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Streamflow modelling by remote sensing: A contribution to digital Earth

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Abstract. Remote sensing contributes valuable information to streamflow estimates. This paper discusses its relevance to the digital earth concept. The authors categorize the role of remote sensing in streamflow modelling and estimation. This paper emphasizes the applications and challenges of satellite-based products in streamflow modelling. Importance and application of streamflow models is firstly described. Then, different classifications of models, modelling processes and several uncertainties sources that affect models prediction are explained. In addition, we explore the advantages of satellite precipitation estimates in modelling, uncertainties in remotely sensed data and some improvement techniques. The connection, relationship and contribution of remote sensing for streamflow modelling to digital earth principle are identified. Finally, we define and illustrate the future directions and necessary developments of streamflow measurement by remote sensing.

1. Introduction

The concept of Digital Earth originates from US vice president Al Gore who, in 1998, integrated and connected digital knowledge with the virtual representation of Earth [1]. Applications of this concept in the hydrology cycle can give a better representation and understanding of the streamflow information. Reliable streamflow measurement is important for water resources management for future planning and economic development strategies.

Traditionally, streamflow is directly measured through manual or automated ground based instruments installed within a monitoring station. However, sparse hydrological monitoring networks and not enough available ground station create problems in many regions, especially developing countries [2]. To overcome the limited reliable hydrology data problem, satellite remote sensing is a suitable way or even the only way to acquire information for data-scarce areas.

The contribution of remote sensing in providing sub-daily basis, continuous and economic hydrometeor data sets regardless of international borders has been well proven and recognized. The authors classify the roles of remote sensing in obtaining streamflow information into two main groups as illustrated in Figure 1: (1) streamflow modelling – remotely sensed data as "input" for a hydrological model [3,4], and (2) streamflow estimation – estimation of streamflow by remote sensing data alone without usage of any hydrological model [5].

Unlike other previous papers that review the usage of satellite imagery in general hydrology application [3,4], we focus on reviewing the applications and challenges of remote sensing in streamflow modelling which is useful for researchers, engineers or water resources managers interested in this topic. Besides that, reflecting recent advances, this paper places more emphasis on remotely sensed data uncertainties and approaches to handling "input" uncertainties of streamflow modelling which is less explored in hydrological applications. Moreover, this paper identifies the dedication of the digital earth concept to streamflow information extraction that is crucial in water resources management.

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The importance of streamflow information is briefly discussed in section two. Several remote sensing applications in streamflow modelling are described in section three. The main input parameter to model, i.e., precipitation, its uncertainties, improvement technique and future directions are discussed in section four. In section five, the contribution of remote sensing in streamflow estimates to digital earth are concisely defined. Based on this broad review, we concluded with several recommendations for future studies in section six.

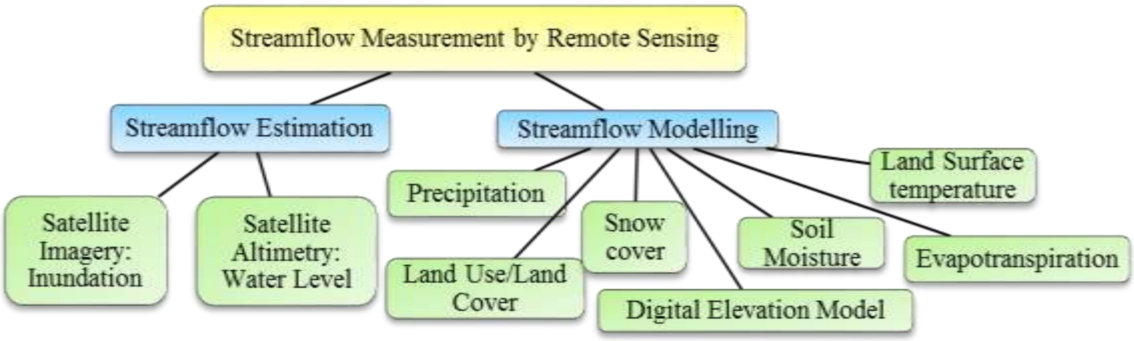

Figure 1. Role of remote sensing in streamflow measurement.

2. Importance of streamflow modelling

Streamflow modelling plays a vital role in water resources management including (1) assessing the impact of past, ongoing and future climate or land use change; (2) operational purposes like flood forecasting, dam and hydroelectric management; (3) integration with other models for advances studies such as designing flood or drought control structures using a hydraulic model, water quality assessment from nutrient transport models, fishery related models for aquatic life evaluation; (4) prediction in ungauged basin (PUB) by generating flow data at basins without monitoring station; and (5) scientific enquiry to improve our understanding of hydrological processes at specific regions [6].

Flood is one of the most destructive natural disasters that bring a lot of damage to people. Streamflow information is very important in flood maps production for flood prevention work. The integration of streamflow and hydraulic model with geographical information system (GIS) is very common in flood mapping [7]. The modelling chain starts off with pre-processing the terrain and climatic input parameter with GIS and then applies into a streamflow model. Next, the results are used as input to hydraulic modelling to simulate the flood wave along the drainage system. Finally, the flood map is produced using GIS with water level information from the hydraulic model. Flood hazard mapping by a fully continuous hydrologic-hydraulic modelling framework was conducted at the Rio Torbido catchment in central Italy. It indicated a good performance with implemented automatic procedures [8].

The International Association of Hydrological Sciences (IAHS) has launched an initiative of PUB to improve performance of hydrological model in ungauged basins [9]. The model simulated river flow data at ungauged basins especially at hilly or forested areas. This is critical for water resources planning purposes. PUB is preliminary depending on data from gauged basins that can be applied in ungauged basins through an extrapolation technique. A successful evaluation of the PUB performance was done at Upper Mississippi River Basin (UMRB) in the United States by using a streamflow model, the Soil and Water Assessment tool (SWAT) [10].

River pollution that leads to a water security problem is a common issue in many countries. Water quality assessment can be done by using several streamflow models such as SWAT, Hydrologic Simulation Program-Fotran (HSPF), Storm Water Management Model (SWMM) and others. These models are able to simulate the impact of urbanization, deforestration, agriculture and industrialization waste on rivers and helps in water quality improvement planning. Lee et al, (2010) [11] reported the estimation of pollution loading: biochemical oxygen demand (BOD), total nitrogen (TN), total phosphorus (TP) using HSPF and SWMM to investigate the urbanization effect on water quality in the Nogok watershed in Korea.

3. Streamflow model and sources of uncertainty

Streamflow model is a mathematical computational model of hydrology processes digitally converting weather variables and topography conditions into river flow information [6]. Many papers providing detailed descriptions of modelling approaches which are categorized from an empirical to a physical model structure; lumped to fully distributed (spatial); and event to continuous (time) based models [6,12, 13]. Commonly, the selection of a suitable model is highly depending on the aim of the project and data availability. For example, the long-term analysis of streamflow studies requires continuous based model, which is enables to simulate in continuous simulation of a series of rainfall that incorporates more than one storm event.

After selection of appropriate model, pre-simulation will be conducted with the use of collected data sets in the model. Then, model calibration is performed by selecting suitable values of model parameters to achieve a close imitation of the real hydrological regime of the watershed using in-situ discharge data sets. Validation takes place after calibration with different period of same in-situ data sets to test the model performance. Uncertainty analysis is a process that comes along with calibration to identify and reduce errors that arise during modelling and includes three main phases: understanding, quantification and reduction [12]. Sources of uncertainty are natural uncertainty, data uncertainty, model parameter uncertainty and model structure uncertainty [12]. In this paper, we are concerned about data uncertainty which is a result of errors in input variables that can be generated by remote sensing technology, such as rainfall, temperature, evapotranspiration and so on. Given that rainfall is the most vital input parameter that directly influences the result of simulation [14, 15], so this paper only reviews the aspects of rainfall in the streamflow modelling.

4. Remotely sensed precipitation uncertainties and its improvement

Generally, remote sensing offers hydrological components information or so-called “input” parameters as shown in Figure 1 in digital form for streamflow modelling. The main advantage of space based “input” is providing continuous, huge coverage and free or low cost data to users. However, its accuracy is often not well known. So how can it be used to solve the hydrologic problem especially in the context of PUB? This section focuses on a detailed discussion of the main “input” parameter in modelling, precipitation, its uncertainties and improvement techniques that may contribute to a better understanding of hydrological processes.

Precipitation is the most important “input” to any hydrological model. The reliability and accuracy of such data are always cited as serious impediments and crucial to successful modelling [14, 15]. The spatial and temporal variability of rainfall, sparse rain gauge distribution, monitoring station conditions, mountainous terrain, sensor errors and other problems could contribute to inaccuracies of precipitation data and may not represent the overall basin condition. Remote sensing provides an alternative approach for precipitation retrieval to perform streamflow modelling. Generally, publicly available precipitation products can be classified in four major groups: rain gauge data, single satellite sensor, multiple satellite sensors and combination of multiple sensors with gauge data [15]. Table 1 lists precipitation data sets that can be freely assessed and downloaded through Internet.

Generally, satellite based precipitation extraction is performed by (1) visible (VIS) or infrared (IR) sensor; (2) passive (PM) and active microwave (AM) method; (3) merging of IR and microwave data; and (4) precipitation radar (PR) [15]. Remote sensing technology has improved in the last decade, but its estimation also brings some degree of uncertainty. We can examine the impact of precipitation uncertainties and choose the best products. Hence, the authors recommend two main steps: (i) precipitation products evaluation for the identification of uncertainties and (ii) an error reduction procedure such as downscaling, calibration, and interpolation merged data. These steps should be carried out to improve the quality of modelling.

Although the evaluation can be only conducted in areas where reliable ground-based rainfall gauge data or preferably radar data exist, such evaluation result will give users a general idea of uncertainties associated in satellite precipitation product for further applications. For instant, Duan et al. (2012) [16] found that version 6 TRMM 3B43 and 3b42 data were reliable (relative RMSE larger than 50%) in the Caspian Sea Region in Iran for most months and years during the period 1999-2003. Dinku et al. (2007) [17] evaluated performance of 10 different satellite rainfall data sets and divided them into two main group: (1) low spatial (2.5^{o}) and temporal (monthly), and (2) high spatial (0.1^{o}-1^{o}) and temporal (3 hourly to 10 daily) resolution over Ethiopia in Africa and found that average RMS for both groups are 28% and 46%, respectively. Downscaling improve the coarse spatial resolution of precipitation product to finer scale. Readers are referenced to e.g. Duan and Bastiaanssen (2013) [18] for the procedures for downscaling and calibration of satellite precipitation products,

The application of satellite precipitation data for hydrological purposes is still very limited [19]. Evaluation of reliability and performance of different satellite precipitation data sets on hydrology processes studies should be conducted continuously in order to promote and assess applicability of those products for streamflow prediction in sparse data areas. There should be a motivation to improve quality of precipitation retrieval techniques. Behrangi et al. (2011) [19] evaluated the performance of several satellite precipitation products a) TRMM Multi-satellite Precipitation Analysis real time (TMPA-RT); b) TMPA bias adjusted (TMPA-V6); c) Precipitation Estimation from Remotely Sensed Information Using Artificial neural Network (PERSIANN); d) PERSIANN bias adjusted (PERSIANN-adj); e) Climate Prediction Center morphing algorithm (CMORPH) for streamflow modelling over Illinpis River Basin in United State. The result indicated that all products generate good simulation at sub-daily and monthly time-scale whereas bias adjustment products decrease the overestimation of both, simulated streamflow and input precipitation problems.

Different interpolation techniques for the production of precipitation data lead to uncertainties in streamflow modelling, therefore the identification of the most suitable approach is necessary. The impact of an interpolation error can be tested by generating ensemble streamflow. Ensemble modelling is a technique to combine a series of base model simulations to produce more accurate results. Hwang et al. (2011) [20] investigate the impact of precipitation uncertainty at Animas and Alapaha in United State by applying ensembles of daily precipitation into Precipitation Runoff Modeling System (PRMS). A similar study was piloted at Pipiripau River basin in Brazil by integrating an ensemble of different sources of precipitation data sets into SWAT [21]. Both studies show that ensemble modelling of precipitation products works well for the improvement of streamflow simulation.

Precipitation products comprise high spatial variability problems that lead to uncertainties [21]. There are two methods to reduce the space based spatial variability problem which are calibration and downscaling techniques [18]. Meteorological variables generated in coarse resolution by global climate change models (GCMs) are usually fed into a hydrological model to evaluate the impact of future climate on water resources. Application of GCMs as input to streamflow model is a source of large uncertainties [22], so GCMs should be downscaled first before used for impact studies. Downscaling can be done either with a statistical method (SD) that develops a statistical relationship between local variables and GCM climate information or with a dynamic approach (DD) which employs regional climate models (RCMs) [23]. An assessment of the effectiveness of three statistical techniques: (1) a multi-objective fuzzy-rule-based classification (MOFRBC), (2) an analog method (AM), and (3) the statistical downscaling model (SDSM) has been carried out to downscale precipitation from GCMs for Vattholmaån River basin in southeastern Sweden. The authors concluded that SDSM provide the best downscaled precipitation [22].

Table 1. Freely available global satellite precipitation data sets that can be used in streamflow modelling (modified from Tapiador et al., 2012 [15]).

Class	Products	Spatial/ Temporal	Period/source
Single sensor	GPROF2010(TMI)	0.25°/daily,monthly	1997-now/[1]
	TRMM PR	0.5°/hourly	1997-now/[2]
	HOAPS-3(SSM/I)	0.5°/mothly	1987-2008/[3]
	GPROF2010(AMSR-E)	0.5°/daily	2002-now[4]
Multiple sensors	CMORPH	8km/30min	1998-now/[5]
	TRMM 3B41RT	0.25°/ hourly	2005-now/[6]
	TRMM 3B42RT	0.25°/3 hourly	2005-now/[7]
Multiple sensors plus gauges	CMAP	2.5°/daily	1979-now/[8]
	GPCP one degree daily	1°/daily	1997-2009/[9]
	TRMM 3B42	0.25°/Daily	1998-now/[10]
	TRMM 3B43	0.25°/Monthly	1998-now/[10]

5. Contribution to Digital Earth

Digital Earth (DE) is defined as a multi resolution, three-dimensional representations of the Earth [1]. Al Gore induced the appearances of Google Earth and Bing map application that integrate vast amounts of geo-referenced data. Nowadays, "the global sustainability" concept should inject into DE to fulfill the challenge of the world 2020 [24]. This review provides contributions to DE in three aspects: data, representation and environment.

The free availability of geo-referenced data is a main concern of DE [1, 24, 25]. Remote sensing acts as the best tool in supplying vast amount of information about the Earth, but not all satellite images are available to the public, in particular the high resolution imagery. This paper provides several free sources for the input parameters that are necessary in the streamflow modelling. In order to improve our understanding of the environment that we live in, data sharing of satellite-based data collection should become common practice.

Gore (1998) claimed that DE is the digital representation and cognition of the real Earth. The satellite sensor captures an image of the earth's surface. Experts transform the image into useful hydrology components such as precipitation and evaporation in a digital form [4]. Multi sensor satellites provide images in the visible to microwave domain. This increases the interpretation capabilities and information on the environment. Therefore, water cycle systems can be represented in a virtual form, either at a global or regional scale.

The main application of remote sensing in DE is monitoring the environment where rapidly retrieval of earth information gives advantages to monitoring the global change using various simulation models [26]. The global environmental issue related to the water crisis such as water resources scarcity and water pollution has global consequences. Here, remote sensing can assess these changes rapidly and provide the necessary information to the public directly through the social network to increase the awareness. Furthermore, long term climatic information retrieved from remote sensing data may be integrated into streamflow models for flood forecasting or climate change assessment as mentioned in section two.

6. Conclusion and future directions

"Sustainability" has become a popular word that reminds humans to stop destroying their environment. Streamflow information is important for the investigation of aquatic life ecology, flood hazard and water quality which have a direct connection to the health of our environment. High quality of long term streamflow information lead to better water resources management, protection and restoration through the sustainable management of natural resources.

In future work, more input parameters and a detailed review of streamflow estimation will be included in a paper as a primer for scientists, educators, water resources engineers and managers who are new and interested in the topic. Besides that, more freely assessable satellite "input" parameters are important to improve understanding of hydrological processes. Therefore, efforts on making satellite products available and giving experts the opportunity to transform them into information which is easily usable to streamflow modelling should be a major concern of DE.

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Data uncertainties related to remotely sensed products cause misleading uncertainty prediction in hydrological model results. Consequently, it is important to integrate addition parameters, such as soil moisture, digital elevation model and evapotranspiration. These parameters help to reduce data uncertainties for satellite retrieved information that enters the hydrological model. A Framework development and advances in understanding streamflow should be carried out to assess the impact of data uncertainties on streamflow simulations. Generally, data uncertainty could be reduced by three major steps: a) selection of better quality input data; b) improvement of selected data by calibration and downscaling; and c) establishment of approaches to extract and assimilate information from available data through the model identification processes [27].

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