Microwave Satellite Data for Hydrologic Modeling in Ungauged Basins

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***Abstract*—An innovative flood-prediction framework is developed using Tropical Rainfall Measuring Mission precipitation forcing and a proxy for river discharge from the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) onboard the National Aeronautics and Space Administration's Aqua satellite. The AMSR-E-detected water surface signal was correlated with *in situ* measurements of streamflow in the Okavango Basin in Southern Africa as indicated by a Pearson correlation coefficient of 0.90. A distributed hydrologic model, with structural data sets derived from remote-sensing data, was calibrated to yield simulations matching the flood frequencies from the AMSR-E-detected water surface signal. Model performance during a validation period yielded a Nash–Sutcliffe efficiency of 0.84. We concluded that remote-sensing data from microwave sensors could be used to supplement stream gauges in large sparsely gauged or ungauged basins to calibrate hydrologic models. Given the global availability of all required data sets, this approach can be potentially expanded to improve flood monitoring and prediction in sparsely gauged basins throughout the world.**

***Index Terms*—Digital elevation models (DEMS), distributed hydrologic modeling, floods, passive microwave sensors, satellite remote sensing.**

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I. Introduction

Globally, sparse *in situ* hydrometeorological networks are the main source for quantitative water resource management. Over the past half-century, hydrologic analyses such as flood and drought risk assessments have been dependent on these *in situ* data sources. Hydrologic runoff models and land surface models are typically driven by observations of rainfall to predict hydrologic extremes. Therefore, adequate observations of hydrologic variables play a critical role in water resource planning and management. Unfortunately, large areas of the Earth's surface lack *in situ* observations that impede accurate quantification of the water budget. Many nations are sparsely gauged, and in some countries, existing measurement networks are declining [1]–[4]. Evidently, the lack of *in situ* observations limits the implementation and calibration of hydrologic models for early warning and decision-making systems in these regions.

To address the limited-data-availability issue in ungauged regions, the International Association of Hydrological Sciences launched research efforts such as the Predictions in Ungauged Basins (PUB) initiative in 2003. One of the PUB science objectives is to integrate remote-sensing data into hydrologic models [5]. More recently, several efforts have been directed on the use of widely available satellite remote-sensing data to complement *in situ* hydrologic observations over vast ungauged regions. Several studies proposed the optimal use of satellite precipitation products for flood prediction [6]–[11]. The advantage of these precipitation data sets is the global availability over regions where ground networks are nonexistent. In addition to satellite precipitation, efforts are under way to monitor changes in river discharge remotely from space.

At present, river discharge cannot be estimated directly from satellite sensors. Remotely observable hydraulic variables such as water level height, width, sinuosity, and area are used to approximate river runoff. Recently, passive microwave sensors have been used to detect river discharge changes. Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) brightness temperatures at 36 GHz and H-polarization have been used to detect floods around the world [12]. This technique relates changes in brightness temperature between wet measurement pixels (M) centered over rivers and dry calibration pixels (C) that are not affected by the river. River flooding is detected by comparing a signal from the wet pixels and that from a nearby calibrating pixel [13], therefore generalizing the technique to make it applicable everywhere, using microwave data from both AMSR-E and Tropical

Rainfall Measuring Mission (TRMM). This technique is used for flood detection and mapping [14] but not for flood forecasting. Some studies revealed the application of the AMSR-E sensor for discharge estimation [5], [11], [15], [16]. Furthermore, there are ongoing efforts to use altimeter and soil moisture data for inland water level and discharge estimation from space [13], [17]–[19].

In this letter, a novel framework is developed by integrating microwave satellite remote sensing along with rainfall estimates from TRMM into a distributed hydrologic model for flood early warning in data-poor regions. This proof-of-concept study proposes a hydrologic prediction system that is based entirely on observations from remote-sensing platforms. The data sets required to set up the model (i.e., digital elevation model, soil types, land use, evapotranspiration, etc.) all are remotely sensed data available in public domains. As such, the applicability of the method and, thus, the capability to provide flood estimates are potentially global. The impetus is to use the AMSR-E brightness temperature to detect surface water changes and to calibrate a hydrologic model. The proxy discharge is the ratio of brightness temperatures of a wet pixel and a dry pixel, more frequently referred to as measurement (M) and calibration (C) area [12], a proxy for river water surface change. The Dartmouth Flood Observatory's River Watch and the Global Flood Detection System (GFDS) of the Joint Research Centre of the European Commission are using this M/C ratio globally for flood detection [14], [20]. We propose to employ the AMSR-E-detected water surface signal (M/C ratio) to benchmark a distributed hydrologic model, for the first time, to estimate floods in ungauged basins.

II. Data, Model, and Framework

A characteristic feature of the framework is the utilization of the AMSR-E-based water surface signal instead of measured river runoff to calibrate a hydrologic model. The Coupled Routing and Excess Storage (CREST) [18] is a distributed model that computes the runoff generation and flow routing processes. The model runs on a user-specified time step and is composed of soil moisture storage, runoff generation, and a flow routing routine. A brief summary of the model components is outlined as follows: 1) data flow module based on cell-to-cell routing; 2) three different layers within the soil profile that affect the maximum storage available in the soil layers (this representation of within-cell variability in soil moisture storage capacity and within-cell routing can be employed for simulations at different spatiotemporal scales); and 3) coupling between the runoff generation and routing components via feedback mechanisms [9], [18]. The CREST model is composed of modules enabling daily estimation of evapotranspiration, soil water content, flow routing, and flow generation within a cell, through the drainage network. The *a priori* values of the physical parameters are derived from geomorphological characteristics from remotely sensed and *in situ* data.

The CREST model uses digital elevation data processed from the Shuttle Radar Topography Mission [21] to generate flow direction, flow accumulation, and contributing basin area. The key forcing data sets are the satellite precipitation

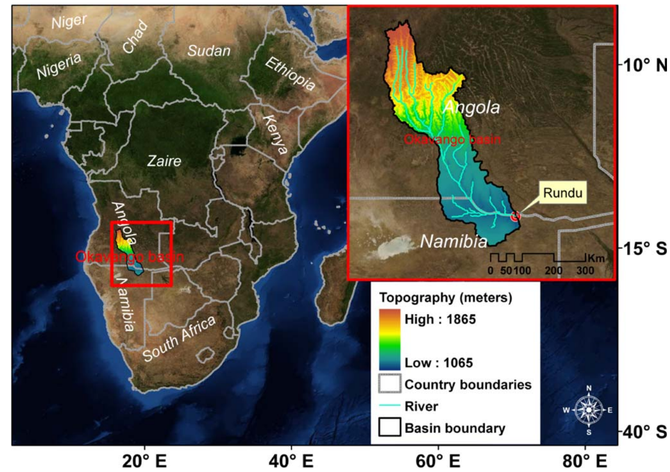

Fig. 1. Upper Okavango Basin with the Okavango River spanning Angola and Namibia. Location of the stream gauging station at Rundu, Namibia.

product from the TRMM Multisatellite Precipitation Analysis (3B42RT) [22] and evapotranspiration from the Famine Early Warning Systems Network (http://earlywarning.usgs.gov/fews/global/index.php). The hydrologic model can be calibrated in many ways, but the method employed herein is an autocalibration technique based on the simple but robust adaptive random search (ARS) method [23], [24]. The CREST model structure and calibration description are detailed in [18], [25], and [26].

The geophysical characteristics such as the low elevation and land cover have a substantial influence on the hydraulic roughness in floodplains. Meteorological parameters, primarily precipitation in the upstream catchment, control the inflow, while precipitation and evapotranspiration over the delta itself contribute to more spatially distributed water availability and to the recharging of the ground water [27]. The general hydrology of the Okavango Delta has been described in the literature [18], [21], [27], [28], and application of satellite remote-sensing techniques for flood monitoring has been discussed in [26] and [29]–[31]. The Okavango River flows through Angola, Namibia, and Botswana, with the predominant runoff-contributing areas coming from Angola [28]. The hydrologic model was implemented in the upper part of the Okavango Basin in Southern Africa (Fig. 1), which is representative of many poorly gauged and ungauged basins. River discharge data were used to evaluate the performance of the proposed method from the Rundu telemetry station, with an upstream catchment area of 95 642 km^2, located on the main stem of the Okavango River (Fig. 2).

III. Satellite-Based Flood Frequency Approach

Flood-monitoring techniques are developed based on the relationship between soil moisture and runoff for other catchments in Africa [29], [32] and also used for hydrologic prediction [33]. Typically, hydrologic models are calibrated from streamflow observations at the basin outlet. We propose to use the satellite-based surface water fluctuation signal to calibrate a hydrologic model. The AMSR-E-based GFDS monitors water surface signal at 10 000 monitoring areas around the world

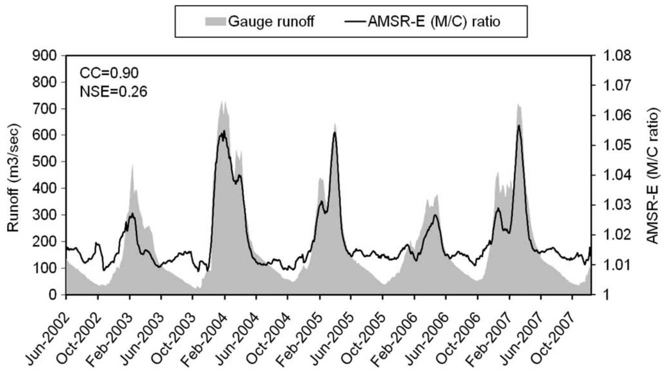

Fig. 2. Time series of (black line) AMSR-E-detected water surface signal (M/C ratio) and (shaded area) gauged runoff.

(http://www.gdacs.org/flooddetection/). The sensor can provide discharge signal at multiple locations in a catchment and thus can reduce the dependence on gauged runoff to calibrate hydrologic models at the basin outlet. This approach is applied to medium- to large-size basins; however, the accuracy of the AMSR-E-based GFDS for basins with drainage areas lower than 50 000 km^2 needs further investigation.

The AMSR-E-detected water surface signal correlated closely with the observed runoff with a correlation coefficient (CC) of 0.90 from 2002 to 2007 at Rundu, upper Okavango Basin in Namibia (Fig. 2). The AMSR-E-detected water surface signal (M/C ratio) captures high flow peaks each year; however, the signal is insensitive to discharge fluctuations during low flows. In this study, we used the observed discharge data to calibrate the CREST model [Fig. 3(a)]. Next, we designed a model calibration strategy for flood prediction (i.e., for high flows) that readily accommodates the AMSR-E-detected water surface signal. The method was designed with the realization that the AMSR-E signal provides no direct information about discharge magnitude but is highly correlated with observed discharge for significant flows.

The calibration method, called the flood frequency approach, first requires the conversion of model-simulated flows to daily exceedance frequencies. A time series of simulated flows was generated for the precipitation period of record, which was 2002–2007 in our case. Then, we performed a flood frequency analysis on the continuous record of streamflow simulations to estimate flood magnitudes and associated return periods. This flood frequency approach using a distributed hydrologic model has been shown to improve the accuracy of flood prediction in ungauged basins and can remove model bias [34], [35]. The novelty of the approach presented herein is that we can calibrate the model by integrating proxy discharge observations using the AMSR-E signal.

The time series of the AMSR-E-detected water surface signal was converted to frequencies in the same manner as the simulations, i.e., by computing the daily exceedance frequency (or probability) based on the period-of-data-flow exceedance curve (or flow duration curve). In this way, frequencies computed from CREST model simulations are directly comparable to those computed from the AMSR-E discharge signal. The ARS calibration method was from 2002 to 2005 to optimize model parameters so that simulated flow frequencies

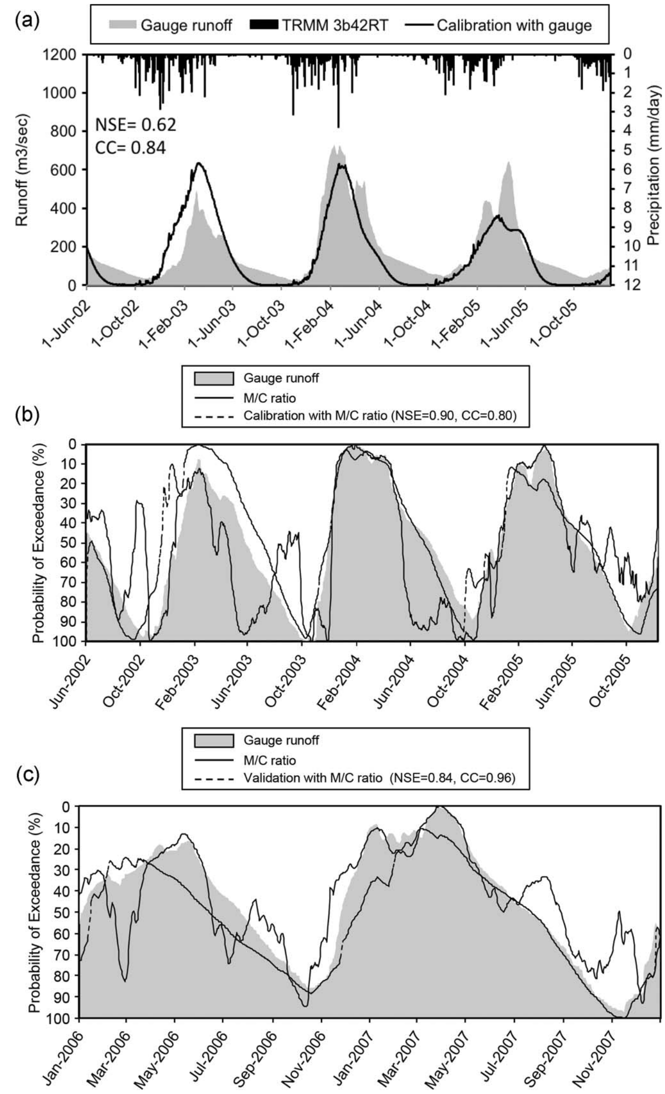

Fig. 3. (a) (Shaded area) Observed gauge runoff, TRMM sensor precipitation, and (solid line) CREST model calibration. (b) (Shaded area) Observed gauge runoff, (solid line) M/C ratio, and (dashed line) exceedance probabilities of CREST calibration using M/C ratio. (c) [same as (b)] for CREST validation period.

matched the frequencies observed from the AMSR-E discharge signal. Results during the calibration period of 2002–2005 show good agreement in the frequency domain between the AMSR-E-detected water surface signal and observed flows with a probability of exceedance $< 25\%$, including peak flows [Fig. 3(b)]. The CREST model calibrated with the AMSR-E-detected water surface signal (i.e., M/C ratio) also agreed well with the time series of observed flow frequencies according to a Nash–Sutcliffe efficiency (NSE) of 0.90 and a CC of 0.80 [Fig. 3(b)]. The high NSE value is partly due to the strong seasonality of discharge.

The hydrologic model was able to represent the behavior of low flows better than the AMSR-E observations due to its use of physical principles. Fig. 3(c) shows the results during the validation period from 2006 to 2007. Similar to the results obtained during calibration, the AMSR-E signal matched the observations very well for high flows with a probability of exceedance $< 25\%$. The detected water surface signal is prone to random errors for low flows, i.e., those with greater probabilities of occurrence. However, when the AMSR-E-based discharge signal was used to calibrate the CREST model, the low flows were much more accurately simulated.

Overall, the AMSR-E-calibrated CREST model had an NSE of 0.84 and a CC of 0.96, indicating that the model parameters estimated from the flood frequency approach are applied well to the validation period. It is noted that the model underestimated the magnitude of the peak flows with the lowest probability of exceedance. Given the limitations of the AMSR-E signal as it relates to the observed water surface signal combined with hydrologic model error, it is suggested that the developed approach be implemented by considering thresholds for probability exceedances. For instance, the model is skillful in predicting the occurrence and nonoccurrence of rare events, i.e., those that occur $< 25\%$ of the time. This binary approach to flood prediction will be very useful to providing simple flood-versus-no-flood estimates to any basin where the AMSR-E signal corresponds (i.e., covaries) with observed discharge.

IV. Discussion and Future Work

This proof-of-concept study demonstrated the efficacy of satellite remote-sensing data for flood prediction in poorly gauged basins. In particular, a distributed rainfall–runoff model calibrated with unconventional data using a flood frequency approach was shown to implicitly simulate the basin's runoff response to rainfall. Moreover, the geophysical and hydrologic parameters for the Okavango Basin are derived from the remote-sensing data. The remotely sensed data products can thus be used to condition different parameters, and equifinality of the parameter set can be minimized. The study has thus demonstrated the capability to set up a distributed hydrologic model and calibrate its parameters using forcing from rainfall and proxy discharge without the need for any *in situ* measurements. The Okavango study basin had the benefit of a stream gauge, so we were able to validate the hydrologic model simulations and thus demonstrate the flood frequency calibration approach using TRMM rainfall and the AMSR-E-detected water surface signal. Although the NSE and CC are high and the differences between the CREST model results are not substantial, it remains difficult to interpret the results due to the uncertainties that result from model and input data uncertainties. Thus, further research should focus on how to evaluate the remote-sensing flood frequency approach with model and input data errors in different smaller basins worldwide under a variety of hydroclimatic and land cover conditions. Future work should also benchmark model performance by comparison to a model that was calibrated conventionally using observed discharge from stream gauges. It is envisioned that near-future satellite missions such as the Soil Moisture Active and Passive mission [31] for global soil moisture, the Surface Water and Ocean Topography mission for river discharge estimates [36], and the Global Precipitation Measurement mission [37] integrated into the proposed framework will materialize into operational flood-prediction systems in ungauged regions of the world.

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