illumination conditions, albedo is highly variable in space and time domain. The increasing use of distributed hydrological models makes it essential to derive albedo with spatial variations. Remote sensing allows to derive accurate and spatially distributed albedo(Franch et al. 2014).There are various albedo products available which are derived from remote sensing data, including the Moderate Resolution Imaging Spectroradiometer (MODIS, Schaaf et al. 2002), the Advanced Very High Resolution Radiometer (AVHRR, Csiszar & Gutman 1999), and the Polarization and Directionality of the Earth Reflectance (POLDER,Maignan et al. 2004). In addition to this, albedo can be derived from Landsat imagery, which has the potential to provide medium resolution (30 m) images (Franch et al. 2014). For this, the digital numbers of Landsat images are typically converted to land surface reflectance, which is assumed equivalent to surface albedo (Gratton et al. 1993; Bach et al. 2003).

2.3 Derivation of leaf area index

The Leaf Area Index (LAI) is a key vegetation biophysical parameter, it is a dimensionless variable and defined as ratio of leaf area to per unit ground surface area. In hydrological models, LAI is an important parameter affects estimation of evapotranspiration and interception, and thus impacts other water balance components such as runoff and groundwater recharge. Estimation of LAI from remote sensing allows to study spatio-temporal variations in various water balance components(Dadhwal et al. 2010). The LAI is highly correlated to vegetation indices such as Normalized Difference Vegetation Index (NDVI). Therefore, NDVI has been widely utilised to estimate LAI in remote sensing community (Tripathi et al. 2014; Zheng & Moskal 2009).The NDVI is estimated from Near Infrared(NIR) and Red bands using the formula: NDVI= (NIR-Red)/(NIR+Red). The LAI can be estimated using the algorithm proposed byMyneni et al. (1992), which is LAI = a×exp(b×NDVI+c). Where the coefficients a and c are determined based on land cover type, soil type, and the NDVI, and b is a constant (~ 1.2).

3. Conclusions

Remotely sensed data have wide applications in hydrology and water resources management. In contrast to in-situ measurements, remote sensing techniques provide better spatial distribution, better coverage and a more convenient way for water resources monitoring and management. The application of remote sensing in hydrology ranges from simple resources mapping to the complex decision making. In the present paper various remote sensing techniques which can be utilizedin hydrological modellingto improve modelling performance are reviewed. The review of remote sensing based hydrological modelling studies indicated that, there has been significant lag between the development of advanced LULC classification and land surface parameter determination techniques and application of these techniques into hydrological modelling.

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