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Interpolation of daily raingauge data for hydrological modelling in data sparse regions using pattern information from satellite data

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Abstract In order to cope with a severe reduction of the raingauge network in the Great Ruaha River basin over the past 30 years, an interpolation scheme using spatial patterns from satellite images as covariate has been evaluated. The regression-based interpolation attempts to combine the advantages of accurate rainfall amounts from raingauge records with the unique spatial pattern information obtained from satellite-based rainfall estimates. A spatial pattern analysis reveals that the simple interpolation of the sparse current raingauge network compares very poorly to the pattern originating from the much denser historic network. In contrast, the rainfall datasets that include patterns from satellite data show good correlation with the historic pattern. The evaluation based on hydrological modelling showed similar and good performance for all rainfall products, including raingauge records, whereas the purely satellite-based product performed poorly.

Key words daily raingauge data; satellite rainfall estimates; regression-based interpolation; hydrological modelling; Tanzania

Interpolation des données pluviométriques journalières pour la modélisation hydrologique dans des régions à données clairsemées en utilisant des informations issues de données satellitaires

Résumé Afin de faire face à une réduction sévère du réseau de pluviomètres dans le grand bassin de la rivière Ruaha au cours des 30 dernières années, un système d'interpolation utilisant des modèles spatiaux obtenus à partir d'images satellitaires comme covariable a été évalué. L'interpolation, basée sur une régression, tente de combiner les avantages des quantités de précipitations précises des enregistrements pluviométriques avec les modèles spatiaux obtenus à partir d'estimations pluviométriques satellitaires. Une analyse spatiale révèle que la simple interpolation du réseau de pluviomètres clairsemés actuel se compare très mal aux configurations fournies par le réseau historique beaucoup plus dense. En revanche, les jeux de données de pluie qui intègrent les données satellitaires montrent une bonne corrélation avec le modèle historique. L'évaluation basée sur la modélisation hydrologique a montré des performances similaires et bonnes pour tous les produits de pluie, y compris pour les jeux d'enregistrements pluviométriques, alors que le produit satellitaire seul fournissait des résultats médiocres.

Mots clefs données pluviométriques journalières ; estimation satellitaire des pluies ; régression basée sur l'interpolation ; modélisation hydrologique ; Tanzanie

1 INTRODUCTION

The density of raingauge networks has declined dramatically over the past three decades in Tanzania. This is a common problem, not limited to developing countries, but following a global trend. The global trend, in the number of raingauges over the 20th century shows a steady increase from 1900 to 1960 followed by a rapid decline from the 1970s onwards (New *et al.* 2001). Today only approximately 25% of the raingauge stations available in the Great Ruaha River Basin (GRRB), Tanzania, in the 1960s–1980s are operating. The reduction of the raingauge network poses serious challenges for hydrological modelling applications, including climate change impacts

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assessment and science-based water management (Hughes 2006, Thiemig *et al.* 2012), and calls for new approaches to spatial interpolation using auxiliary data. Fortunately, the decline in raingauge density coincided with the launch of earth observation satellites in the early 1980s. Of special interest are the geostationary meteorological satellites (e.g. METEOSAT), which are located favourably for African applications due to their equatorial orbit. In addition to the adequate spatial resolution and good view angle properties for Tanzania, these satellites are equipped with both visible and thermal sensors with high temporal resolution, typically ½ hour (Schmetz *et al.* 2002), which allows for the estimation of daily precipitation at a spatial resolution of approximately 0.1 degree (Arkin and Meisner 1987). Today many satellite-based precipitation products exist, although they often show relatively poor performance when validated at a daily time scale against raingauge observations (Symeonakis *et al.* 2009, Liechti *et al.* 2012). However, satellite-based observations contain valuable spatial pattern information that cannot be achieved through a sparse raingauge network (Petty and Krajewski 1996, Grimes and Diop 2003). When comparing different satellite-based rainfall estimates (SRFE), these often exhibit large differences in rainfall amounts (Dinku *et al.* 2007, Asadullah *et al.* 2008), but generally agree well on the spatial patterns (Stisen and Sandholt 2010, Thiemig *et al.* 2012).

The mutual benefits of raingauge records (precise rainfall amounts) and satellite retrievals (spatial pattern information) have led to the development and application of several techniques to merge the two types of data. These range from classical geostatistical methods, such as interpolation with covariates (Verworn and Haberlandt 2011), kriging with external drift (Tobin *et al.* 2011), block kriging (Grimes *et al.* 1999) and quantile matching (De Vera and Terra 2012), to new approaches, such as pattern-oriented memory (Matos *et al.* 2013) and copulas (Bárdossy and Pegram 2013). Likewise, the merging of raingauge data and radar quantitative precipitation estimates (QPE) through bias correction (He *et al.* 2011), co-kriging (Krajewski 1987, Sinclair and Pegram 2005) and Kalman filtering (Seo and Breidenbach 2002) has been developing considerably over decades. Generally, the more complex methods are typically used when working on coarser time scales or when raingauge records are abundant (Wagner *et al.* 2012).

In the current study, four products of daily precipitation are evaluated through application in a hydrological modelling scheme including three subcatchments with varying raingauge density. The four precipitation products are: (a) a satellite-based precipitation product (CPC-FEWS RFE2.0) developed specially for the African continent; (b) simple inverse distance weighted interpolation of a network of unevenly distributed raingauges covering the 86 000 km^2 GRRB; and (c, d) two merged products, in which the available raingauge data are interpolated using a regression-based interpolation method including spatial patterns from the satellite-based precipitation product (Wagner *et al.* 2012). The merged product utilizes the local accuracy of the observed rainfall in combination with the unique spatial pattern information of the satellite data. The produced dataset will be similar to the traditional raingauge interpolation in the vicinity of the raingauges while obtaining the long-term spatial pattern characteristics of the satellite data.

The aim of the study has been to improve the spatial pattern of interpolated daily rainfall for the Great Ruaha Basin. The study focuses on the recent period (2001–2009) in which only a fraction of the original (1960–1980) raingauge network remains.

The applicability of the precipitation products is evaluated through the performance of a distributed hydrological model (MIKE SHE) which is recalibrated for each precipitation product. The use of distributed hydrological models for evaluating spatial precipitation data can be advantageous for several reasons (Bitew *et al.* 2012, Gebregiorgis and Hossain 2013). One is the scale issues involved in comparing point measurements from raingauges to gridded precipitation estimates from remote sensing or interpolation. These scale issues are reduced when evaluating the precipitation product on a catchment scale. Secondly, when calibrated against downstream river discharge, the hydrological model will account for the entire water balance and, therefore, it can potentially illustrate unrepresentative location of raingauges or improper spatial interpolation (Stisen and Sandholt 2010). However, through model calibration, biases in precipitation input can be compensated by evapotranspiration if only river discharge is used in the objective function. Similarly, inappropriate spatial model parameterization and structure can influence the evaluation of precipitation input, although these model deficiencies will typically have a

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similar impact on all evaluated rainfall products and could potentially be indicated by unrealistic and non-physical model parameters after calibration.

2 STUDY AREA

The GRRB is situated the tropical south of Tanzania and occupies an area of 86 000 km^2. The basin is characterized by a large spatial variability in elevation, vegetation and climate (Fig. 1). The hydrology of the area is largely controlled by the precipitation gradient described by increasing precipitation going from north (400 mm/year) to south (2000 mm/year). In addition to the large spatial variability, the migration of the Intertropical Convergence Zone dictates the distinct wet and dry seasons from November to April and May to October, respectively.

The water resources in the GRRB are vital for the national productivity through food production in large irrigated areas and hydropower production at the Mtera and Kidatu plants, which in combination deliver 284 MW or more than 50% of the hydropower in Tanzania (Kadigi *et al.* 2008). Besides the large irrigation schemes, small-scale farmers contribute to local income and food security, while the Ruaha National Park and the Ihefu Wetland are valuable and vulnerable water-dependent ecosystems. The extreme spatial and temporal variability of rainfall puts further pressure on a limited water resource. All water resource related stakeholders in the Great Ruaha Basin are witnessing a decline in the dry season river flows (Lankford *et al.* 2004). Consequently, integrated water management that includes detailed and reliable hydrological models is required (Kashaigili *et al.* 2005, Mwakalila 2005).

The current study analyses the rainfall patterns in the entire GRRB, although the hydrological modelling focuses on three selected sub-basins (Fig. 2): the Usangu, the Little Ruaha and the Lukosi. The selection is mainly based on the availability of river discharge measurements, but at the same time the three sub-basins represent different levels of raingauge density. As can be seen from Fig. 2, the rainfall data over the sub-basins of Usangu, Little Ruaha and Lukosi for the period 2001–2009 are represented by eight, five and zero raingauges, respectively, making the Lukosi an ungauged catchment. This obviously posed a great challenge to hydrological modelling, which has been studied extensively in the past scientific decade under the International Association of Hydrological Sciences (IAHS) (Hrachowitz *et al.* 2013).

3 SATELLITE-BASED RAINFALL ESTIMATE

The satellite-based rainfall estimate (SRFE) utilized in this study is the Climate Prediction Center-Famine Early Warning System (CPC-FEWS) daily precipitation estimate, RFE2.0, available at a 0.1 degree grid scale for the African continent from October 2000 to the present (Xie and Arkin 1996, 1998). This precipitation estimate is primarily based on thermal infrared (TIR) images from the geostationary METEOSAT satellite operated by the European Space Agency (Schmetz *et al.* 2002). The TIR-based estimates are merged with microwave SSM/I data and a network of online raingauges from the global telecommunication system (GTS). This implies that the CPC-FEWS estimates are somewhat bias-corrected using raingauge data; however, only a single GTS station, located downstream of the modelled sub-basins, exists within the GRRB.

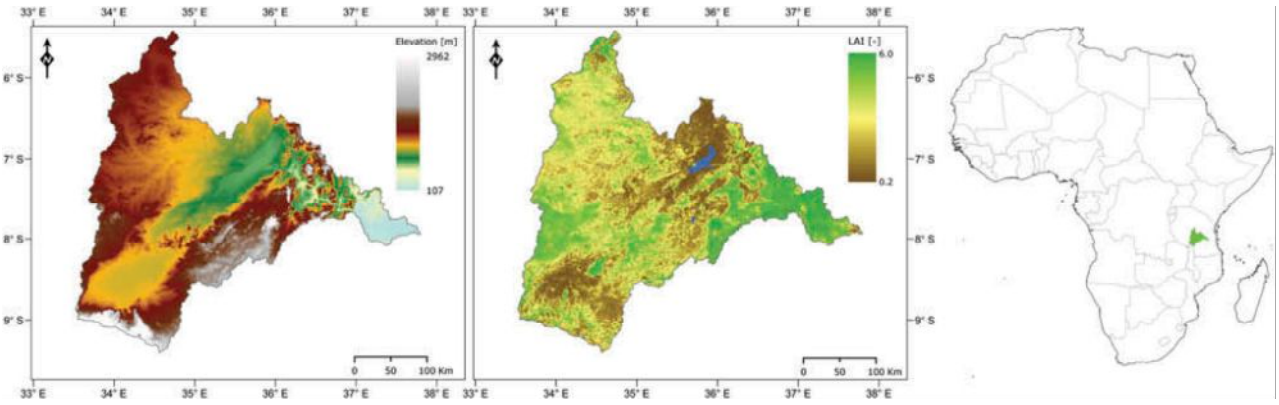


Fig. 1 Elevation (m a.s.l.) from the SRTM dataset and mean annual leaf area index (LAI) for the period 2001–2009 obtained from the MODIS MCD15A2 product.

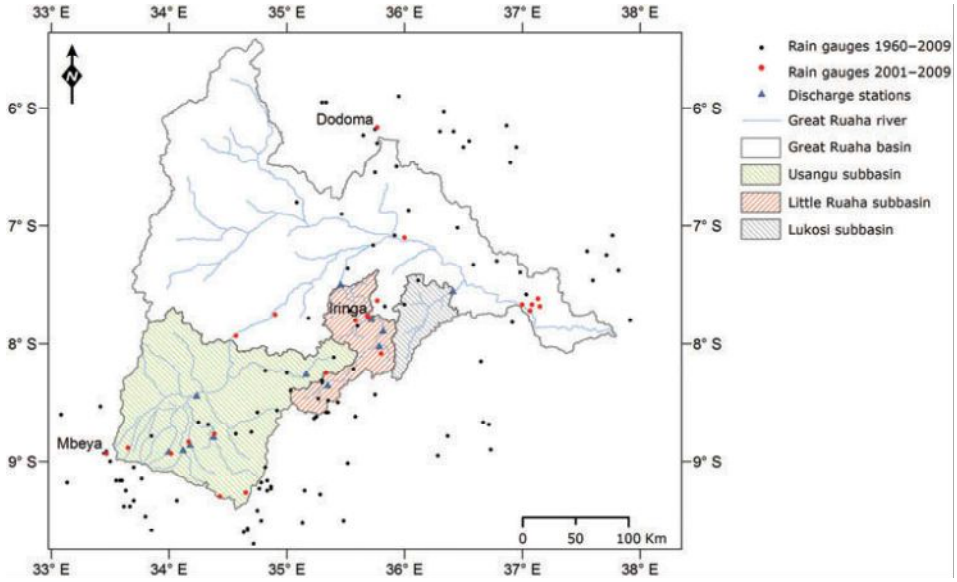


Fig. 2 Available raingauge and discharge data in the GRRB and modelled sub-basins.

The FEWS RFE2.0 product has been evaluated along with five other satellite-based rainfall products for a similar hydrological modelling scheme for the Senegal River basin in West Africa (Stisen and Sandholt 2010) and it came out as the superior product, presumably due to the specific algorithm adjustment made for the African continent, compared to the other global products. The gridded rainfall estimate is mapped on a 0.1 degree grid of 60 by 50 elements as all subsequent interpolations. The CPC-FEWS data will be evaluated as direct input to the hydrological model based on time series of gridded daily CPC-FEWS maps. In addition, average annual and monthly spatial patterns are derived from the CPC-FEWS data by calculating the annual mean and monthly means for the entire period (2001–2009). These annual and monthly rainfall patterns will subsequently be used to guide the interpolation of raingauge observations.

4 METHODOLOGY

4.1 Rainfall interpolation

The total raingauge records include 175 stations, with daily data from the period 1960–2009, located within or in the vicinity of the GRRB. Of these 175 stations, 130 were selected for the final analysis. The selected stations (shown in Fig. 2), contained more than 5 years of consecutive records. The criterion of 5 years of records was based on an analysis of the few complete records, which showed that any combination of 5 year continuous records would give a reasonable estimate of annual mean rainfall for a given station. As can be seen from Fig. 2, there is a very uneven spatial distribution of the 130 raingauges, due to the preferred locations close to roads, railways and densely populated areas. This makes sound spatial interpolation critical and reliable estimates of areal rainfall difficult.

Perhaps even more pronounced than the spatial distribution is the dramatic decline in active raingauges over the studied period, 1960–2009, as illustrated in Fig. 3. The decline began in the early 1990s when approximately 85 stations were running and levelled out in 2000 when only 22 stations remained. The stations remaining for the period 2001–2009 are

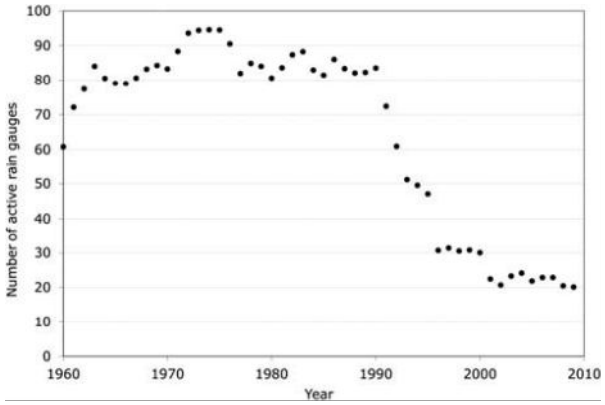


Fig. 3 Number of active raingauge stations in and around the GRRB for the period 1960–2009.

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indicated in Fig. 2 and highlight the problems of the uneven spatial distribution, which was even evident if all 130 stations were available. Large parts of the north western GRRB are basically ungauged and, even in the modelled Lukosi sub-basin, there are no raingauges remaining for the period 2001–2009. The reason for the decline was mainly cuts during a national structural reform in Tanzania; however, the trend of declining numbers of raingauges is not limited to Tanzania or other developing countries, but is seen worldwide, where dense raingauge networks are often thinned out or replaced by weather radars or simulation models (New *et al.* 2001).

Satellite remote sensing is one way of getting better spatial information on precipitation. Both purely remote sensing-based estimates and merged products utilizing a combination of satellite imagery, observations and models are available (Huffman *et al.* 1995, Joyce *et al.* 2004) and widely used in hydrological modelling (Thiemig *et al.* 2012). In spite of the unique spatial properties of satellite data, precipitation estimation is far from straightforward and such estimates are often biased and perform poorly when compared to raingauge observations, especially at the daily time scale (Dinku *et al.* 2007). The main advantage of the remote sensing-based methods for precipitation estimation lies in the temporal continuity and the spatial pattern information, which cannot be obtained from sparse ground-based observations.

The interpolation method evaluated here tries to combine the strengths of both raingauge observations and satellite data, by putting high weight on the observations close to the raingauges and by trusting the observed rainfall amount more than the remote sensing estimated amounts. However, the overall spatial pattern from the remote sensing estimate is favoured over the crude interpolation of raingauges.

4.1.1 Inverse distance weighting Inverse distance weighting (IDW) is a common and simple way of spatial interpolation, where observations are weighted based on their distance to a given point by a nonlinear relationship expressed by an exponent (typically equal to 2). The method, which was first proposed by Shepard (1968), is widely used due to its simplicity and its applicability to even sparse and irregular datasets. In the current study, IDW is applied on a daily basis to raingauge observations assuming the relationship can be described by the square of the distance. The 130 raingauge time series are not gap filled, hence only stations with valid raingauge observations are included on a given day. This implies that the basis for spatial interpolation is diminishing during the study period, due to the reduction of the raingauge network. The annual average rainfall based on the IDW has been split into two periods, 1960–2000 (Fig. 4(b)) and 2001–2009. As can be seen from Fig. 4(b), the spatial pattern resulting from the IDW interpolation is highly influenced by the location of the individual raingauges that stand out as islands of high and low values, while grids far from any raingauge approach a value close to the mean of all raingauges.

4.1.2 Regression-based inverse distance weighting In an attempt to exploit the benefit of both the satellite-based rainfall estimate and the raingauge data, a regression-based IDW is applied. The regression-based interpolation is founded on the existence of covariates for rainfall that are mapped at a higher resolution than the raingauge network. Typical covariates are elevation, distance from the coast, or other general climate gradients (Stisen *et al.* 2008). Spatial patterns from three covariates were tested against mean annual rainfall for the 130 raingauge locations. The three tested covariates were; elevation, latitude and the annual mean FEWS pattern (2001–2009). Only FEWS showed potential as covariate, with a coefficient of determination (R^2) of 0.73 (Fig. 4(c)), unlike latitude ($R^2 = 0.43$) and elevation ($R^2 = 0.01$) (the latter two not shown).

Having established a potential covariate for rainfall, the regression-based interpolation was implemented according to the procedure described in Wagner *et al.* (2012). However, compared to Wagner *et al.* (2012), raingauge data were used without gap filling to avoid forced spatial correlation between raingauge observations. Spatial patterns from the FEWS data obtained at annual, monthly and, subsequently, daily time scales were tested. A regression equation between rainfall and the FEWS spatial pattern is calculated for each wet day, defined as days where more than 10% of the operating raingauges indicate rainfall. The raingauge estimate used in the regression was the mean rainfall for a 7-day period around the current day in order to improve the robustness of the regression (Wagner *et al.* 2012). Furthermore, the significance of the regression was tested using a T-test with a significance level of 10%. In the case of significant regression, an initial spatial rainfall estimate is based on the regression equation and the covariate. Subsequently, the residuals between that

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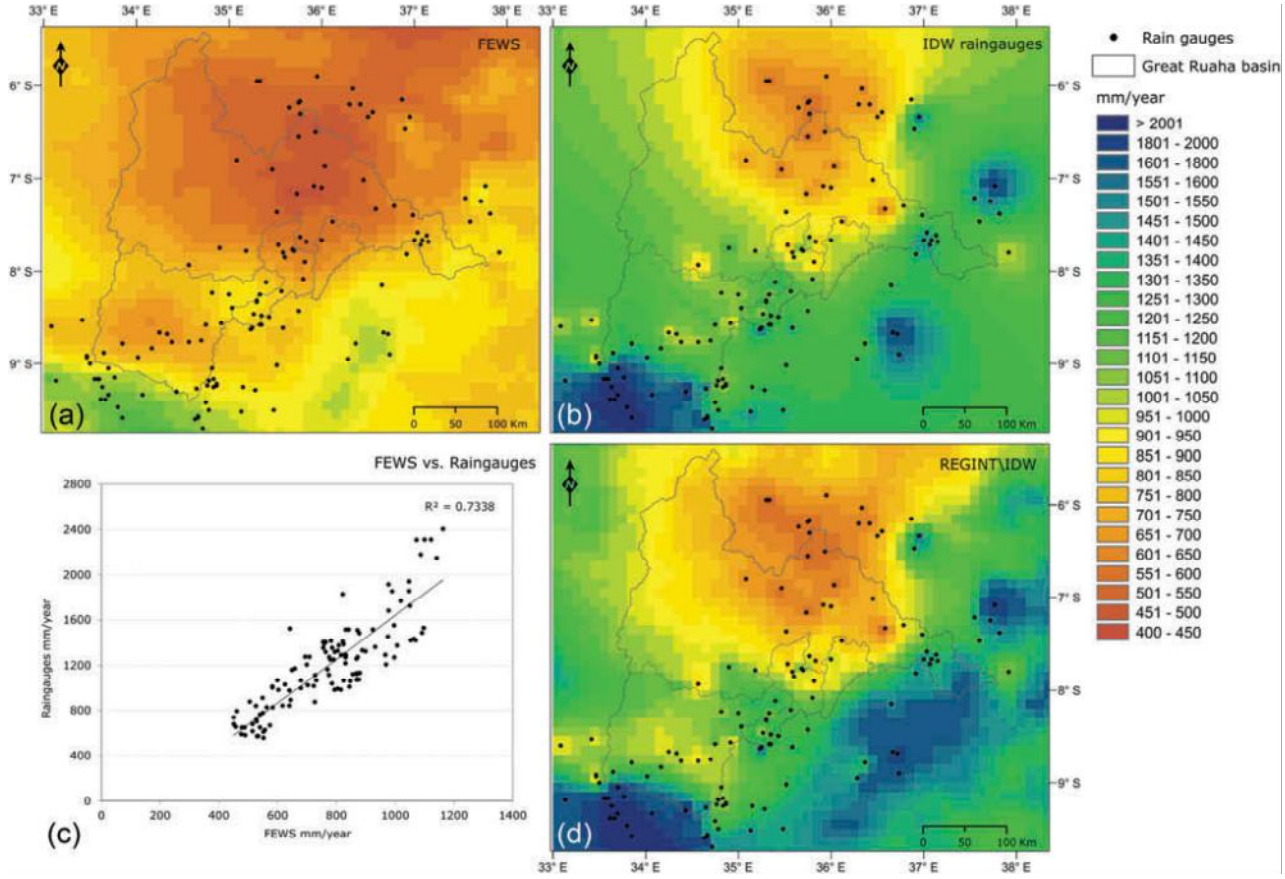


Fig. 4 (a) Annual rainfall estimates from FEWS (2001–2009), (b) IDW interpolation of raingauges (1960–2000), and (d) regression-based IDW using monthly spatial patterns from FEWS (1960–2000). (c) The correlation between raingauges and FEWS.

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estimate and the actual daily raingauge records for the current day are interpolated using simple IDW and subtracted from the initial regression estimate. On dry days, or, in cases where the regression was not significant, the raingauge data were interpolated using the IDW scheme, or alternatively for the recent period (2001–2009), raingauge data were substituted with the FEWS estimate on the current day.

4.2 Hydrological model

4.2.1 Model code In order to evaluate the different rainfall products a spatially distributed hydrological model is set up for the three sub-basins using the MIKE SHE modelling framework (Abbott *et al.* 1986). The applied version of MIKE SHE is based on a detailed surface component including distributed calculations of evapotranspiration, unsaturated zone flow, overland flow and a routing scheme based on a dense river network. The groundwater component is simplified to a linear reservoir solution due to lack of subsurface information and calibration data and to reduce computation times. This version of MIKE SHE has been used previously for large scale applications in data-sparse regions (Andersen *et al.* 2001) and also for evaluating spatially distributed rainfall products (Stisen and Sandholt 2010).

4.2.2 Model set-up and input data The models covering the three sub-basins of Usangu (21 000 km^2), Little Ruaha (5200 km^2) and Lukosi (3000 km^2) are set up in a 1000-m grid resolution and parameterized with freely available global datasets for elevation, vegetation, soil types and soil parameters (Table 1). The 90-m digital elevation model from the NASA Shuttle Radar Topographic Mission (SRTM) (Farr *et al.* 2007) is used to delineate catchment boundaries and river networks before reducing the resolution to 1000 m. From the Harmonized World Soil Database (Nachtergaele *et al.* 2009), soil classes and soil texture information are available at a 1 km resolution globally and used

Table 1 Data input, their source and spatial resolution.

Data type	Data source	Applied resolution	
		Spatial	Temporal
Distributed maps			
Elevation, DEM	NASA, Shuttle Radar Topographic Mission	1 km	—
Soil types and parameters	Harmonized World Soil Database	1 km/6 soil types	—
Leaf area index	MODIS MCD15A2 LAI product	1 km/13 classes	24 days
Root depth	Function of LAI	1 km	24 days
Crop coefficient	Function of LAI	1 km	24 days
Time series			
Precipitation	Tanzanian Meteorological Agency, CPC-FEWS	11 km	Daily
Reference ET	CRU, University of East Anglia	55 km	Monthly
Discharge	Rufiji Water Basin Office, Iringa	12 stations	Daily

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to define six dominating soil classes and associated soil physical parameters, which are derived through the RETC database (Van Genuchten *et al.* 1991). Remote sensing based estimates of leaf area index (LAI) are available from 2001 at 1 km resolution every 8 days from the MODIS LAI product MCD15A2, which merged images from both the Aqua and Terra platforms. The MODIS LAI data are further processed by smoothing the time series of each 1-km grid by a Savitsky-Golay filter (Jönsson and Eklundh 2004) and applying a 24-day moving average. In order to combine the distributed vegetation parameterization with simulation of irrigation demands, the remotely sensed data are finally classified in 13 classes based on the annual mean and seasonal pattern of each 1-km grid. Irrigation is calculated in the model through a soil moisture deficit calculation in areas prescribed as irrigated. These areas are mapped in Kashaigili *et al.* (2005) and cover around 700 km^2.

Besides precipitation, which is described above, the model requires reference evaporation (ET_{ref}) as a secondary driving climate variable. The data required to calculate ET_{ref} are not available at an appropriate quality and spatial distribution for the modelled areas. Therefore, the global gridded dataset from the Climatic Research Unit (CRU) at the University of East Anglia, UK. These data are available at spatial and temporal resolutions of 0.5 degrees and 1 month, respectively. Finally, daily data from 12 river discharge stations operated by the Rufiji Water Basin Office in Iringa are used for model calibration and validation.

The models are set up for what can be characterized as current conditions. The simulation period is limited to 2001–2009 for several reasons. One is the availability of data, since discharge data are most complete for this period and MODIS data for vegetation parameterization and CPC-FEWS RFE2.0 data for precipitation have been available since 2001. Also human development, including expansion of agriculture, has been great over the past 50 years, making it difficult to assume unchanged land-use conditions for a period outside the period for which MODIS data are available. Finally, the main objective of the study is to investigate different rainfall interpolation strategies during the recent decade with very few raingauges (Fig. 2) coinciding with the availability of satellite data.

4.2.3 Calibration scheme The calibration of each of the three sub-catchment models is performed as a multi-site calibration in which all discharge stations are included in the optimization of one parameter set for each sub-basin. The parameter optimization is based on the Population Simplex Evolution method, which is a global search algorithm suited for parallel execution and implemented in the MIKE ZERO modelling framework. Between six and eight free model parameters are selected for each sub-catchment model, depending on catchment complexity and availability of calibration data. The calibrated model parameters are time constants for interflow and baseflow in the linear reservoirs, a bypass function for the unsaturated zone and a scaling factor for root depth across vegetation classes. The objective function is based on daily river discharge records from 12 stations (two are only used for validation) in the three sub-basins and formulated as RMSE for the period October 2000 to October 2005. In addition to the calibration period, the models are spun up for 1 year following a hotstart from a previous simulation and continued, after the calibration period, into the validation period ending in October 2009.

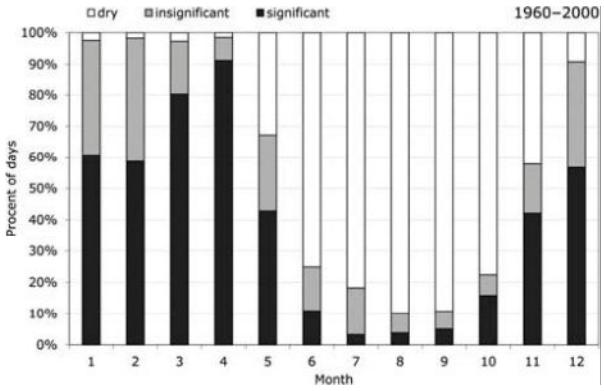


Fig. 5 Results of T-test of significant correlation between monthly FEWS patterns and daily raingauge observations for the period 1960–2000.

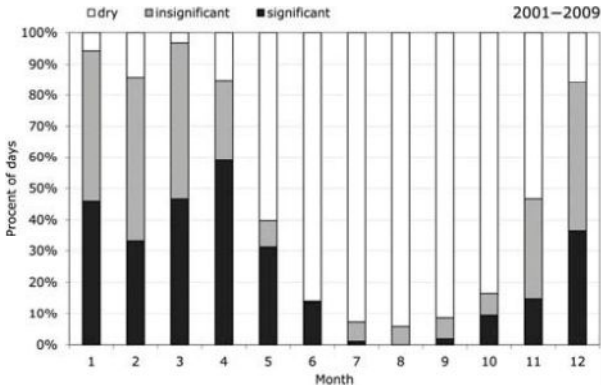


Fig. 6 Results of T-test of significant correlation between monthly FEWS patterns and daily raingauge observations for the period 2001–2009.

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5 RESULTS

5.1 Rainfall interpolation

5.1.1 Interpolations, 1960–2000 As a proof of concept, the regression-based interpolation scheme was first implemented for the period 1960–2000, when most raingauges were available. Due to the missing overlap in time between the FEWS pattern and the historic raingauge record (1960–2000), this application requires an assumption of stationarity in the long-term spatial pattern of rainfall. Out of two applied covariates, annual FEWS patterns and monthly FEWS patterns, the latter resulted in most days of significant regression correlation and therefore the monthly FEWS patterns were applied. As indicated in Fig. 5, around 70% of the rainy season days (December–April) showed a significant regression correlation, indicating the value of FEWS patterns as covariate for the historic raingauge record. The resulting annual mean rainfall distribution when averaging all 41 years of daily interpolated fields using the regression-based method is shown in Fig. 4(d). In addition, Fig. 4(a)–(c) illustrates (a) the FEWS estimate, (b) the simple IDW interpolation of raingauges and (c) the correlation between FEWS and the raingauge data.

5.1.2 Interpolations, 2001–2009 Having established the methodology, the main aim of the study has been to improve the spatial interpolation for the data-poor period 2001–2009. By applying the same approach for this period, the number of days with significant regression correlation drops, as shown in Fig. 6, where only around 45% of the rainy season days (December–April) allow for a regression-based interpolation. However, the overlap in time between the period of analysis and the daily FEWS estimates allows for two ways of filling the gaps on days that are dry or when regression-based interpolation is not valid. One, named REGINT/FEWS, fills the gaps with the current FEWS estimate and the other, REGINT/IDW, fills the gaps with simple IDW interpolation of raingauges. In Fig. 7, annual mean rainfall from daily estimates for the period 2001–2009 based on (a) FEWS, (b) IDW, (c) REGINT/FEWS and (d) REGINT/IDW is illustrated. An attempt was made to base the regression on daily FEWS data correlated to daily raingauge data, but with a much reduced number of days with significant correlation (25%), the methods did not prove robust for the low number of raingauges available.

As illustrated in Fig. 7(a)–(d) the resulting annual rainfall maps for the period 2001–2009 are quite different for the four gridded rainfall datasets. Since the true spatial pattern is unknown, the four patterns are evaluated against the IDW pattern for the period with abundant data (1960–2000), which is assumed to be the best estimate of a true spatial pattern. In order to avoid the most uncertain parts of the reference map (IDW 1960–2000, Fig. 4(b)) only grids located within a radius of 50 km from one of the 130 original raingauges are included. The resulting scatterplots are seen in Fig. 8(a)–(d), illustrating the correlation between the four rainfall distributions (2001–2009) and the reference map. It is noteworthy that the spatial correlations are the highest (R^2 = 0.76, 0.69 and 0.61) for the three rainfall maps (Fig. 7(a), (c) and (d)) that include FEWS data, even though the FEWS data are completely independent of the IDW 1960–2000 map. In contrast, the IDW interpolation for the period 2001–2009 has the

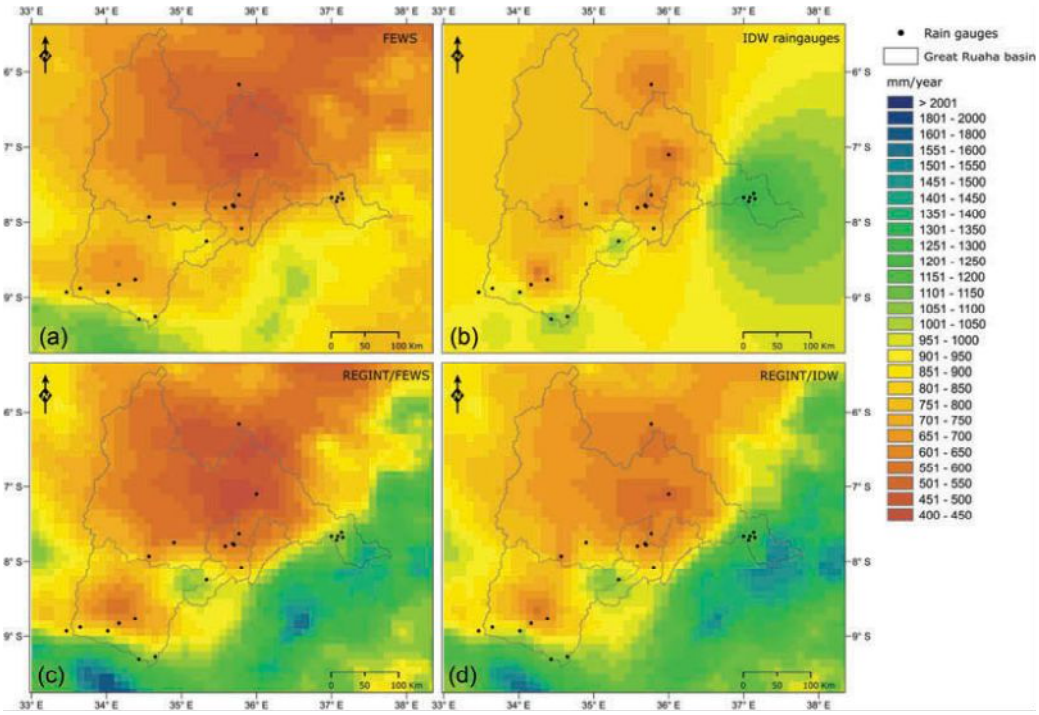


Fig. 7 Annual rainfall estimates from (a) FEWS (2001–2009), (b) IDW interpolation of raingauges (2001–2009), (c) regression-based interpolation filled with daily FEWS data and (d) regression-based interpolation filled with IDW data. Both (c) and (d) use monthly spatial patterns from FEWS (2001–2009) in the interpolation.

lowest correlation (R^2 = 0.39) to the reference map. This illustrates the potential of the satellite data to reproduce a realistic spatial pattern in the absence of abundant raingauges. It is also evident from Fig. 8 that the clear bias of the FEWS data (Fig. 8(a)) is reduced by merging the spatial pattern information with the available raingauge records (Fig. 8(c) and (d)), although some bias can occur due to the difference in time periods on the axis of the figures.

However, the spatial pattern within each of the three modelled sub-catchments seems to vary little, which might limit the ability of the hydrological modelling exercise to distinguish between the different rainfall products. Table 2 gives an overview of the statistics for each dataset for the entire GRRB and the three modelled sub-basins. In general, FEWS has lower annual mean rainfall compared to the three interpolated datasets, and the regression-based interpolation schemes produce larger standard deviations compared to both FEWS and the IDW interpolation.

5.1.3 Alternative raingauge scenario, 2001–2009 Not just the density of the raingauge network but also the location of raingauges can play a vital role in the interpolated rainfall fields and subsequent hydrological modelling application. Given the large contrasts in climate and hydrology of the GRRB, most runoff is generated in a few relatively small recharge zones in the mountain ranges. Here rainfall largely exceeds evaporation in the wet season in contrast to the lowland, where recharge is almost negligible. Therefore, a correct representation of rainfall in the recharge zones is of specific importance for runoff modelling. Luckily a few raingauges have remained in operation in the recharge zones in the Usangu and Little Ruaha sub-catchments (Fig. 2). In order to highlight the importance of these stations and the potential of the regression-based interpolation for ungauged conditions, a scenario has been tested in which one raingauge, located in the wet highlands on the divide between the Usangu and Little Ruaha sub-catchments, has been removed from the 2001–2009 records.

The IDW and REGINT/FEWS interpolation schemes were rerun without this raingauge and the resulting annual rainfall maps are illustrated in Fig. 9. Without the removed raingauge, which had higher rainfall than the surrounding raingauges, the spatial pattern of the IDW interpolation (Fig. 9(a)) in the wet highlands changes compared to Fig. 7(b). In contrast, the high rainfall in the central mountains

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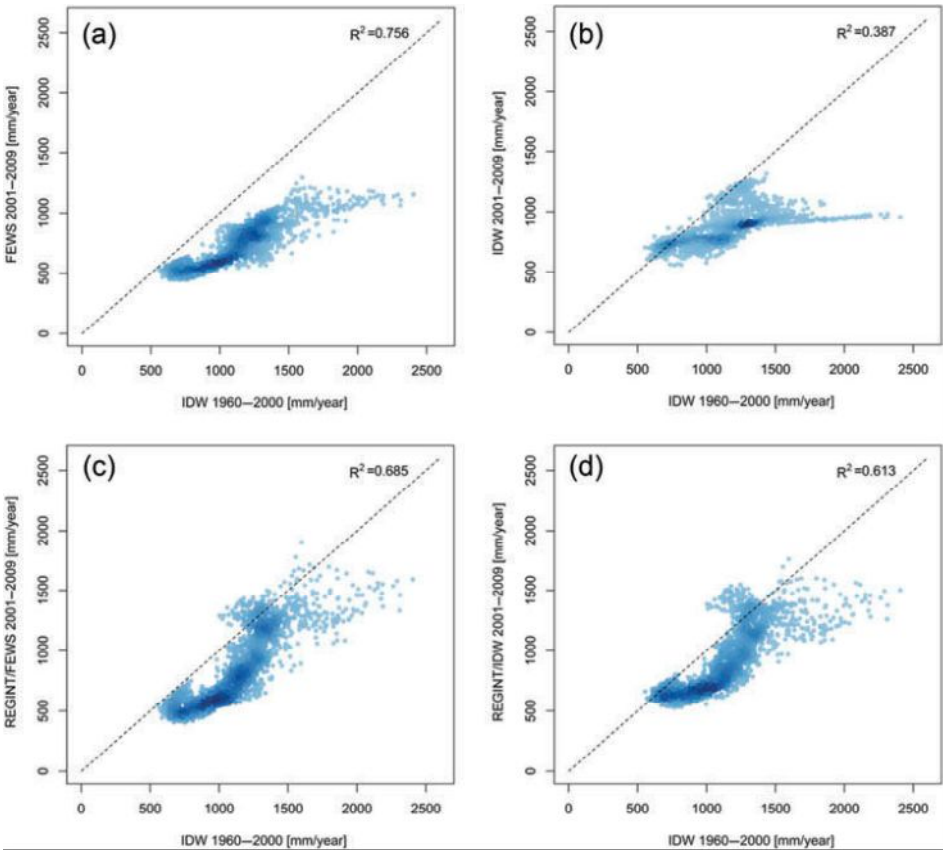


Fig. 8 Correlation in spatial pattern between the IDW interpolation based on abundant data (1960–2000) and the interpolation schemes applied for the reduced dataset (2001–2009): (a) FEWS, (b) IDW, (c) REGINT/FEWS and (d) REGINT/IDW.

Table 2 Statistics of annual rainfall for the entire GRR and individual sub-basins for 2001–2009.

	Mean (mm/year)	STD (mm/year)	Min (mm/year)	Max (mm/year)	Range (mm/year)
FEWS					
Great Ruaha	656	114	448	978	530
Usangu	770	71	650	978	328
Little Ruaha	706	108	516	886	370
Lukosi	654	67	560	831	271
IDW					
Great Ruaha	797	128	559	1313	754
Usangu	826	88	577	1058	481
Little Ruaha	786	121	630	1016	386
Lukosi	802	63	675	934	259
REGINT/FEWS					
Great Ruaha	678	181	404	1438	1035
Usangu	803	132	564	1170	606
Little Ruaha	747	177	483	1049	566
Lukosi	710	121	552	1034	482
REGINT/IDW					
Great Ruaha	760	174	529	1548	1019
Usangu	842	121	556	1136	580
Little Ruaha	800	156	576	1067	491
Lukosi	782	112	597	1047	450

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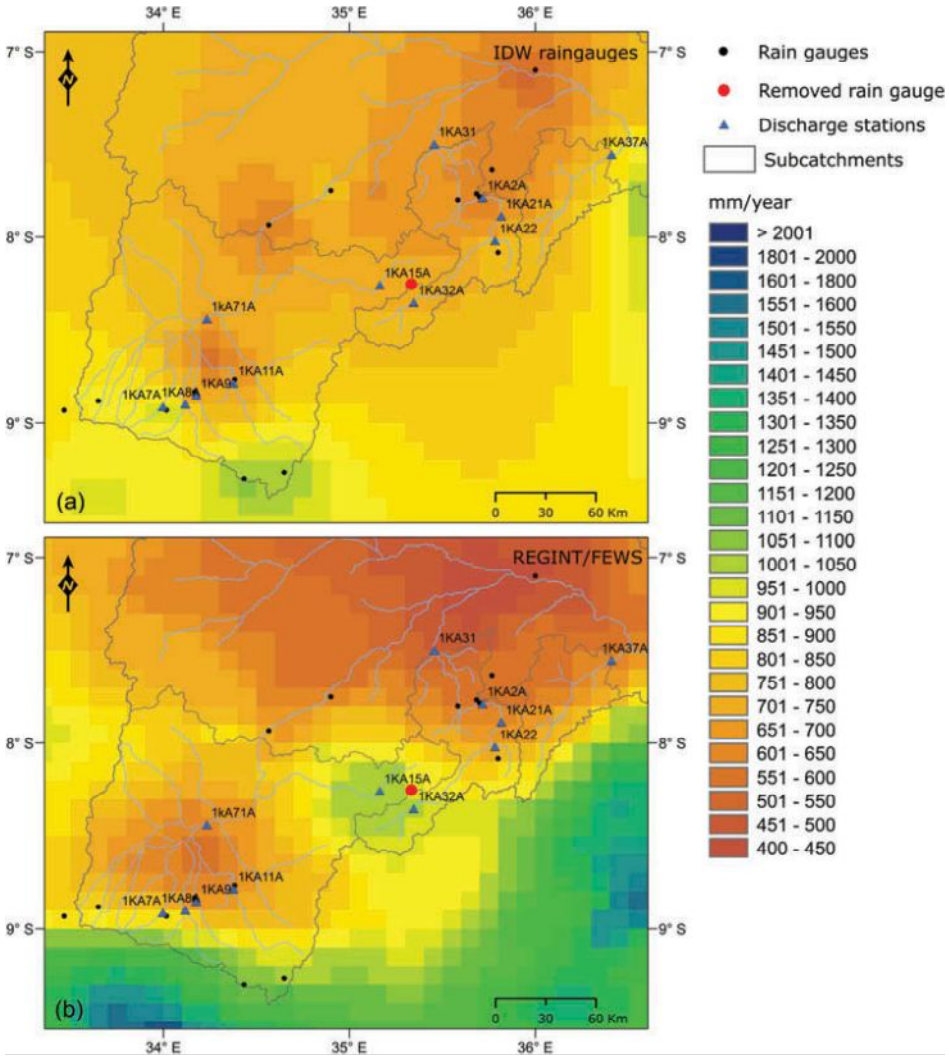


Fig. 9 Annual rainfall estimates from (a) IDW (2001–2009) and (b) REGINT/FEWS (2001–2009), based on the alternative rainfall record with one omitted raingauge (dot).

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remains in the regression-based interpolation (Fig. 9 (b)) due to the pattern information contained in the FEWS data. The large differences in rainfall around the omitted raingauge in Fig. 9(a) and (b) will have a direct impact on the modelled discharge at the three discharge stations 1KA15A in the Usangu sub-basin and 1KA21A and 1KA32A in the Little Ruaha sub-basin (Fig. 9).

5.2 Hydrological modelling

5.2.1 Model-based evaluation of rainfall interpolations The results of the hydrological modelling, in which each sub-basin model is calibrated to a specific rainfall dataset, are presented for each discharge station for the calibration (Table 3) and validation (Table 4) periods. Although the models are calibrated against RMSE of daily discharge only, the evaluation is performed on three criteria: the RMSE (m^3/s), the water balance error (WBE, %) and the Nash-Sutcliffe efficiency (NSE, Nash and Sutcliffe 1970).

Clearly the raw FEWS data result in the poorest model performance across most stations, probably because a systematic bias forces the model optimization into an undesired parameter space and/or because, in spite of having good spatial rainfall information, the satellite-based product is uncertain on rainfall amounts and can miss large events or estimate false rainfall. The three rainfall products including actual raingauge data perform almost equally well, and are generally

Table 3 Calibration statistics on daily data for the period October 2000 to October 2005. Best NSE values are highlighted in bold.

Station	Area (km^2)	FEWS			IDW			REGINT/FEWS			REGINT/IDW		
		RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)
Usangu													
1KA71A	10 825	21.1	−2	0.73	23.3	5	0.67	20.4	3	**0.75**	23.3	7	0.68
1KA11A	1620	10.4	23	0.36	8.0	9	**0.62**	8.9	19	0.53	8.2	19	0.60
1KA15A	1221	4.1	0	0.60	4.0	24	0.63	3.7	−11	**0.68**	3.7	12	**0.68**
1KA9	446	11.9	62	0.09	10.5	47	**0.29**	11.3	50	0.17	10.5	42	**0.29**
Little Ruaha													
1KA31	5195	9.3	8	0.66	6.6	−14	0.83	7.1	−1	0.80	6.3	−5	**0.84**
1KA2A	2896	6.6	11	0.71	4.6	−1	0.86	5.3	4	0.82	4.5	3	**0.87**
1KA21A	2619	6.8	16	0.57	4.2	1	0.84	5.3	6	0.74	4.1	4	**0.85**
1KA32A	838	1.7	−1	0.57	1.3	−23	0.76	1.4	−11	0.70	1.1	−17	**0.81**
1KA22	461	1.9	26	0.01	1.3	16	0.52	1.3	9	**0.54**	1.3	14	0.52
Lukosi													
1KA37A	3064	10.0	28	0.09	6.9	8	0.56	7.4	4	0.50	6.4	5	**0.62**

Table 4 Validation statistics on daily data for the period October 2005 to October 2009. Best NSE values are highlighted in bold.

Station	Area (km^2)	FEWS			IDW			REGINT/FEWS			REGINT/IDW		
		RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)
Usangu													
1KA71A	10 825	35.4	−73	0.05	26.9	−45	0.39	21.6	−32	**0.61**	22.8	−31	0.57
1KA11A	1620	10.2	−3	0.52	8.5	−8	0.67	8.9	12	0.63	8.0	13	**0.71**
1KA15A	1221	3.7	−13	0.72	3.4	−3	**0.76**	4.8	−36	0.54	3.5	−11	0.75
1KA8A	783	15.0	36	0.21	12.3	39	0.46	13.3	35	0.37	11.5	31	**0.53**
1KA9	446	6.7	37	0.41	5.8	40	0.55	6.2	36	0.49	5.4	32	**0.62**
1KA7A	169	1.8	18	0.50	1.3	19	0.71	1.1	10	**0.79**	1.2	5	0.75
Little Ruaha													
1KA31	5195	7.8	15	**0.84**	8.8	−8	0.80	8.6	6	0.81	8.9	2	0.79
1KA2A	2896	8.7	29	0.69	5.6	5	**0.87**	6.2	15	0.84	5.9	9	0.86
1KA21A	2619	12.3	35	0.47	7.7	13	**0.79**	9.6	22	0.68	8.0	17	0.78
1KA32A	838	2.3	28	0.59	1.6	2	0.81	1.6	15	0.81	1.5	8	**0.82**
1KA22	461	2.4	35	0.23	1.9	26	0.48	1.7	21	**0.58**	1.9	23	0.52
Lukosi													
1KA37A	3064	11.3	28	0.20	10.3	26	0.34	9.4	20	**0.45**	10.3	26	0.34

able to represent the inter-annual dynamics, although individual high flow events are not captured well. There is a slight tendency for the regression-based interpolation schemes to perform the best, but differences are marginal on all three evaluation criteria.

One reason for the marginal differences is probably the ability of the models to compensate for input differences through parameter optimization. This is a fundamental and common problem when doing calibration and evaluation against a single objective function (Stisen *et al.* 2011). In addition, the interpolated annual maps are quite similar when looking at the three modelled sub-basins, which makes the distinction between them difficult in a multi-annual water balance modelling exercise. This is partly due to the fact that, even in the data-sparse period, raingauges are available at strategic locations in the main runoff generating zones, making even the IDW interpolation capture the rough structure of the spatial pattern.

5.2.2 Model-based evaluation using the alternative raingauge scenario The rainfall data interpolation based on the alternative raingauge

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scenario, where a single raingauge at a key location has been removed, is also tested through the hydrological models. This is done firstly by running models with the alternative rainfall data while maintaining the optimized parameter set for the equivalent interpolation scheme based on all raingauges. This scenario represents a validation run in which a raingauge that was available during the calibration period no longer exists. Secondly, the models are recalibrated using the alternative rainfall data, representing a scenario in which the omitted raingauge never existed and therefore is not included in either the calibration or the validation periods. All results using the alternative raingauge records are given in Tables 5 and 6 for the calibration and validation periods, respectively. Only results for the three discharge stations located immediately downstream of the region around the omitted raingauge are included. It is very clear from the results in Tables 5 and 6 that the regression-based interpolation scheme REGINT/FEWS is far more robust when a single key raingauge is omitted. This is especially the case when the models are not recalibrated with the new dataset (first two result columns in Tables 5 and 6), but also evident when the models are recalibrated (last two result columns). The models using the REGINT/FEWS dataset have much higher NSE values especially during the validation period. This is also illustrated in Fig. 10(a) and (b), where the hydrographs for stations 1KA15A and 1KA21A are plotted for the first scenario without recalibration. These hydrographs clearly illustrate the insufficient performance of the model forced with IDW interpolated data. The overall discharge, especially for station 1KA15A, is largely underestimated (IDW scenario) resulting in poor RMSE, WBE and NSE compared to the model forced with the regression-based rainfall interpolation (REGINT/FEWS scenario).

6 DISCUSSION

Several studies have shown that uncorrected SRFEs perform poorly compared to simple interpolation of even coarse raingauge observation networks in hydrological modelling applications (Artan *et al.* 2007, Stisen and Sandholt 2010). This has also been highlighted in the current study where the hydrological modelling has mainly focused on the overall water balance and the inter-annual variability of wet and dry years, respectively. In spite of being

Table 5 Calibration period October 2000 to October 2005. Scenarios based on alternative rainfall dataset with omitted raingauge station. Best NSE values are highlighted in bold.

Station	Area (km^2)	IDW			REGINT/FEWS			IDW-recal			REGINT/FEWS-recal		
		RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)
Usangu													
1KA15A	1221	5.6	61	0.27	3.79	−18	**0.67**	5.2	47	0.38	3.5	−6	**0.71**
Little Ruaha													
1KA21A	2619	6.3	23	0.64	5.2	1	**0.75**	5.7	15	0.70	5.3	2	**0.74**
1KA32A	838	1.5	9	0.67	1.4	−18	**0.71**	1.3	−3	**0.73**	1.5	−19	0.67

Table 6 Validation period October 2005 to October 2009. Scenarios based on alternative rainfall dataset with omitted raingauge station. Best NSE values are highlighted in bold.

Station	Area (km^2)	IDW			REGINT/FEWS			IDW-recal			REGINT/FEWS-recal		
		RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)	RMSE (m^3/s)	WBE (%)	NSE (–)
Usangu													
1KA15A	1221	5.7	52	0.35	3.9	−24	**0.69**	5.4	39	0.41	3.9	−15	**0.70**
Little Ruaha													
1KA21A	2619	13.4	44	0.38	10.6	24	**0.61**	12.3	38	0.47	9.5	20	**0.69**
1KA32A	838	2.7	41	0.45	1.9	19	**0.73**	2.2	33	0.61	1.6	13	**0.80**

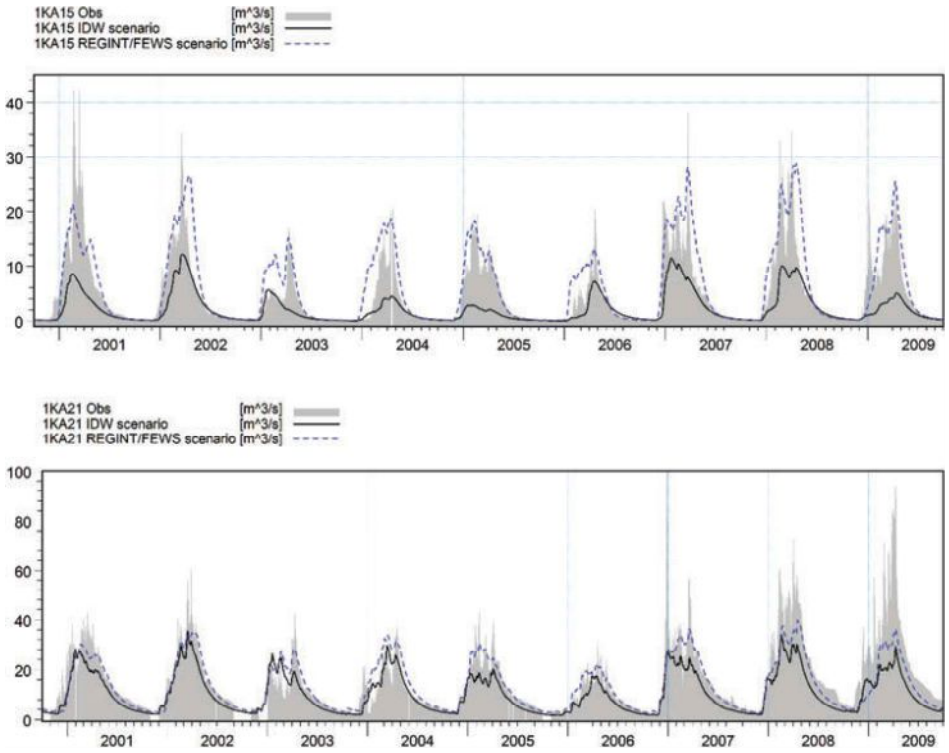


Fig. 10 Simulated and observed hydrographs for the 1KA15A and 1KA21A discharge stations. Simulations are based on a validation run using the alternative raingauge scenario without recalibration.

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run at a daily time scale, the model is generally not able to reproduce the short-term dynamics of individual rain events and therefore the evaluation of the rainfall products is mainly on long-term bases, inter-annual variability and spatial patterns. Perhaps a more event-based flood modelling analysis could have highlighted differences between the precipitation datasets; however, the purpose of the current study has been to improve the spatial patterns of rainfall model input for robust long-term simulations. The hydrological modelling will subsequently be utilized in relation to issues of water resources management and climate change scenarios.

]The analysis of spatial patterns is limited by the lack of discharge stations for model evaluation in some regions. Other or clearer conclusions could potentially have been drawn from analysing hydrological model results for the neighbouring Kilombero River basin located south and south-east of the GRRB, where very large differences between the four gridded rainfall datasets were observed (Fig. 7).

By assuming stationarity in spatial rainfall patterns the merging procedure applied for the recent period (2001–2009) was also applied to the period prior to the availability of SRFEs. This application showed a high correlation between raingauge records and current SRFE patterns, which indicates potential for guiding the interpolation of historic raingauge records with present day, satellite-based rainfall patterns. An application has also been investigated with success recently using pattern-oriented memory theory on a historic raingauge dataset in the Zambezi River Basin (Matos *et al.* 2013).

The methodology applied in the current study, using a regression-based interpolation scheme, is relatively easy to implement and only requires freely available satellite rainfall estimates. This makes it suitable for hydrological modellers and water managers facing the common challenges of sparse raingauge networks and large spatial variability in precipitation.

7 CONCLUSION

Raingauge data are indispensable since satellite RFEs are uncertain and biased. In the current study, the simple interpolation of a sparse raingauge network outperformed the purely satellite-based rainfall estimate even in the ungauged Lukosi basin. This illustrates that even regionally adjusted state-of-the-art satellite RFEs cannot replace raingauge observations when evaluating the water balance and inter-annual variability. However, the study also highlights the

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advantages of including the spatial pattern information from satellite estimates as a covariate in the interpolation of raingauge observations. This has been illustrated by the much higher correlation obtained between the spatial patterns from the satellite estimate and the interpolation of the denser historic raingauge network compared to the spatial correlation between the interpolation of raingauges from the dense historic and the sparse current network. Furthermore, the analysis has illustrated the sensitivity of raingauge location on the simple interpolation compared to the more robust regression-based interpolation, where the interpolated spatial pattern is less dependent on the location of raingauges or interruption in precipitation records. It is absolutely vital for hydrological modelling and other water resources assessments that the dramatic decline in raingauge numbers that has been observed globally and in Africa over the past 40 years (New *et al.* 2001) ceases and is reversed. This is especially important in countries such as Tanzania, where the climate variability is enormous and where the remaining raingauge network has not been merged with a national network of precipitation radars, as it has been in other parts of the world (Fulton *et al.* 1998). The spatial information obtained by satellite data is valuable for supporting the raingauge networks, but cannot replace real observations.

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