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Measuring water availability with limited ground data: assessing the feasibility of an entirely remote-sensing-based hydrologic budget of the Rufiji Basin, Tanzania, using TRMM, GRACE, MODIS, SRB, and AIRS

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Abstract:

This study explores the feasibility of an entirely satellite remote sensing (RS)-based hydrologic budget model for a ground data-constrained basin, the Rufiji basin in Tanzania, from the balance of runoff (Q), precipitation (P), storage change (ΔS), and evapotranspiration (ET). P was determined from the Tropical Rainfall Measuring Mission, ΔS from the Gravity Recovery and Climate Experiment, and ET from the Moderate Resolution Imaging Spectroradiometer, the surface radiation budget, and the Atmosphere Infrared Radiation Sounder. Q was estimated as a residual of the water balance and tested against measured Q for a sub-basin of the Rufiji (the Usangu basin) where ground measurements were available ($R^2 = 0.58$, slope = 1.9, root mean square error = 29 mm/month, bias = 14%). We also tested a geographical information system (GIS)-driven (ArcCN-runoff) runoff model ($R^2 = 0.64$, slope = 0.43, root mean square error = 39 mm/month). We conducted an error propagation analysis from each of the model's hydrologic components (P, ET, and ΔS). We find that the RS-based model amplitude is most sensitive to ET and slightly less so to P, whereas the model's seasonal trends are most sensitive to ΔS. Although RS–GIS-driven models are becoming increasingly used, our results indicate that long-term water resource assessment policy and management may be more appropriate than 'instantaneous' or short-term water resource assessment. However, our analyses help develop a series of tools and techniques to progress our understanding of RS–GIS in water resource management of data-constrained basins at the level of a water resource manager. Copyright © 2012 John Wiley & Sons, Ltd.

KEY WORDS remote sensing; hydrologic budget; Rufiji; Usangu; runoff; AIRS; SRB; TRMM; GRACE; MODIS

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INTRODUCTION

Remote sensing (RS) and geographical information systems (GIS) have emerged as a potentially useful water resource management tool. As RS capabilities have increased, GIS has improved as a decision support tool with the necessary resolution and repeatability to manage and map water resources (Rao and Kumar, 2004). A combined RS–GIS approach facilitates data integration, allowing for improved cross-basin management strategies (Georgakakos, 2004; McDonnell, 2008), and these approaches have already proven beneficial in a variety of contexts (Bevis *et al*., 1992; Kustas and Norman, 1996; Alsdorf *et al*., 2000).

However, RS–GIS tools are limited in capacity by quality and data availability. Satellite sensors often have limited spatial, temporal, and spectral resolutions, and atmospheric conditions can further degrade their accuracy (Moran *et al*., 1997; Benz *et al*., 2004; Campbell, 2006). These limitations have largely restricted RS–GIS in hydrological studies to regional or large-basin scales and only to portions of the hydrological budget (Schultz, 1994; Quattrochi and Goodchild, 1997; Schmugge *et al*., 2002).

In recent years, the reliability of satellite products has greatly improved, mitigating some of these data limitations. Changes in total water storage are measurable through satellite mass-based approximations of total water thickness to a precision of centimetre per month (Syed *et al*., 2008). Precipitation is measurable through multiple post-processing phases of currently available satellite data (i.e. Tropical Rainfall Measuring Mission, TRMM) to a resolution of millimetre per day (Huffman *et al*., 2007). New RS-based evapotranspiration products are also being released and evaluated (Jiménez *et al*., 2011; Vinukollu *et al*., 2011).

With these recent satellite products now online, it is theoretically possible to measure the entire water budget of a large basin only using RS–GIS. This is so recent of a possibility that few studies have demonstrated this possibility empirically (Sheffield *et al*., 2009; Wagner *et al*., 2009;

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Gao *et al*., 2010; Sahoo *et al*., 2011). However, these studies investigate basins that have ample ground data, whereas they would potentially be even more useful in heavily used basins with sparse ground data such as in the developing world. Moreover, one of the concerns is that RS–GIS tools are only possible for basins at a scale much larger than those of interest for a typical water resources manager, making RS–GIS difficult to apply in water management and policymaking (Rayner *et al*., 2005). Given these empirical gaps, we ask *what is the feasibility of entirely RS–GIS-based water budget models in data-constrained basins at a scale closer to that of interest for a water resource manager*?

Africa presents a particularly challenging and applicable problem in this regard. Africa has critical monitoring needs yet lacks consistent and high-quality *in situ* data (Hastings and Clark, 1991). The reason for such a lack of data is often the difficulty in paying skilled technicians competitive wages to continue collecting such data (Scholes, 2009). Although there have been studies that have analysed portions of the hydrologic budget in African settings (Stankiewicz and de Wit, 2005; de Wit and Stankiewicz, 2006), only two entirely RS–GIS-driven budgets have been conducted in Africa (Stisen *et al*., 2008; Stisen and Sandholt, 2010). Given this dearth of entirely RS–GIS-driven hydrologic studies in data-scarce basins with critical water resource management needs, we sought to conduct an exploratory study to assess the feasibility of a budget model applied towards such conditions.

For this study, we chose the Rufiji basin in Tanzania. We chose this basin for two reasons. First, RS–GIS has also already been used to address water resources for the Usangu basin, a sub-basin of the Rufiji basin, because there is still some consistent and reliable ground data for this sub-basin, so we sought to build on previous work by extending to the larger parent basin (Kashaigili *et al*., 2003; Cour *et al*., 2004; Kashaigili *et al*., 2005; Mwakalila, 2005; Kashaigili *et al*., 2006; Mwakalila, 2008).

Second, the Rufiji basin's water resource management is critical to Tanzania, yet insufficient basin-wide ground data exist to manage these water resources effectively. Tanzania is Africa's leading producer in a variety of key agricultural goods such as beans and bananas (FAO, 2009). More importantly, Tanzania's agriculture is responsible for 85% of the country's exports and 80% of the industry and consumes 89% of the country's freshwater resources (CIA, 2009). The Rufiji basin is the country's largest basin, covering 20% of Tanzania, and provides much of the country's resources for agriculture, livestock, fisheries, mining, and sediment transport (Bernacsek, 1980; Mwalyosi, 1990). Because of the basin's key economic and livelihood positions, water resource monitoring for the basin has been conducted since the 1950s (Bureau of Resource Assessment and Land Use Planning, 1970). However, beginning in the 1980s and especially after the mid-1990s, water resource monitoring dwindled, and data are now largely unavailable for the basin because of infrequent and inconsistent monitoring (Hubert and Raphael, 2008).

In particular, our study has four objectives: (1) an attempt to close and assess the accuracy of an entirely RS-based water balance for the data-rich Usangu sub-basin against the available ground data, (2) assessment of the feasibility of monitoring the entire data-poor Rufiji basin budget entirely with RS, (3) conducting an analytical uncertainty analysis in the water balance model, and (4) a discussion of the feasibility of RS–GIS models on long-range water resources management. This study is exploratory to build a framework and context for future developments in RS-based water resources management for regions with hydrologic data constraints.

METHODS

Study area

The Rufiji basin (Figure 1) is approximately 177 420 km^2, 20% of Tanzania's land area (Rufiji Basin Water Board, 2007). The Rufiji river basin consists of three major sub-basins: the Great Ruaha, Kilombero, and Luwegu (Temple and Sundborg, 1972; Mwalyosi, 1990). The geology of the basin is largely characterized by limestone, shale, and metamorphic rock (gneiss and schists) (Hankel, 1987; Mwalyosi, 1990). Overlaying this geology are largely cambisols, present mainly in the elevations of about 500–1000 m of the basin; significant deposits of fluvisols, predominantly in the basin's deltaic and river floodplains; and ferralsols and nitisols, iron-rich soils often associated with the basin's limestones and shales (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009). The vegetation is predominantly grasslands, savannas, and shrubland with marginal forestry and irrigated land (World Resources Institute, 2003). With regards to agricultural development, the basin's production is largely agriculturally under-developed as only 15% of the total arable land in all of Tanzania is actually used for crop production. Yet the country still remains strongly reliant on

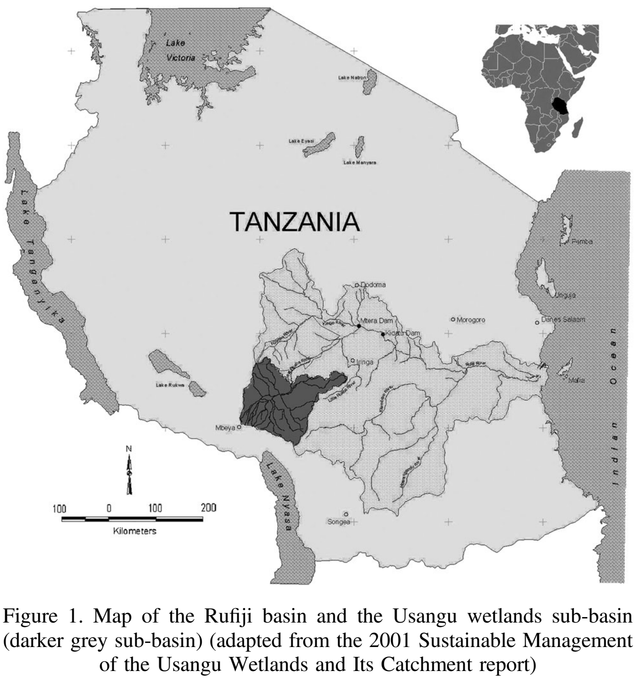

Figure 1. Map of the Rufiji basin and the Usangu wetlands sub-basin (darker grey sub-basin) (adapted from the 2001 Sustainable Management of the Usangu Wetlands and Its Catchment report)

agriculture for their economic development as 46% of the country's gross domestic product comes from agriculture (Rowhani *et al*., 2011).

To validate the water balance model and compare it with other models, we used sub-basin ground data and basin-wide land cover and soil data. Ground data came from the Sustainable Management of the Usangu Wetlands and Its Catchment (SMUWC, 2001) project and the International Water Management Institute (SMUWC, 2001). The Usangu basin (darker grey sub-basin in Figure 1) is part of the Great Ruaha sub-basin and covers approximately 20 810 km^2 or about 12% of the entire Rufiji basin (Kadigi *et al*., 2004). As was described earlier, the Rufiji basin is limited in ground data to drive a water balance model as well as validate an RS-based water balance model. Moreover, gathering more basin-wide data was cost prohibitive. Although the Usangu and Rufiji are not directly comparable because of their differing sizes, micro-topography, and offset locations, the Usangu sub-basin provides the best available data with which to extrapolate Rufiji basin estimates.

Water balance

The basin's water resources were determined using RS through the water balance equation

$$Q = P - \Delta S - ET \tag{1}$$

where Q is the runoff (mm/month), P is the precipitation (mm/month), ΔS is the change in total water storage (groundwater + soil moisture + canopy water storage + standing water, mm/month), and ET is the actual evapotranspiration (mm/month). Two common problems have been reported in these types of analyses: data spikes and bias. The impact of data spikes is typically reduced through quality control filtering or temporal averaging (McNeil and Cox, 2007; Awange *et al*., 2011). Here, we calculate the 3-month moving average for retrospective analysis, and we present both the bias-corrected and uncorrected results.

The RS data were processed and analysed in MATLAB software. A Rufiji basin shapefile was provided by the Global Data Runoff Centre (2008), which we used to generate a mask file. Each set of RS data was visualized in ImageJ, Panoply, and/or ArcGIS 9.3 to ensure that the mask file was properly geo-referenced to the data. Then, our datasets were clipped using the mask file. We spatially average all pixels across the basin to treat the basin as a single, lumped model unit.

We use two additional runoff models for model intercomparison purposes: (1) a curve number (CN)-based approach and (2) a runoff model from the Global Land Data Assimilation System (GLDAS) (Rodell *et al*., 2004). The first is partially RS driven, and the second is based on a modelling algorithm using ground data. For the CN-based approach model, soil and land cover data came from the Harmonized World Soil Database (HWSD), v. 1.1,[1] and the GLOBCOVER global land cover map for 2005–2006.[2] HWSD classifies over 16 000 different soil mapping units into a 30″ (~1 km^2) global raster database through the use of various national, regional, and internationally classified soil maps (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009). GLOBCOVER is a global land cover database that classifies 22 global land cover classes to a resolution of 300 m and absolute and relative geo-location error of 77 and 51 m, respectively (Defourny *et al*., 2006; Bicheron *et al*., 2008). Given the size of our basin of investigation, HWSD and GLOBCOVER both serve as adequate inputs for soil and land cover-driven runoff models that served as a comparison source for the RS-based water balance model.

The only period that the various satellite products overlapped not only with each other but also with the available ground data was in 2003–2004, so we conduct the exploratory analysis for this timeframe although we also show data outside this period to assess potential extrapolation implications.

Precipitation (P)

We used two different precipitation datasets from the TRMM: one is from the real-time Multi-satellite Precipitation Analysis system (TMPA-RT, 3B43 V6) and the other is TRMM 3b42 (Huffman *et al*., 2007). TRMM is a joint USA–Japan initiative designed to specifically measure tropical and sub-tropical rainfall, which includes Tanzania. TRMM uses an active precipitation radar, passive TRMM microwave imager, and Special Sensor Microwave/Imager radiometer system to retrieve rainfall data (Kummerow *et al*., 1998). Specifically, rainfall data are retrieved from reading natural microwaves emitted from the Earth's surface (passive microwave) and the backscattered signals from the illuminated satellite radar signals (active microwave/radar) (Engman and Gurney, 1991; Smith and Mullins, 2001). The horizontal resolution of TRMM P is 4.3 km (Kummerow *et al*., 1998).

In the initial stages of TRMM, device error was sometimes up to 24% between the TRMM radar and radiometer, making ground calibration important for interpretation (Kummerow *et al*., 2000). TRMM later combined both rainfall and total precipitable water measurements, which substantially reduced data error (up to 85% reduction in error bias and up to 38% reduction in error standard deviation) (Hou *et al*., 2000). TMPA-RT has further reduced error in some cases to about 7% overall error bias and a root mean square difference as low as 1.17 mm/day through two processing phases, one 9 h after real time and then post-real time after 10–15 days (Huffman *et al*., 2007). TMPA-RT has already been used successfully in many tropical region applications and can now even be downscaled to account for vegetation (Collischonn *et al*., 2008; Su *et al*., 2008; Immerzeel *et al*., 2009).

However, TRMM 3b43 or TRMM TMPA-RT data are not purely from RS as the algorithms used calibrate TRMM to global rain gauge data provided from the Global Precipitation Climatological Center (Rudolf, 1993). We compared both TRMM 3b42 and TRMM 3b43 to rainfall ground data, incorporating a 1 month lag with the TRMM 3b42 data, as prescribed in past studies (Chokngamwong

[1]http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/
[2]http://www.gofc-gold.uni-jena.de/sites/globcover.php

and Chiu, 2008; Kikuchi and Wang, 2008; Li *et al*., 2008; Fotopoulos *et al*., 2011). We used TRMM 3b43 for the RS-based model but also conducted lag correlational analyses to demonstrate the differences if TRMM 3b42 was used to run the RS-based model as opposed to using TRMM 3b43.

Ground data for P were used to validate the RS-based P estimates. Ground data for P were available from 1998 to 2000 and were obtained from between 6 and 20 upstream rain gauges in the Usangu Wetlands sub-catchment (SMUWC, 2001). These data were available daily, so we accumulated the rain gauge data to the monthly level and then spatially averaged (arithmetic) the data across rain gauges. All the rain gauges fit within one $1° \times 1°$ grid box of the RS-based water balance model. To properly compare the sub-basin Usangu ground data we had with the RS-based model, we took the values obtained for the model and area-weighted it to the dimensions we knew for the Usangu sub-basin (20 817 km^2).

Total water storage (ΔS)

ΔS is one of the most difficult components to measure both *in situ* and remotely (Engman and Gurney, 1991; Smith and Mullins, 2001). *In situ* methods are locally restrictive and cannot reach large depths, and they are often destructive. Soil moisture from RS is limited in areas with dense canopies.

We obtained ΔS from the Gravity Recovery and Climate Experiment (GRACE) (Tapley *et al*., 2004), which is readily used in neighbouring regions to this study such as southern Africa (Krogh *et al*., 2010). GRACE maps the Earth's gravitational field, providing data on a monthly basis.[3] To use these data, particularly for land hydrology, we processed level 2, release 4 GRACE data, which remove oceanic and atmospheric contributions to the Earth's gravity field, leaving continental water ΔS contributions (Chen *et al*., 2005; Bettadpur, 2007).

We elected to use GRACE for a variety of reasons. First, GRACE is the only currently available RS mission for measuring sub-surface water change. Second, the Rufiji basin (~177 420 km^2) is close to the threshold of 200 000 km^2 where GRACE data have reasonable suitability (Rodell and Famiglietti, 2001). Moreover, GRACE was successfully used at basin scales less than 200 000 km^2 [$r = 0.83$, $r = 0.63$ (for changes below 2 m), root mean square error (RMSE) = 25.2 mm/month] (Yeh *et al*., 2006), indicating that basin scales of 150 000 km^2 may be allowable for the threshold for GRACE usage. Third, such an approach is similar to that carried out for the nearby Zambezi basin (Chen *et al*., 2005) (average RMSE between 2.21 and 3.01 cm equivalent water height). Following numerous refinements made to GRACE data (Wahr *et al*., 1998; Cheng and Tapley, 2004; Swenson and Wahr, 2006; Swenson *et al*., 2008; Landerer and Swenson, 2012),[4] we used GRACE data with a 300 km Gaussian radius filter and with scaling factors that restore much of the energy that such filtering artificially removes from the GRACE land data grids. For missing dates, e.g. June 2003 and January 2004, the data were gap-filled using linear interpolation.

GRACE data were compared with the GLDAS (Rodell *et al*., 2004). The GLDAS dataset used here was that generated from Noah land surface models. This model is a collaboration amongst various US government and academic agencies, which incorporates multiple ground data and RS data sources from the Global Energy and Water Cycle Experiment, the Office of Hydrological Development of the National Weather Service, the National Environmental Satellite Data and Information Service, and the US Air Force, amongst many others (Ek *et al*., 2003; Rodell *et al*., 2005). We used GLDAS here because past studies used GLDAS to calibrate GRACE data with good accuracy (RMSE between 0.7 and 4.5 cm equivalent water height) (Chen *et al*., 2005, 2006; Syed *et al*., 2008). As with past work (Syed *et al*., 2008), we derive total water storage from GLDAS using the four layers of soil moisture and the canopy moisture the GLDAS/Noah dataset provides. To compare GRACE with GLDAS, we convert GRACE from a measurement of water storage anomalies (over the long-term mean of the data), which is what the available raw data provide, into change in water storage. To perform this, we subtract the long-term mean (2003–2007) of the data from both GRACE and GLDAS to allow for the comparison.

Because of the missing observational dates in GRACE data, we modified a correction factor for such analysis provided by Rodell *et al*. (2004) to calculate runoff for monthly data (Rodell, 2011, personal communication). The result was that our simplified water balance model in Equation 1 became the following equation:

$$\frac{Q_2 + Q_1}{2} = \frac{P_2 + P_1}{2} - \frac{ET_2 + ET_1}{2} - (\Delta S_2 - \Delta S_1) \quad (2)$$

Subscripts 2 and 1 represent the current month of analysis and the past month of analysis, respectively.

Evapotranspiration (ET)

We used the RS-driven actual evapotranspiration (*ET*) algorithm (PT-JPL) from Fisher *et al*. (2008), which was validated at 36 FLUXNET sites, including 21 sites in the tropics (Fisher *et al*., 2008, 2009). To drive the *ET* algorithm, we needed air temperature, relative humidity, normalized difference vegetation index (NDVI) and soil-adjusted vegetation index (SAVI), and net radiation. Near-surface air temperature and relative humidity were measured and derived from using the Atmosphere Infrared Radiation Sounder (AIRS) aboard the Aqua satellite. Net radiation was retrieved using the surface radiation budget (SRB) dataset. NDVI and SAVI were measured using the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra satellite.

The AIRS uses infrared radiation (3.7–15.4 µm) from 2378 spectral channels to gather medium-range weather forecasting data (Aumann *et al*., 2003). Coupled with measurements from the Advanced Microwave Sounding

[3]For mission details, see http://www.csr.utexas.edu/grace/

[4]For more detailed information, visit the following website: http://grace.jpl.nasa.gov/data/gracemonthlymassgridsland/

Unit A, surface temperature is measurable within an absolute accuracy of 1 K and a relative accuracy of 0.5 K (Aumann *et al.*, 2003; Fetzer *et al.*, 2003). In mountainous or desert regions, AIRS air temperature error increases to 11 K (Gao *et al.*, 2008). For water vapour pressure, AIRS is measurable to within an absolute accuracy of 20% and a relative accuracy of 10% (Aumann *et al.*, 2003; Fetzer *et al.*, 2003). AIRS relative humidity, temperature, and surface pressure monthly ascending (daytime) data were first obtained. The publicly available AIRS dataset we used (AIRX3STM) calculates monthly mean levels as the arithmetic means of the daily product and weights the value for each grid box by the number of input counts for each day.[5] These data come in 12 vertical layers between 1000 and 100 Mb. Using the surface pressure data, we linearly interpolated between the two pressure layers that lie immediately above and below the surface pressure to obtain the appropriate surface relative humidity and temperature data for each $1° \times 1°$ pixel (Ferguson and Wood, 2010, for an example of this approach). We evaluate the near-surface derived data against measurements from ground meteorological stations.

The MODIS is a multispectral medium-to-long-wave infrared sensor (36 bands, 0.405–14.385 μm) (Justice *et al.*, 1998, 2002). MODIS NDVI is relatively accurate when compared with localized *in situ* NDVI measurements made in African contexts such as Senegal (Dahra, Senegal: $R^2 = 0.96$, slope = 0.97, RMSE = 0.028) (Fensholt *et al.*, 2006). For our analysis, we used monthly level 3 MODIS NDVI data, which is a $1° \times 1°$ spatial globally gridded dataset made from a 0.05° Climate Modeling Grid global coverage product.[6]

The SRB is a satellite-driven dataset designed to support the Global Energy and Water Cycle Experiment (Pinker *et al.*, 2003; Randall *et al.*, 2003; Zhang *et al.*, 2006). The satellite sources come from the International Satellite Cloud and Climatology Project, the GEOS-4 reanalysis product, the Total Ozone Mapping Spectrometer, the Television and Infrared Operational Satellite Operational Vertical Sounder, and the Stratospheric Monitoring Group's Ozone Blended Analysis.[7] When compared with various ground radiation sources, SRB is relatively accurate (R^2 typically greater than 0.90 for v2.6, root mean square difference typically less than 24 W/m^2) (Zhang *et al.*, 2006). Similar to past studies (Troy and Wood, 2009), we subtracted the quality-checked SRB product's upward shortwave and longwave radiation from its downward shortwave and longwave radiation to get the net radiation.

We produced two sets of *ET* data by generating the algorithm with all RS in one instance and substituting Climate Research Unit (CRU) interpolated and gridded ground station air temperature and water vapour pressure data for AIRS in the other instance. We compared AIRS temperature and CRU globally gridded ground data available for up to 2006 (CRU v3.0) (University of East Anglia CRU, 2008). We also compared the ET data used here against the full land surface model derived *ET* from Noah/GLDAS (Chen *et al.*, 1996; Rodell *et al.*, 2004; Jiménez *et al.*, 2011).

Table I summarizes the RS products driving the RS-based water balance model, the ground data products used for validation, the ArcGIS CN-driven model used for comparison, and the temporal and spatial resolutions of all products used.

Runoff (Q)

Ground data for sub-basin model validation came from seven flow gauges in the Usangu sub-basin that the International Water Management Institute provided (McCartney, 2009, personal communication).

We directly compare the CN-based approach with Usangu ground data and with the RS model for both the sub-basin and the entire Rufiji basin. The CN-based approach uses the ArcGIS-driven ArcCN-runoff model to calculate runoff using land cover and soil data (Zhan and Huang, 2004). This model uses Soil Conservation Service (SCS, 1985, SCS, 1986) runoff CNs to empirically derive runoff. This method was derived and run in ArcCN-runoff in the following manner (Ponce and Hawkins, 1996; Zhan and Huang, 2004):

$$Q = \frac{(P - 0.2S_R)^2}{P + 0.8S_R} \tag{3}$$

S_R is the maximum soil retention and is approximated as

$$S_R = \frac{1000}{CN_{\text{landsoil}}} - 10 \tag{4}$$

P was obtained from TRMM data, and CN_{landsoil} is the SCS (1986) CN.

To determine CN_{landsoil}, we superimposed the HWSD data onto the geo-referenced Rufiji basin mask profile on ArcGIS 9.3. Because HWSD soil data are classified as FAO (2006) drainage groups that cannot be directly used to determine CN, we re-classified these data at the sub-basin level into US Department of Agriculture hydrological soil groups (HSG) (SCS, 2007). We then superimposed the GLOBCOVER data and used both the land cover data and the previously classified HSG groups to determine the appropriate CN using SCS (1985, 1986) tables. To ensure that we were consistent in this process, we used past literature that have coded and compared FAO drainage and US Department of Agriculture HSG groups to guide our classification (Mutua and Klik, 2006; Descheemaeker *et al.*, 2008; Hong and Adler, 2008).

We compared CN-based runoff estimates with those of the RS-based model and those of the GLDAS runoff models at both the Usangu sub-basin and Rufiji basin (Rodell *et al.*, 2004). Previous work has used such data to run river basin routing models to determine water storage dynamics more accurately (Han *et al.*, 2009).

[5]For more detailed information, see http://mirador.gsfc.nasa.gov/collections/AIRX3STM__005.shtml
[6]For more detailed information, see http://mirador.gsfc.nasa.gov/collections/MODVI__005.shtml
[7]For more information on these specific products, consult http://eosweb.larc.nasa.gov/PRODOCS/srb/table_srb.html

Table I. Satellite datasets and ArcGIS-driven models for the Rufiji basin water balance

Variable	RS drivers	Validation/Comparison	Resolution[a]	Sources
Q	Water balance model (mm/month)	Ground data (only available from 1999 to 2000) ArcCN-runoff (using GLOBCOVER, HWSD, and TRMM) GLDAS: net runoff data	Monthly 1° × 1°	This study IWMI FAO (2006) Defourny *et al.* (2006) Hawkins (1978) Kannan *et al.* (2008) Zhan and Huang (2004)
P	TRMM/TMPA-RT 3b43[b] (mm/day)	Ground data (only available f rom 2003 to 2004) TRMM 3b42 (rainfall data without algorithms to calibrate to rain gauge as a robustness check)	Monthly 1° × 1°	Huffman *et al.* (2007) SMUWC (2001)
ΔS	GRACE[c] : equivalent water thickness (cm/month)	GLDAS: four-layer soil moisture + canopy storage (cm/month)[d]	Monthly 1° × 1°	Wahr *et al.* (1998), Chambers (2006), Chen *et al.* (1996)
ET	MODIS: NDVI/SAVI AIRS[f] : air temperature (K) Vapour pressure (Pa) SRB[h] : net radiation (W/m^2)	CRU, v3.0[e] : air temperature (°C) Vapour pressure (hPa) GLDAS: evaporation	Monthly MODIS: 1° × 1°[g] CRU: 1° × 1° AIRS: 1° × 1° GLDAS: 1° × 1° SRB: 1° × 1°	Stackhouse *et al.* (2000) Justice *et al.* (2002) Aumann *et al.* (2003) CRU v3.0

[a] For TRMM, original data were 0.25° × 0.25°. For CRU and GLDAS datasets, original data were 0.5° × 0.5°. These grids were all spatially averaged into 1° × 1° grids to match the rest of water balance as noted in Section 2.2.
[b] http://daac.gsfc.nasa.gov/data/datapool/TRMM/
[c] http://grace.jpl.nasa.gov/data/mass/
[d] http://disc.gsfc.nasa.gov/hydrology/data-holdings
[e] http://badc.nerc.ac.uk/data/cru/, units converted to match those of AIRS.
[f] http://mirador.gsfc.nasa.gov/ (for both MODIS/Terra and AIRS)
[g] This 1° × 1° grid is derived from a 0.05° × 0.05° modelling grid coverage.
[h] http://eosweb.larc.nasa.gov/PRODOCS/srb/table_srb.html

Error and sensitivity analysis

To determine the RS-based model's accuracy and bias vis-à-vis ground or model data, we used the conventional statistical indicators of R^2, slope, and RMSE, obtained using a zero y-intercept. To understand which component most influences the water balance, we also performed a sensitivity analysis. A form of the perturbation method was performed where each component was 'forced'" with a range that is ±50% of the component's actual value, and the percentage change in Q was recorded (McCuen, 1973).

We also determined analytically how the error of each component propagates in the RS-based model. We use the method of moments (MOM) to quantify this error propagation (Hansen, 1982; Warnick and Chew, 2004). This model was derived from a first-order approximation of the Taylor series expansion (Morgan *et al.*, 1990). If the components are independent of each other (no covariance between any two components), this MOM expansion reduces to Gaussian error propagation. Such an approach is used reliably in numerous hydrological studies (e.g. Madsen *et al.*, 1997; Fisher *et al.*, 2008).

The MOM first-order Taylor series approximation of the error propagation is

$$\mathrm{var}(Q) = \sum_{i=1}^{n}\sum_{j=1}^{n} \mathrm{cov}\left[x_i, x_j\right] \frac{\partial Q}{\partial x_i}\frac{\partial Q}{\partial x_j} \tag{6}$$

where x_i and x_j are the water balance components (ET, P, or ΔS) used to derive Q, given that

$$\begin{aligned} \mathrm{cov}[x_i, x_i] &= \mathrm{var}(x) = s_i{}^2 \\ \mathrm{cov}\left[x_i, x_j\right] &= \mathrm{cov}\left[x_j, x_i\right] = r_{i,j} s_i s_j \end{aligned} \tag{7}$$

where r is the Pearson correlation between the ith and jth model component and s is the sample standard deviation. Using these properties, we simplified Equation 6 to the following:

$$s_Q = \sqrt{\sum_{i=1}^{n} s_{x_i}\left(\frac{\partial Q}{\partial x_i}\right)^2 + \sum_{i=1}^{n}\sum_{j=i+1}^{n} r_{i,j} s_i s_j \frac{\partial Q}{\partial x_i}\frac{\partial Q}{\partial x_j}} \tag{8}$$

If the variables are independent of each other or $\mathrm{cov}[x_i, x_j] = \mathrm{cov}[x_j, x_i] = 0$, then Equation 8 becomes a simple Gaussian error propagation function where

$$s_Q = \sqrt{\sum_{i=1}^{n} s_{x_i}\left(\frac{\partial Q}{\partial x_i}\right)^2} \tag{9}$$

Using the water balance model from Equation 1, we determine the following partial derivatives:

$$\begin{aligned} \frac{\partial Q}{\partial P} &= 1 \\ \frac{\partial Q}{\partial \Delta S} &= -1 \\ \frac{\partial Q}{\partial ET} &= -1 \end{aligned} \tag{10}$$

When we use these partial derivatives from Equation 10, Equations 8 and 9 become the following for the RS-based water balance model:

$$s_Q = \sqrt{s_P{}^2 + s_{ET}{}^2 + s_{\Delta S}{}^2 - r_{P,ET}s_P s_{ET} - r_{P,\Delta S}s_P s_{\Delta S} + r_{ET,\Delta S}s_{ET}s_{\Delta S}}$$
$$s_Q = \sqrt{s_P{}^2 + s_{ET}{}^2 + s_{\Delta S}{}^2} \quad (11)$$

Equation 11 can also be presented as a standard error of the mean

$$se_Q = \frac{s_Q}{\sqrt{n}} \quad (12)$$

where *se* is the standard error and *n* is the number of samples obtained for *Q*.

We also ran two additional correlation analyses. First, we ran pairwise Pearson correlations to determine which water component (*ET*, *P*, or ΔS) most correlates with *Q*. Second, following other studies (Wang *et al*., 2006; Kikuchi and Wang, 2008), we ran a lagged correlation analysis to see whether the optimum correlation occurred at near real time or lagged behind ground data measurements.

RESULTS

Precipitation (*P*)

Ground data for *P* from the Usangu sub-basin were first compared with TRMM 3b43 data, which exhibited a reasonably good agreement ($R^2 = 0.77$, slope = 0.73, RMSE = 28.1 mm/month) (Figure 2). From Figure 2, we see that the results improved after 1999 ($R^2 = 0.89$, slope = 0.82, RMSE = 18.9 mm/month for 1999–2000). This is not entirely unexpected as a calibration problem was found just after TRMM's launch in 1998 and early studies found up to 40% difference between the TRMM's radar and radiometer data (Kummerow *et al*., 2000).

TRMM 3b42 data were also compared with the Usangu sub-basin ground data. Upon initial glance, it would seem that TRMM 3b42 considerably diverges from TRMM 3b43 data, with exception of slope ($R^2 = 0.37$, slope = 0.90, RMSE = 96.9 mm/month). However, previous studies suggest that a time lag may be necessary when using TRMM 3b42 in hydrological analyses such as flood forecasting (Li *et al*., 2008; Fotopoulos *et al*., 2011) or in analyses comparing rainfall with ground data (Chokngamwong and Chiu, 2008; Kikuchi and Wang, 2008). When we apply a 1 month lag to the same 1999–2000 data, the TRMM 3b42 data improve considerably, comparable with TRMM 3b43 ($R^2 = 0.60$, slope = 0.81, RMSE = 6.6 mm/month). This result reinforces what past studies suggest, that using a lag may be necessary when using TRMM 3b42 data in hydrological research. However, overall, TRMM 3b43, as expected, has better comparability with ground data than TRMM 3b42.

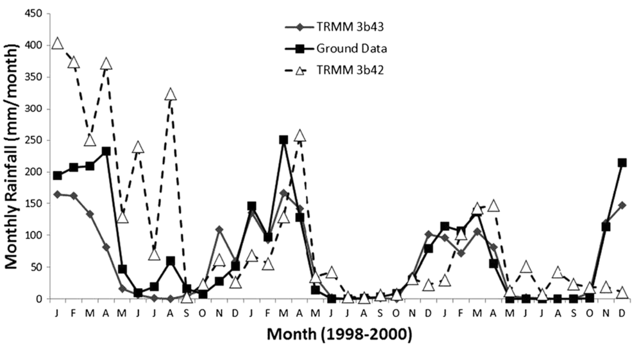

Figure 2. Graph of Tropical Rainfall Measuring Mission (TRMM) and ground data for precipitation for the Usangu sub-basin and the Rufiji basin

Storage (ΔS)

GLDAS-modelled ΔS was compared with GRACE ΔS for the Rufiji basin (Figure 3). Although the agreement was not as good as that with *P* (Usangu: $R^2 = 0.34$, slope = 1.03, RMSE = 57 mm/month; Rufiji: $R^2 = 0.47$, slope = 1.11, RMSE = 51 mm/month), these results were comparable with those results obtained from past studies $R^2 = 0.40-0.69$ and (RMSE ranging from 7 to 45 mm/month) (Syed *et al*., 2008; Yeh *et al*., 2006).

Evapotranspiration (*ET*)

The SRB/MODIS/AIRS-driven ET (Figure 4) compared similarly with SRB/MODIS/CRU-driven ET (Usangu: $R^2 = 0.97$, slope = 1.02, RMSE = 5.2 mm/month; Rufiji: $R^2 = 0.98$, slope = 1.04, RMSE = 3.5 mm/month). Such a result indicates that the SRB radiation data and the MODIS NDVI/

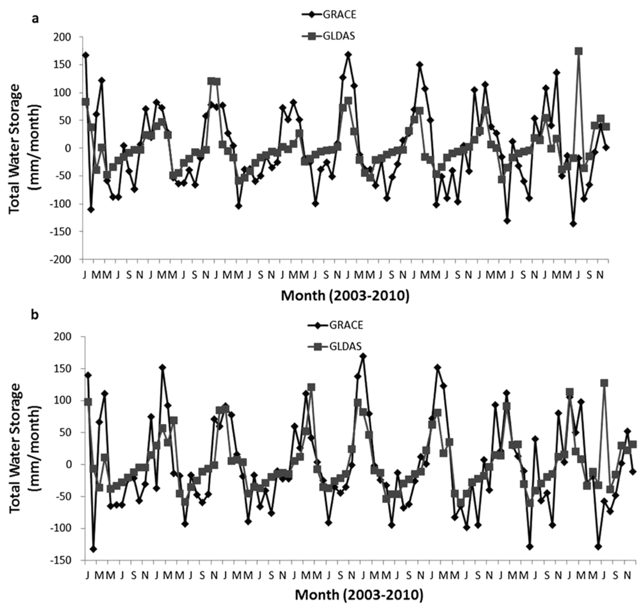

Figure 3. Gravity Recovery and Climate Experiment (GRACE) data and Global Land Data Assimilation System (GLDAS) data for the Usangu sub-basin (a) and the Rufiji basin (b)

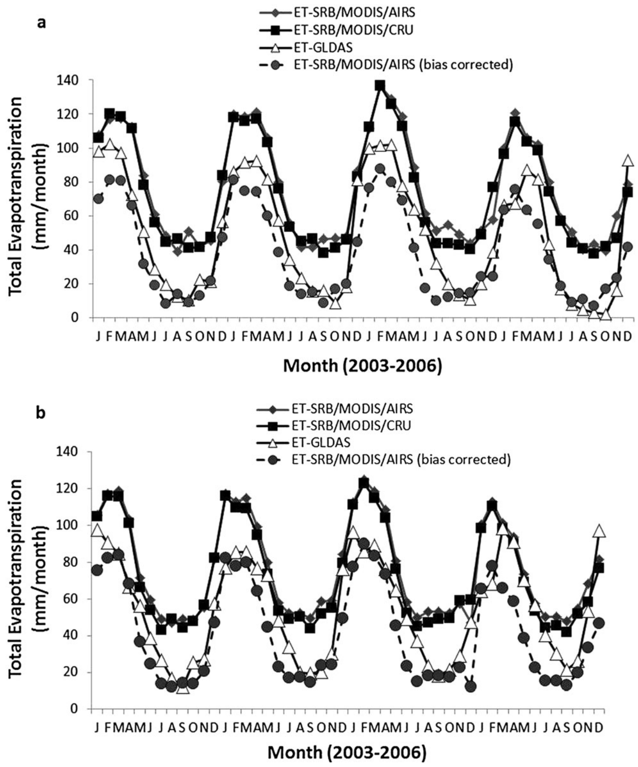

Figure 4. Evapotranspiration (ET) for both the Usangu sub-basin (a) and Rufiji basin (b). SRB, surface radiation budget; MODIS, Moderate Resolution Imaging Spectroradiometer; AIRS, Atmosphere Infrared Radiation Sounder; CRU, Climate Research Unit; GLDAS, Global Land Data Assimilation System

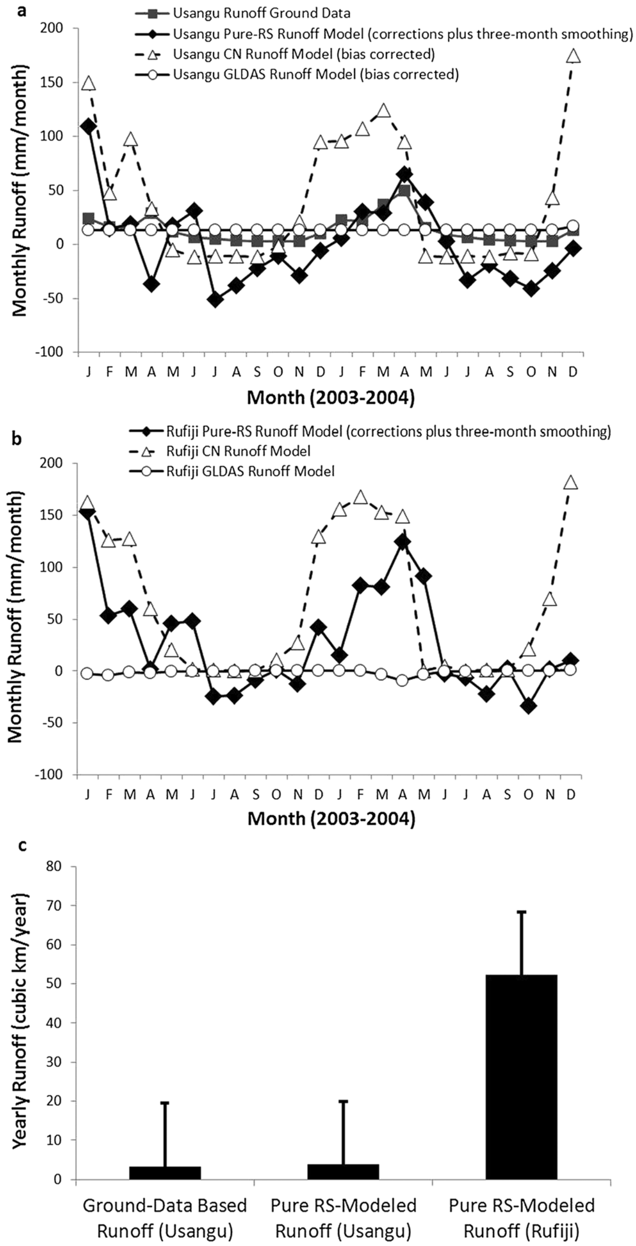

Figure 5. Model validation with ground data and comparison with other models for the Usangu sub-basin (a), comparison with other models for the Rufiji basin (b), and yearly runoff from the Usangu ground data and model data for both the Usangu sub-basin and Rufiji basin (c). RS, remote sensing; CN, curve number; GLDAS, Global Land Data Assimilation System

SAVI data drive much of the difference in ET measurements as opposed to temperature and water vapour pressure data, just as other studies reported (Fisher *et al.*, 2008).

In comparing the RS-based ET model (ET-SRB/MODIS/AIRS) with ET from GLDAS, we obtain moderately reasonable correlation, although with a noticeable offset (Usangu: $R^2 = 0.46$, slope = 1.3, RMSE = 22.7 mm/month; Rufiji: $R^2 = 0.51$, slope = 1.29, RMSE = 18.2 mm/month). This is expected as other studies have shown that the ET model used here tends to have a systematic upward bias and GLDAS-based ET models have a systematic downward bias when compared with other ET products (Jiménez *et al.*, 2011). When we correct for ET bias as other RS-based studies have done (Sheffield *et al.*, 2009), the ET (ET-SRB/MODIS/AIRS) comparison with GLDAS improves (Usangu: $\text{mean}_{\text{AIRS}} = 37.9$ mm/month, $\text{mean}_{\text{GLDAS}} = 48.3$ mm/month, $R^2 = 0.87$, slope = 0.77, RMSE = 9.7 mm/month; Rufiji: $\text{mean}_{\text{GLDAS}} = 54.2$ mm/month, $\text{mean}_{\text{AIRS}} = 41.3$ mm/month, $R^2 = 0.78$, slope = 0.78, RMSE = 12.4 mm/month).

Runoff (Q)

Putting all of the components of the water balance model together (P, ET, and ΔS), we compared model-predicted Q with ground data in the Usangu basin (Figure 5a).

In this figure, we show the original balance model, the balance model with bias correction, the GRACE correction model derived from applying the work of Rodell *et al.* (2004) to monthly data (Equation 2), and the balance model with 3 month smoothing applied. For the Usangu basin, the original balance model (not shown) was poorly correlated and was time-lagged to available ground data ($R^2 = 0.21$, slope = −1.8, RMSE = 47 mm/month). With bias correction (not shown), the countercyclical behaviour of the model was corrected, but the correlation and error were still poor ($R^2 = 0.02$, slope = 0.82, RMSE = 93 mm/month). With the incorporation of the 3 month moving averaging smoothing technique in tandem with bias correction, the correlation and error markedly improve ($R^2 = 0.39$, slope = 1.9, RMSE = 29 mm/month). The comparison of the RS-based model with the Usangu sub-basin ground data shows that our 3 month smoothed model seems to have better comparability than the bias-corrected GLDAS model ($R^2 = 0.02$, slope = 0.56, RMSE = 8.7 mm/month) and slightly better comparability with the bias-corrected CN model ($R^2 = 0.36$, slope = 3.5, RMSE = 47 mm/month). Although highly error prone, the RS-based model and, to a slightly lesser degree, the CN-based model may represent an improvement from what is already available for basins of a lower scale and with restricted ground data availability. However, the large errors obtained demonstrate both the exploratory nature of this work and the general limitations that all RS–GIS tools have in monitoring data-constrained basins at such low scales.

To analyse the RS-based model for the entire Rufiji basin, we compare our model with the GLDAS-based and CN-based models for the entire Rufiji basin (Figure 5b). We find that as with the Usangu sub-basin, the CN-based and RS-based models continue to have similar comparability ($R^2 = 0.37$, slope = 0.43, RMSE = 39 mm/month), whereas the GLDAS model compares poorly with and is even countercyclical to both the CN-based approach and the entirely RS-based model (with CN: $R^2 = 0.08$, slope = −9.2, RMSE = 65.9 mm/model; with RS-based model: $R^2 = 0.42$, slope = −14.7, RMSE = 37 mm/month).

These results should be interpreted cautiously for two reasons. First, the CN-based approach is driven with TRMM data, which is also an input to the RS-based model because we do not have ground data for the whole basin. Therefore, the correlations between these models may be in part due the common P driver in both models. However, given that the correlation is less than 0.7 ($r = 0.61$), multicollinearity is not a strong concern between these models, indicating that these two models do sufficiently measure runoff differently. Therefore, although interpreted with caveats, our exploratory evidence indicates that the entirely RS-based model (Equation 2) as well as the CN-based approach seems to have better comparability than the currently available GLDAS models for understanding runoff both at the Usangu sub-basin and Rufiji basin levels.

Second, comparing with the CN-based model does not necessarily indicate our model's scalability potential. Granted, CN models provide more ground-based soil characteristics, which in turn, are used to calculate the water budget. However, given that the Usangu sub-basin differs greatly in its soil and land characteristics as compared with the rest of the basin (Temple and Sundborg, 1972; Mwalyosi, 1990), we cannot adequately ascertain whether our results indicate our model's generalizability across the entire basin. All we can note here is that the correlation between the models does indicate the potential for our model to scale to the entire basin but cannot definitively confirm that notion.

Neglecting subsurface runoff,[8] we compared our model's yearly discharge with that determined from ground data of the entire Usangu sub-basin. We find that our purely RS-based model (with bias and Rodell corrections + smoothing) compares reasonably with the ground-based discharge (ground data: 3.3 km^3/year; RS-based model: 3.8 km^3/year, bias = 14%), further indicating that our model, although error prone, does seem to improve our ability to at least engage in annual water basin management. When comparing our estimate of the entire Rufiji basin's annual discharge (52 km^3/year) with the best available estimates from past studies of the Rufiji basin from the 1950s to 1970s, discharge for the entire Rufiji basin was approximated as 900 m^3/s or 28 km^3/year. Yet also, during the same time, the discharge varied greatly from 70 to 11 000 m^3/s (Mwalyosi, 1990), which indicates a potential range of 2.2–347 km^3/year.

As discussed before, the high variability in soil, land, and hydrological characteristics leads us to hesitate in assessing the reliability and generalizability of the RS-based and CN-based models on the entire Rufiji basin. Moreover, comparison against best available estimates from past literature is a highly uncertain comparison, qualitative at best, as the Rufiji has likely undergone much hydrological change since the 1970s. From what we can only surmise, such rough estimates of the annual discharge of the Rufiji basin, from past literature, indicate that our model is indeed coarse, as expected. However, given the high variability in annual discharge Rufiji measurements, our results are within the range of annual discharge previously approximately known for the basin.

Sensitivity analysis, error propagation, and statistical analysis

From the perturbation sensitivity analysis, on average, Q is most sensitive to changes in ET (216–432% change in runoff for 25–50% variable perturbation), slightly less so to P (190–379% change in runoff for 25–50% variable perturbation), and least sensitive to changes in ΔS (1–3% change in runoff for 25–50% variable perturbation) (Figure 6).

If we assume that the error propagation is Gaussian, the error propagation for the Rufiji basin was an additional

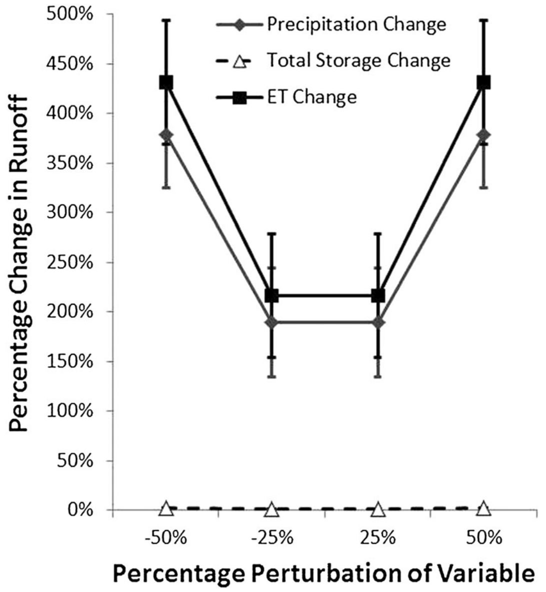

Figure 6. Water balance sensitivity analysis to perturbations ranging from −50% to +50% of the component's monthly averaged value. ET, evapotranspiration

[8]To perform this, we set subsurface or negative runoff to 0. To ensure we did not change the correlation from our model, we ran an error analysis and found that our results were nearly the same as those that included subsurface runoff and even improved in some aspects ($R^2 = 0.36$, slope = 1.2, RMSE = 25 mm/month).

14.9 mm/month in Q. However, if we assume a more generalized MOM approximation, the error propagation was 12.8 mm/month. MOM had lower error propagation than the Gaussian approximation because of the attenuation effects of the negative partial derivatives from Equation 11 that result from the RS-based water balance model. We see similar trends for the Usangu sub-basin. Assuming a Gaussian distribution, error propagation is 13.2 mm/month. The more generalized MOM yields an error propagation of 10.8 mm/month.

When we run a pairwise Pearson correlation between all variables, we find a different set of results (Table II). Although our model seems most sensitive to ET (and slightly less so to P), ΔS is more significantly correlated with the RS-based model's estimated runoff ($p < 0.001$ for both Usangu and Rufiji). We surmise that these results may indicate that ΔS most influences the RS-based model's temporal trends, whereas ET and, slightly less so, P most influence the RS-based model's amplitude. Because ΔS most influences the RS-based model's temporal trends, this may help explain the model's low R^2 because compared with the other hydrological components (P and ET), ΔS has the lowest R^2 when compared with other models or with ground data. Past studies of the Usangu sub-basin indicate that this is plausible because the annual rainfall in the sub-basin (in this study: ~500–700 mm; 2003–2004: 567–748mm) is almost all lost because of ET, given the sub-basin's semi-arid climate (Malley *et al.*, 2009, for example). Given that, one would surmise that the driver of discharge is ΔS as little rainfall is able to eventually become discharged given such evaporation rates.

Additional analyses

Given that TRMM 3b43 data, used to drive our runoff analysis, are calibrated with rain gauges and performed so post-real time, we sought to conduct some additional analyses using 3b42 TRMM data to drive our RS-based

Table II. Pairwise Pearson correlation matrices for both the Usangu sub-basin and Rufiji basin

	TRMM	*ET*	ΔS	*Q*
		Rufiji		
TRMM	1.00			
ET	0.85***	1.00		
ΔS	0.61**	0.49*	1.00	
Q	0.03	−0.06	−0.76***	1.00
		Usangu		
TRMM	1.00			
ET	0.74***	1.00		
ΔS	0.77***	0.54**	1.00	
Q	−0.36	−0.48*	−0.82***	1.00

*$p < 0.05$,
**$p < 0.01$,
***$p < 0.001$.

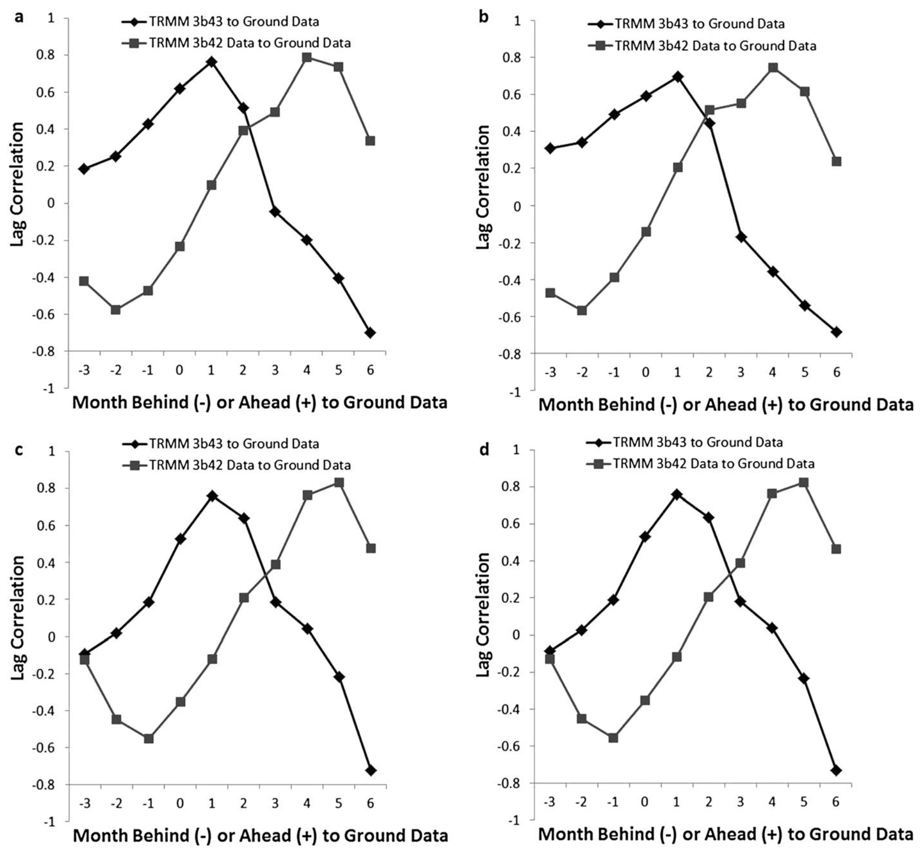

Figure 7. Lagged correlation for Tropical Rainfall Measuring Mission (TRMM) 3b43 and TRMM 3b42-driven runoff where monthly runoff is calculated as a function of either average daily runoff (a), minimum daily runoff (b), maximum daily runoff (c), or maximum daily runoff in the wet season and minimum daily runoff in the dry season (d)

Table III. Model errors compared with other studies

Component	This study			Other studies (best reported)		Sources
		R^2	RMSE (mm/month)	R^2	RMSE (mm/month)	
P	Usangu, based on ground data validation	0.77	28.1	0.68–0.92	39.2–184.8	Ebert *et al.* (2007), Sheffield *et al.* (2009), Sorooshian *et al.* (2002), Sorooshian *et al.* (2000), Wagner *et al.* (2009)
ΔS	Usangu	0.34	57.0	0.40–0.69	7–45	Yeh *et al.* (2005),Syed *et al.* (2008)
	Rufiji (comparison with GLDAS storage model)	0.47	51.0			
ET	Usangu	0.46	22.7	0.90	16	Fisher *et al.* (2008)
	Rufiji (comparison with GLDAS ET model)	0.51	18.2			
Q	Rufiji	0.64 (max, compared with CN model)	39.0 (12.8[a])	0.37–0.93	1.1–33% (of water balance error)[c]	Stisen *et al.* (2008)
	Usangu[b]	0.58 (max, compared with ground data)	29.0 (10.8[a])			

RMSE, root mean square error; GLDAS, Global Land Data Assimilation System; ET, evapotranspiration; CN, curve number.
[a] Amount of error propagation in addition to RMSE.
[b] Bias = 14%.
[c] Based on 250 000 km^2 basin size the study uses for its model.

runoff model. Using TRMM 3b42, we find that our correlation is comparable, but as expected, our error increases. However, the balance also becomes countercyclical (Usangu, bias corrected: $R^2 = 0.33$, RMSE = 82 mm/month, slope = -5).

To better understand this countercyclical behaviour, we conducted a lagged correlation analysis following Wang *et al.* (2006) to quantify how much lag there is between the maximum correlation between our model and the ground data using both TRMM 3b42 and TRMM 3b43 data. We ran four lagged correlation analyses (Figure 7). The first assumes that the RS-based model is sensitive to the average daily ground data runoff when following monthly runoff trends. The second assumes that the RS-based model is sensitive to the maximum daily ground data runoff when following monthly runoff trends. The third assumes that our RS-based model is sensitive to the minimum daily ground data runoff when following monthly runoff trends. Finally, we assume that our RS-based model is sensitive to maximum daily ground data runoff during the basin's wet season and the minimum daily ground data in the dry season.

The TRMM 3b43-driven models are consistent throughout all four analyses, and the optimum correlation is usually at no or 1 month lag. Although the optimal correlation is similar throughout all four analysis (maximum R^2 range: 0.49–0.58), the maximum positive correlation happens when monthly runoff is derived from average daily runoff at a 1 month lag ($R^2 = 0.58$).

However, the TRMM 3b42-driven models are most optimally correlated at lags of 4–5 months. Although the optimal correlation is similar throughout all four analysis and even stronger than those from the TRMM 3b43-derived runoff model (maximum R^2 range: 0.55–0.69), the maximum positive correlation happens when monthly runoff is derived from maximum rainfall but with a lag of 5 months ($R^2 = 0.69$). Such findings corroborate and indicate the extent of the countercyclical nature of the results observed using TRMM 3b42 precipitation data.

DISCUSSION

To put our study into context, the model errors in this study are compared with those from other sources using similar RS products (Table III).

Our runoff predictions are less accurate in the Rufiji basin than those found in the literature from other basins (Stisen *et al.*, 2008). However, interestingly, our study, although exploratory in nature, has comparable accuracy for each water balance component when compared with those reported from past studies using similar satellite products (Sorooshian *et al.*, 2000; Sorooshian *et al.*, 2002; Ebert *et al.*, 2007; Fisher *et al.*, 2008; Stisen *et al.*, 2008; Syed *et al.*, 2008; Sheffield *et al.*, 2009). Such findings indicate that RS–GIS tools are improving for analysing water balance. At least in terms of each hydrologic component in the water balance (P, ET, and ΔS), this study indicates that RS–GIS is even increasingly becoming useful in measuring the water balance in data-constrained basins. However, we do also find that significant improvements are necessary before these tools can generate a reliable water balance model for such basins. Given the large errors and smoothing required, we find that in the application of RS–GIS in data-constrained basins at scales of managerial interest, such tools likely only allow managers to engage in annual water resource management. Such time frames are potentially useful for creating long-term water policies, but not so useful for real-time water management.

However, the intention of our work is not to provide a definitive model for data-constrained basins. Even though few recent studies have begun to engage in purely or heavily RS-based runoff analyses (Stisen *et al.*, 2008; Wagner *et al.*, 2009; Gao *et al.*, 2010; Stisen and Sandholt, 2010; Sahoo *et al.*, 2011), these studies usually are only shown to reliably monitor heavily gauged basins and analyse basins far larger than the scale of a typical water resource manager. Our intention is to determine the current boundaries of the state of the art in RS–GIS for a data-sparse basin. We do this through utilizing the most up-to-date RS–GIS tools available to analyse not just a data-constrained basin but a basin at a scale closer to that of interest to a water resource manager.

Towards these aims, we first bring the most up-to-date RS–GIS tools available for water resource management (TRMM, AIRS, SRB, GRACE, and MODIS). Second, we expand the component and model error analysis used in past studies to engage in more detailed correlational (R^2, lagged correlation, and pairwise Pearson correlation analysis), error propagation (both Gaussian and MOM), and sensitivity (perturbation) analyses. In this manner, we aim to provide a better accuracy assessment of RS–GIS models in greater detail than previous studies and to know what those errors are for a basin scale of interest to a water resource manager.

Because we use only a single basin for our exploratory study, an obvious avenue for future research is to apply, test, and validate the RS-based and CN-based models and data drivers we propose here to other locations of similar basin size and level of data constraint. Our intent for this study is to begin this process of understanding and analyse in greater detail the current state of the art with regard to using RS–GIS for measuring a basin's entire water budget. To do so, we sought to examine the possibility of a basin with the following characteristics: (1) limited ground data and (2) a scale closer to that of interest to a water resource manager. In choosing to engage in a single exploratory study of the Rufiji basin in Tanzania, we have the advantage of being able to engage in much more detailed error, uncertainty, and correlational analyses and utilize localized insights that allow us to understand the utility of RS-based approach at a level more suited to water resource management. As far as we are aware, no study has engaged with purely RS-based water budget models to this level of analytical detail and to such a localized level. Therefore, although we acknowledge the trade-offs and errors of engaging in a single data-constrained basin study, we were able show how RS–GIS tools may be used to address the problem of data sparsity in water resource management.

CONCLUSION

In this paper, we present a purely RS-driven model for a data-limited river basin in Africa, which is of a scale closer to that of interest to a water resource manager: the Rufiji basin in Tanzania. In this paper, we seek to assess the state of the art with regard to using RS–GIS tools and approaches to analyse such basins. We did this through using data available from a single yet significant sub-basin (the Usangu sub-basin, 20 810 km^2) and trying to determine the potential for using such a model to analyse the entire basin (Rufiji basin, 177 420 km^2). Through this exploratory study, we use the most up-to-date RS data available (TRMM, GRACE, AIRS, SRB, and MODIS) to assess how feasible RS–GIS approaches are for analysing the water balance for a data-constrained basin. We further add detailed error, sensitivity, and correlational analyses to specify the exact nature of the error in our model and the contributions of each hydrological component (P, ET, and ΔS) to our model.

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