Building a coherent hydro-climatic modelling framework for the data limited Kilombero Valley of Tanzania

Alexander Koutsouris

Abstract
This thesis explores key aspects for synthesizing data across spatiotemporal scales relevant for water resources management in an Eastern Africa context. Specifically, the potential of large scale global precipitation datasets (GPDs) in data limited regions to overcome spatial and temporal data gaps is considered. The thesis also explores the potential to utilize limited and non-continuous streamflow and stream water chemistry observations to increase hydrological process understanding. The information gained is then used to build a coherent hydro-climatic framework for streamflow modelling. In this thesis, Kilombero Valley Drainage Basin (KVDB) in Tanzania is used as an example of a data limited region targeted for rapid development, intensification and expansion of agriculture. As such, it is representative for many regions across the Eastern Africa. With regards to the data synthesis, two satellite products, three reanalysis products and three interpolated products were evaluated based on their spatial and temporal precipitation patterns. Streamflow data from KVDB and eight subcatchments were then assessed for quality with regards to missing data. Furthermore, recession analysis was used to estimate catchment-scale characteristic drainage timescale. Results from these streamflow analyses, in conjunction with a hydrological tracer-based analysis, were then used for improved understanding of streamflow generation in the region. Finally, a coherent modelling framework using the HBV rainfall-runoff model was implemented and evaluated based on daily streamflow simulation. Despite the challenges of data limited regions and the often large uncertainty in results, this thesis demonstrates that improved process understanding could be obtained from limited streamflow records and a focused hydrochemical sampling when experimental design natural variability were leveraged to gain a large signal to noise ratio. Combining results across all investigations rendered information useful for the conceptualization and implementation of the hydro-climatic modelling framework relevant in Kilombero Valley. For example, when synthesized into a coherent framework the GPDs could be downscaled and used for daily streamflow simulations at the catchment scale with moderate success. This is promising when considering the need for estimating impacts of potential future land use and climate change as well as agricultural intensification.

Keywords: Hydrology, Precipitation, Recession analysis, End-member mixing analysis, EMMA, GLUE, HBV, downscaling, Quantile mapping, CFSR, CMORPH, CRU, GPCC, ERA-i, MERRA, TRMM, UDEL, Satellite, Reanalysis, Kilombero, Tanzania, Eastern Africa, Africa.

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BUILDING A COHERENT HYDRO-CLIMATIC MODELLING FRAMEWORK FOR THE DATA LIMITED KILOMERO VALLEY OF TANZANIA

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To the giants upon whose shoulders we all stand upon.
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Sammanfattning


Datasyntesen innefattade två nederbördsprodukter baserade på satellitdata, tre baserade på återanalysprodukter samt två baserade på interpolering av observervationsdata från regnmätare. Dessa åtta produkter utvärderades baserat på deras nederbördsmönster i rum och tid. Utöver detta utvärderades vattenföringsdata från Kilomberodalens avrinningsområde samt åtta delavrinningsområden utifrån mängden saknad data i respektive tidsserie. Vidare användes resultaten från hydrologisk recessionsanalys för att uppskatta den karaktäristiska avrinningstiden för avrinningsområden. Resultaten från recessionsanalysen samt hydrologiskt spårämnesförsök användes sedan för att utöka kunskapen om avrinningsbildning och vattenföring i området samt som stöd i valet av hydrologiskt modelleringar verktøy. Avslutningsvis användes HBV-avrinningsmodellen för att simulera daglig vattenföring.

Trots utmaningen i att arbeta i ett databegränsat område och de osäkerheter i resultat som detta tenderar till visar resultaten att det var möjligt att använda begränsad vattenföringsdata och vattenkemidata för att utöka den hydrologiska processförståelsen av området. Detta möjliggjordes genom ett experimentellt upplägg som utnyttjade till ett stort signal-tillsbrusförhållande under rådande förhållanden av naturlig variabilitet. Kombinerade resultat från alla genomförda studier kunde utnyttjas vid konceptualiseringen och implementeringen av ramverket för hydroklimatologisk modellering av Kilomberodalens avrinningsområde. Till exempel kunde de globala nederbördsdataseten användas för lokal modellering av flödesdata med viss framgång efter syntes och implementering i det integrerande ramverket för hydroklimatologisk modellering. Detta är lovatande med tanke på behovet av att undersöka vilken påverkan möjliga framtida förändringar i markanvändning, klimat samt jordbruk har på den lokala och regionala miljön.
Thesis content
This thesis consists of a summary and four appended papers. The papers are referred to as Paper I-IV in the summary.

List of papers


Co-authorship

**Paper I:** I initiated and conceptualized the study with input from Steve Lyon and Deliang Chen. I collected, compiled and analyzed the data. I also interpreted the results and was the main writer of the resulting text. Steve Lyon and Deliang Chen both contributed to the text.

**Paper II:** I compiled and analyzed hydro-meteorological data with regards to quality control and descriptive statistics. I compiled spatial data and conducted the related spatial analysis. I also contributed to the text. Steve Lyon as lead author initiated and conceptualized the study. He also did the recession analysis and performed the interpretation of the results. Jerker Jarsjö and Ype van der Velde gave input on the conceptualization of the study as well as contributed to the writing. Asha Sharma acquired, compiled and analyzed the evapotranspiration data as well as contributed to the writing. Friederman Scheibler, Madaka Tumbo, Keven Robert and René Mbanguka helped contextualizing the research.

**Paper III:** I conceptualized and designed the study with input from Steve Lyon. I planned and executed the fieldwork to collect the hydro-chemical data used in this study as well as conducted the hydro-chemical modelling. I led the interpretation of the results and was the lead writer of the text. Steve Lyon contributed to the writing.

**Paper IV:** I initiated and conceptualized the study with input from Jan Seibert and Steve Lyon. I compiled and prepared the data as well as conducted the modelling. I interpreted results and was the main writer of the resulting text. Steve Lyon and Jan Seibert both contributed to the text.
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<tr>
<td>$B$</td>
<td>Matrix of end-member concentrations</td>
</tr>
<tr>
<td>$b$</td>
<td>Matrix length 1</td>
</tr>
<tr>
<td>$C$</td>
<td>Concentration</td>
</tr>
<tr>
<td>$c$</td>
<td>Matrix length 2</td>
</tr>
<tr>
<td>$cal$</td>
<td>Calibration period</td>
</tr>
<tr>
<td>$cdf$</td>
<td>Cumulative density function</td>
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<tr>
<td>$d$</td>
<td>Day of study period</td>
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<tr>
<td>$E$</td>
<td>Calibrated evapotranspiration</td>
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<tr>
<td>$ecdf$</td>
<td>Empirical cumulative density function</td>
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<tr>
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<td>$ET_p$</td>
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<td>Characteristic drainage timescale</td>
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<td>End-member fractions</td>
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<tr>
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<td>Efficiency for log reference</td>
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<tr>
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</tr>
<tr>
<td>$n$</td>
<td>Length of end-member fraction vector</td>
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<tr>
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<td>Observed data</td>
</tr>
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<tr>
<td>$P$</td>
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<td>$Q$</td>
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<td>Solute</td>
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<tr>
<td>$S$</td>
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<td>Time window (61-days)</td>
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<td>$val$</td>
<td>Value</td>
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<tr>
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<td>Stream water sample tracer concentrations</td>
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<tr>
<td>$X$</td>
<td>Downscaled GPD estimate</td>
</tr>
<tr>
<td>$y$</td>
<td>Average specific discharge</td>
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<tr>
<td>$Y$</td>
<td>Original GPD precipitation estimate</td>
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<tr>
<td>$Z_{norm}$</td>
<td>Ti-normalized concentration</td>
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<thead>
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<th>Term</th>
<th>Description</th>
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<tbody>
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<td>BIAS</td>
<td>Bias</td>
</tr>
<tr>
<td>CC</td>
<td>Correlation coefficient</td>
</tr>
<tr>
<td>CFSR</td>
<td>Climate forecasting system reanalysis</td>
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<tr>
<td>CMORPH</td>
<td>Climate Prediction Center (CPC) morphing method v1.0 CRT</td>
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<td>GLUE</td>
<td>Generalized likelihood uncertainty estimation</td>
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<tr>
<td>GPCC</td>
<td>Global Precipitation and Climatology Center v6</td>
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GPCP  Global precipitation climatology project
GPDs  Global precipitation datasets
IAHS  International Association of Hydrological Science
ICP  Inductively coupled plasma
IOZM  Indian Ocean zonal mode
IR  Infrared
ITCZ  Intertropical convergence zone
KC  Kiburubutu catchment
KVDB  Kilombero valley drainage basin
KV  Kilombero valley
MC  Mpanga catchment
MERRA  Modern Era Retrospective-Analysis for Research and Applications
ModB  Model based bias correction
MODIS  Moderate resolution imaging spectroradiometer
NS  Nash-Sutcliffe coefficient of efficiency
OF  Overland flow
PMW  Remotely sensed passive microwave
PUB  Prediction in ungauged basins
QM  Quantile mapping
$R^2$  Coefficient of determination
RBWO  Rufiji basin water office
RMSE  Root mean square error
SAGCOT  Southern Agricultural Growth Corridor of Tanzania
SD  Standard deviation
SRTM  Shuttle Radar Topography Mission digital elevation mode
SW  Soil water
TRMMv7  Tropical Rainfall Measuring Mission (TRMM) multi-satellite precipitation analysis research-grade product v7
UDEL  University of Delaware Air Temperature and Precipitation v3.01
Introduction

Data limitations can inhibit water resources management

The number of precipitation and streamflow observation stations maintained globally has been declining over recent decades (Becker et al., 2013; Hannah et al., 2011). The degradation of the global hydro-climatic observation network is further aggravated by historic observational records that often are discontinuous and tend to contain inconsistencies (Sawunyama and Hughes, 2008). As an example of just how limited precipitation observations are globally, consider the Global Precipitation and Climatology Center (GPCC) database which may be the most complete global rain gauge dataset available. The number of gauges contained within the GPCC database peaked in 1991 with 42,511 concurrent rain gauges being included (Figure 1). The number of gauges dropped to 9,726 rain gauges in 2011. Even at its peak, the rain gauges in the GPCC database represent at most 2% of the global landmass if a single gauge is assumed to represent a 5 km radius and the gauges are assumed to be evenly distributed (Kidd et al., 2017). The rain gauge coverage is however heavily unevenly distributed across the globe, leading to large regions that are not covered (Figure 1). Over this same period, river discharge observations have seen a similar global trend with a clear decrease in the number of observation stations being maintained (Hannah et al., 2011). Further, and similar to the global coverage of precipitation observations, large parts of global land areas are poorly gauged or ungauged (Sivapalan 2003; Hrachowitz 2013). Clearly, hydro-climatic data are limited and on the decline globally.

Using modelling frameworks to bridge data gaps

While worrisome in the general scientific sense, the decline of reliable precipitation and streamflow monitoring also directly limits our capacity to manage water resources. Historically, shortcomings in hydro-climatic data have been a limiting factor when developing water management plans or studying the effects of intensified agriculture on water resources (e.g. Bárdossy and Das, 2006; Li et al., 2013a; Washington et al., 2004). This complicates the already critical need to improve water resources management in areas with heavy degradation of water quality and lowered land productivity (Vörösmarty et al., 2010) Nowhere does society feel this complication more acutely than in regions where the rural livelihood, food produc-
tion and climate are highly interconnected. For example, when populations depend on rain fed agriculture for both income and food security, they are directly dependent on reliable hydro-climatic estimates for informing water management decisions and estimating food production (Nicol et al., 2015). These are typically the same regions where population growth, poverty alleviation and limited food security drives a desire for agricultural development and expansion – both of which require well-informed water resources management to approach sustainability. A clear example of this can be seen when considering the utilization of dry land irrigation as a means for agricultural expansion. Even though dry land irrigation has been shown to increase food security and reduce poverty (Graciana 2011), it also entails inherent long-term sustainability risks since it may cause adverse effects such as ecosystem degradation, soil salinization and/or groundwater draw down (ERB 2006; Leng et al., 2014). There can also be adverse effects not only in the area being irrigated but also for downstream ecosystems (ERB 2006). Agricultural development (dry land or otherwise) therefore requires sound water resource management informed by the best hydro-climatic data available if it is envisioned to be done sustainably and have limited negative impacts on ecosystem services. This creates a difficult impasse when facing decreasing data availability despite the increasing need for improved water resource management to help secure food supplies globally.

One manner by which to address this impasse could be through the development of modelling frameworks that reflects our best hydro-meteorological characterization for a given region. This would allow for inconsistencies and gaps in data to be filled (or at least compensated for) with our process understanding of land-water interactions (Lyon et al., 2008). When appropriately constrained, hydro-climatic models offer tools to better understand and forecast future impacts associated with land-use and climate changes (Tessema et al., 2014). In this regard, hydro-climatic modelling frameworks allow us to explore various scenarios of change and thereby enabling development of sustainable water management plans. By considering the balance between various natural and anthropogenic water uses, modelling frameworks could also potentially help in alleviating the competition between existing ecological and projected agriculture intensification water requirements (REPOA, 2004). Of course, it comes as no surprise that the cornerstone for any such modelling endeavor is still sound and trustworthy data to support model construction and evaluation (e.g. Andréassian et al., 2001; Perrin et al., 2007). Rather than being crippling, this connection to data may be potentially useful as modelling frameworks provide a consistent structure in which to integrate various types and spatiotemporal scales of data and information.

Considering the aforementioned prevalence of spatiotemporal gaps in our global precipitation monitoring efforts have been made to develop (and evaluate) global precipitation datasets (GPDs) that are spatially and temporally complete (e.g. Dee et al., 2011; Harris et al., 2014; Huffman et al., 2007). GPDs consider various combinations of satellite based products, reanalysis (climate modelling) products and interpolated observed data products (Joyce et al., 2004; Mitchell and Jones, 2005; Saha et al., 2010). GPDs often attempt to combine the various strengths of different estimation techniques to compensate for inherent weaknesses. The accuracy of GPDs to estimate precipitation have been evaluated in many regions across the world covering a range of different climatic zones (e.g. Romilly and Gebremichael, 2011; Peña-Arancibia et al., 2013; Khan et al., 2014; Flocas et al., 2004). While GPDs can provide an alternative manner for estimating rainfall at a coarse scale when local rain gauge data are limited, regional estimation accuracy varies heavily depending on the observed data availability and accuracy in the studied region, the local to regional scale topography, and the spatial scale and time step of the analysis (e.g. Dinku et al., 2007; Maidment et al., 2013; Romilly and Gebremichael, 2011; Zhang et al., 2012). All of these factors introduce both temporal and spatial variability in precipitation patterns that become increasingly important moving down to scales relevant for local water resources management.

To this end, downscaling techniques are commonly employed to correct GPDs for local variability in precipitation patterns and when considering GPD datasets within regional hydro-climatic modelling frameworks (Teutschbein et al., 2011; Themeßl, 2011). There are two
main downscaling techniques currently employed: dynamic downscaling and statistical downscaling. Dynamic downscaling is based on coupling a regional climate model representing land-surface interactions to a global climate model by capturing the physics of weather circulations. While dynamical downscaling have been successfully implemented it is often considered too computationally heavy for operational use (Boé et al., 2007; Sarr et al., 2015). Statistical downscaling, on the other hand, is based on empirical relationships between coarse scale datasets (e.g. GPDs) and local datasets (e.g. rain gauge observations) to correct for local variations in precipitation patterns. Statistical downscaling render results comparable with dynamical downscaling (Boé et al., 2007; Sarr et al., 2015). Statistical downscaling can also often be advantageous from an applied management perspective due to the gentler learning curve associated with its implementation and the generally lower computational demand relative to dynamic downscaling (Wilby et al., 2000). The utility of statistical downscaling methods in data limited regions have, however, been questioned since they rely heavily on observational datasets (Maraun, 2013). As such, there is still a need to explore the ability management on a case-by-case basis due to issues associated with the “uniqueness of place” such that a one-size-fits-all solution may not exist.

The same could be said with regards to regional relevance when considering streamflow data within a hydro-climatic modelling framework. Resulting from a growing realization in the scientific community of the challenges presented for water resources management by streamflow data limitations, the International Association of Hydrological Sciences (IAHS) put forward a call to improve the physical understanding of hydrological processes. The goal of this coordinated effort was to decrease the requirements of in situ calibration of hydrological models – the so-called prediction in ungauged basins (PUB) problem (Sivapalan, 2003). The central idea was that improved process understanding can allow for extrapolation of model calibrations from gauged basins to simulate streamflow in similar or nearby ungauged basins. Much effort exploring the portability of hydrological modelling has been done since the proclamation of the PUB decade in 2002 (Hrachowitz et al., 2013). This has led to developments in the synthesis of remote sensing (e.g. Li et al., 2013b), understanding of scale dependence (e.g. Das et al., 2008), process and parameter regionalization (e.g. Archfield and Vogel, 2010) and uncertainty analysis within hydrological modelling frameworks (e.g. Jacquin and Shamseldin, 2007; Schoups and Vrugt, 2010). In spite of the major advances in hydrological modelling achieved over the past decade, Hrachowitz (2013) concludes that much progress is still needed in order to achieve robust streamflow prediction via hydrological models owing largely to issues associated with the “uniqueness of place” often faced at the catchment scale where water resource management typically occurs. Potential paths forward are, among others, developing methods for simulating streamflow, or at the very least for characterizing catchments, that are less sensitive to data gaps and/or allow for synthesis of various types of hydrological information and knowledge (Revilla-Romero et al., 2015).

While hydro-climatic modelling frameworks may offer some hope for bridging spatiotemporal data gaps and creating structures for assessing water resource management, it is clear that they will always have a strong reliance on the data availability and quality to provide regional context and improve parameterization. However, maintaining regional consistency with regards to spatiotemporal variations in dominant hydro-climatic processes does not necessarily imply increased modelling complexity (Carrillo et al., 2011). For example, Steenhuis et al. (2009) and Collick et al. (2009) put forward a simple, semi-distributed hydro-climatic modelling framework for highland systems in Ethiopia using a water balance approach that divides a watershed into different regions that respond differently under hydro-climatic variations. This conceptual difference starts from a basic assumption that models developed for temperate climates might not be suitable for the climates and/or mountainous regions that dominate much of Eastern Africa. While simple, starting from an assumption where “uniqueness of place” moves into the forefront in model development is pragmatic and powerful. Collick et al. (2009) further demonstrated that regionally-relevant modelling frameworks can provide simple (but robust) tools for watershed management planning and conservation. Such
a paradigm holds promise when seeking to leverage hydro-climatic understanding in more and more remote (and in particular data limited) regions to allow for important improvements regarding the management of less and less available resources.

Tanzania’s Kilombero Valley as a regionally-relevant case study
Tanzania is a clear example of a data limited region facing increased pressure on water resources (and thus requiring improved management). This pressure is due to plans targeting increased and intensified agriculture. Similar to the rest of Eastern Africa and much of the global south, the food demand across Tanzania is expected to increase in the future with an increasing population (SAGCOT, 2012). Currently only 6.3% of Tanzania is irrigated out of the 7.1 million hectares of arable land considered to have high-to-medium irrigation potential. In addition, over 80% of the currently irrigated lands use traditional irrigation schemes (URT, 2013). Again similar to much of Eastern Africa, there is also a large potential for increased food production and decreased reliance on rainfall through developing agricultural practices via expansion and modernization of irrigation systems (Altchenko and Villholth, 2015). In response to this potential and need, the Southern Agricultural Growth Corridor of Tanzania (SAGCOT) initiative is one of the current development plans put forward by the Tanzanian government. SAGCOT is a public-private partnership aimed to facilitate investors and donors for agricultural development and agricultural related infrastructure (SAGCOT, 2012). The main focus of SAGCOT is to improve national agricultural productivity, food security and livelihoods targeting development of small-scale agriculture as well as a rapid increase of large-scale agriculture in the Tanzania over the coming 20 years. While SAGCOT has several aspects, targeting specific regions for agricultural development forms the core. Kilombero Valley is one representative agricultural region considered a focus area of SAGCOT. In Kilombero Valley (KV), estimates show that only 38,260 hectares are irrigated out of the available 392,600 hectares suitable for irrigation and agricultural development (ERB, 2006). As a first stage of agricultural expansion in KV SAGCOT has 20,000 ha earmarked for large-scale rice and sugar cane cultivation (SAGCOT, 2012). In addition to the water requirements of current and future agriculture sector there are also other competing national interests such as from the energy sector in the form of downstream hydropower and securing ecological values situated both in KV and further downstream. In Kilombero Valley this latter dichotomy between ecological water requirements and agriculture intensification water requirements is highlighted by the presence of a RAMSAR classified wetland system across the valley floor (www.ramsar.org). In addition to its unique ecosystem, KV’s main wetland is also the main provider of drinking water and food security for the local population, with the latter coming through both wetland agriculture and fishing (IMWI, 2010). There is also a fear that increased food demand could potentially shift Tanzania into a water scarce region which further highlights the need for land and water resource planning (SAGCOT, 2012). Kilombero valley is thus part of the aforementioned global trend of regions experiencing a decline in hydroclimatic observations while at the same time being targeted for agricultural intensification to meet an increasing global food production demand. Data availability and quality must be addressed and considered explicitly in any attempt to develop a regionally relevant hydroclimatic modelling framework to help, for example, in designing water management strategies for agricultural intensification.
Figure 2. Schematic image of KVDB during the wet season and the main components of the water balance: streamflow ($Q$), rainfall ($P$), evapotranspiration ($E$) and changing groundwater storage ($\Delta S$). The relation between the water balance components and papers of the thesis is also shown.

Furthermore, increased process understanding of the main components of the water balance (Figure 2) can be leveraged to increase the robustness of water resource modelling efforts, particularly in data limited environments where estimations of water balance components tend to contain large uncertainties (Refsgaard, 1997). This thesis therefore aims to investigate the utility of hydro-climatic data available for Kilombero Valley as a representative Eastern African regional case study. It considers the potential to bridge data gaps through the development of a coherent hydro-climatic modelling framework which is based on local hydrological process understanding. In connection to agricultural intensification across Eastern Africa, the thesis mainly focuses on understanding two key aspects relevant for water management in Kilombero Valley. These are the precipitation input to the region ($P$) and the flow of water through the landscape (collectively $E$, $Q$, and $\Delta S$) (Figure 2). As such and from a Kilombero Valley perspective, the main objectives of this study are to:

1. Investigate the potential to utilize and downscale large-scale datasets (e.g. Global Precipitation Datasets) to estimate precipitation inputs for catchments in data limited regions (Papers I and IV).
2. Investigate the potential to utilize limited in-stream observations (e.g. discontinuous discharge monitoring and hydrological tracer information) to garner process understanding of catchments in data limited regions (Papers II and III).
3. Build a coherent hydro-climatic modelling framework for Kilombero Valley based on the best possible characterization and understanding given the region’s data limitations (Papers I-IV).

The results of this thesis are discussed from the perspective of potential pathways forward to close data gaps and help inform water management development for not only Kilombero Valley but also within the Eastern African regional context. A central hypothesis across this work is that limitations of local observations can be overcome through synthesis of addition information derived over various spatiotemporal scales within a consistent hydro-climatic modelling framework.
Site description

Kilombero Valley (KV) is situated in central Tanzania (Figure 3). It has an area of about 34,000 km² and is part of the East African Rift Valley, encapsulated by the steep Mahenge Enscarpment in the northwest and the Mbarika Mountains in the southeast. The Mahenge Enscarpment has elevations of up to 2500 m and is mainly covered by tropical rain forest and mountainous forest. The Mbarika Mountains have elevations of up to 2500 m and are mainly covered by mountainous forest. The valley floor is at an elevation of 200 m and is covered by open scrublands, herbaceous vegetation and a large seasonal wetland (Figure 4). The wetland dominates the valley floor covering 7000 km² of its area (Figure 3). Hydrologically, KV is drained by the Kilombero River which has its outlet in the eastern part of KV, forming Kilombero Valley Drainage Basin (KVDB). After leaving KVDB the Kilombero River joins the Rufiji River, contributing to approximately two thirds of the annual flow of the Rufiji River.

There are several areas of prominent ecological value present in KV. The seasonal wetland dominating the valley floor was designated as an internationally important RAMSAR site in 2002 (www.ramsar.org) due to its vitality for the large population of water birds, the presence of endemic species such as the Kilombero Weaver bird (Ploceus burnieri) and for containing 75% of the Puku antelope (Kobus vardonii). The Northeastern KVDB is part of the Udzungwa Mountains national park containing tropical and mountainous forests that are protected due to their large biodiversity. In fact, the Udzungwa Mountains national park is the second largest national park in Africa and contains several endemic species such as the primate Udzungwa red colobus (Procolobus gordonorum) and the Rufous-winged sunbird (Cinnyris rufipennis) (Rovero and De Luca, 2007). In addition, the eastern part of KVDB, including the lower areas of Kilombero River, is part of the Selous Game Reserve world heritage site. This is a large wilderness area of predominantly savanna and woodlands featuring, for example, significant populations of African elephant (Loxodonta africana), black rhinoceros (Diceros bicornis) and a large population of the Nile Crocodile (Crocodylus niloticus) (RAMSAR, 2002; UNESCO, 2014).

The climate in KV is sub-tropical with a distinct (and more-or-less bi-modal) rainy and dry season. The average daily temperature is around 22.5°C and the average annual precipitation is between 1200 mm and 1400 mm. The seasonality of KVDB is mainly driven by the passing of the Intertropical Convergence Zone (ITCZ) (Camberlin and Philippon, 2002). The ITCZ’s migration first southward and then northward corresponds to the short rains (November–January) and the long rains (March–May), respectively. The inter-annual variability of the short rains is well understood and has been shown to closely correlate with El Niño–Southern Oscillation (ENSO) (e.g. Stoeckenius, 1981; Goddard and Graham, 1999) and the Indian Ocean zonal mode (IOZM) (e.g. Webster et al., 1999; Mölg et al., 2006). The inter-annual variability of the long rains, however, is less well understood. Here, several large scale climate patterns clash creating an inter-annual variability driven by ‘internal chaotic atmospheric variations’ based on weak relationships to ITCZ, ENSO, IOZM and several other patterns (Camberlin and Philippon, 2002). The differentiation and timing of the short and long rains is more or less pronounced depending on variations in the large-scale climate patterns. This causes the rainy season of KV to be more or less bimodal depending on the year (Koutsouris et al., 2016). From a hydrological perspective, December through April contributes to 85-90% of the annual precipitation in KVDB and, as such, these months define what throughout this thesis is called the ‘wet period’. The ‘dry period’ is defined as June through October.
Kilombero Valley Drainage Basin (KVDB) is defined by the stream gauging station furthest downstream for Kilombero River (1KB17). The annual flow at the outlet is on average 590 m$^3$s$^{-1}$. Streamflow in KVDB is also monitored at several sub-catchments some of which are considered in this thesis (Figure 3; Table 1). The catchments of these streamflow gauging stations range from small and steep forested upland catchments to larger catchments of both steep mountainous and flat valley landscape. Of these sub-catchments, two warrant special consideration in the context of this thesis as they are considered in several of the papers: Mpanga Catchment (MC) and Kiburubutu Catchment (KC). MC is located in the northwestern part of KV (Figure 3). It has a catchment area of 2500 km$^2$ and the main river is Mpanga River (Table 1). The annual average flow of at the outlet is 38 m$^3$s$^{-1}$. The upstream areas of MC are part of the Udzungwa Mountains while its downstream areas are situated on the valley floor, containing both open natural vegetation and agricultural areas. KC is located in the northeastern part of KV (Figure 3; Table 1). It has a catchment area of 580 km$^2$ and the main river is Lumemo River (Table 1). The annual average flow at the outlet is 3 m$^3$s$^{-1}$. The entirety of KC is located in Udzungwa Mountains (though there are some seasonally flooded areas.
at lower elevations). For all subsequent assessments and purposes for KVDB, landscape properties are based Shuttle Radar Topography Mission digital elevation model (SRTM) and Food and Agriculture Organization’s Africover and GeoNetwork datasets (fao.org/geonetwork) while hydrological characteristics are based on data received from the Rufiji Basin Water Office (RBWO). Further and relevant for this thesis, Paper I focuses on KVDB as a whole, Paper II features nine catchments across KVDB, Paper III focus on KC, and Paper IV focus on the two sub-catchments MC and KC (Table 1).

**Data overview**

A number of hydro-climatological datasets are available covering KVDB (Table 2). These cover various scales in both space and time and various levels of quality and consistency owing to their sources. GPDs were used for investigating the potential to utilize large-scale datasets to estimate precipitation inputs for catchments in data limited regions like KV corresponding to Objective 1 of this thesis. GPDs are available as three main types: satellite based products, reanalysis (climate modelling) products and interpolated observed data products (Joyce et al., 2004; Mitchell and Jones, 2005; Saha et al., 2010). Observed records of precipitation were also used within Objective 1 of this thesis. Observed streamflow data were used for both evaluating the potential for statistical downscaling GPDs in data limited regions corresponding to Objective 1 and for investigating the potential to utilize discontinuous streamflow data to garner process understanding for catchments corresponding to Objective 2 of this thesis. Observed precipitation and streamflow data were made available from Rufiji Basin Water Office (RWBO). Hydrochemical data were used for Objective 2 of this thesis. Hydrochemical data were obtained through in field water sampling. Synthesis across all datasets was considered when addressing Objective 3 of this thesis.

**Global Precipitation Datasets (GPDs)**

Three main types of GPDs were used in the evaluation of the applicability of GPDs in data limited regions: satellite based products, reanalysis products and interpolated observed data products.

Satellite GPD products are constructed based on remotely sensed data. The exact methodology and data input to estimate precipitation amount differs between the products available. The first of the two satellite products included in this study was Tropical Rainfall Measuring Mission (TRMM) multi-satellite precipitation analysis research-grade product v7 (Huffman et al., 2007; Huffman and Bolvin, 2014) (Table 2). While often called 3B42v7 it will here be referred to as TRMMv7 for simplicity. The second satellite product was Climate Prediction

<table>
<thead>
<tr>
<th>Dataset Type</th>
<th>Description</th>
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<td>TRMMv7</td>
<td>Huffman et al., 2007; Huffman and Bolvin, 2014</td>
</tr>
<tr>
<td>Satellite GPDs</td>
<td>Climate Prediction</td>
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*Figure 4. Kilombero Wetland during wet (left) and dry (right) period. Photos were taken in a close proximity of each other (photographs by Alexander Koutsouris).*
Center (CPC) morphing method v1.0 CRT (CMORPH) (Joyce et al., 2004; Xie et al., 2011). Both of these satellite products base their precipitation estimates on remotely sensed passive microwave (PMW) and infrared (IR) measurements. PMW measures microwave scattering due to ice particles in clouds that are formed during precipitation events and IR is used to measure cloud top temperature (Huffman et al., 2007; Joyce et al., 2004). Since the PMW measurements are not spatially complete, TRMMv7 uses the IR measurements calibrated based on PMW to fill the gaps while CMORPH use IR to compute the motion and ‘morphing’ of precipitation systems to fill data gaps (Huffman et al., 2007; Joyce et al., 2004). Both TRMMv7 and CMORPH then bias correct precipitation estimates using observed precipitation records from Global Precipitation Climatology Centre (GPCC) and Global Precipitation Climatology Project (GPCP) respectively.

Reanalysis GPD products are constructed by assimilating a large range of data types, both from observed and remotely sensed sources, into a global climate model. The assimilated data is then used for forecasting the weather at a (commonly) sub-daily time step aiming to achieve the best possible state with physical coherence between parameters. Reanalysis products differ based on data input, data assimilating process and the physics of the global climate model (Dee et al., 2014). Three reanalysis products were used in this study (Table 2): Climate Forecasting System Reanalysis (CFSR) (Saha et al., 2010), the European reanalysis interim (ERA-i) (Dee et al., 2011) and the Modern Era Retrospective-Analysis for Research and Applications (MERRA) (Rienecker et al., 2011). CFSR and MERRA uses a 3D-variational data assimilation approach where all data assimilated for a specific time step is assumed to be valid for that particular time step. ERA-i uses a 4D-variational data assimilation approach where assimilated data is temporally interpolated to the specific time step.

Interpolated GPDs are based on ground based observations of precipitation such as from rain gauges. They are commonly constructed by using observations with long periods of observations to calculate the climatology and interpolate those climatologies to a global grid (e.g. Willmott et al., 1985). The anomaly (i.e. difference in measured value and climatology) is then calculated for all stations available for each particular month. The anomaly from a point station is then extrapolated over a larger area based on a weighting function. Precipitation estimates are then retrieved based on the climatology and the anomaly. The different products differ in the amount and type of observed data used, method for harmonization of the data and the interpolation method of climatologies and anomalies. Three interpolated products were used in this study: Climate Research Unit Time Series 3.21 (CRU) (Harris et al., 2014), the Global Precipitation and Climatology Center v6 dataset (GPCC) (Becker et al., 2013) and the University of Delaware Air Temperature and Precipitation v3.01 dataset (UDEL) (climate.geog.udel.edu/~climate/). CRU uses triangulated linear interpolation to generate gridded climatologies (Harris et al., 2014) while GPCC and UDEL uses a spherical inverse distance weighting scheme (Becker et al., 2013).
Table 1 Catchment characteristics for the catchments within the Kilombero Valley, Tanzania considered within this thesis (Modified from Paper IV)

<table>
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<tr>
<th>Catchment ID</th>
<th>L1 (KVDB)</th>
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<th>L3</th>
<th>L4 (MC)</th>
<th>S1 (KC)</th>
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<th>S3</th>
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<td>8577</td>
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<td>8</td>
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<td>15</td>
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*Includes small proportions of Arenosols, Cambisols, Leptosols and Fluvisols
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<td>-</td>
<td>2015-2016</td>
<td>weekly</td>
<td>Paper III</td>
<td>III</td>
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Locally observed precipitation, streamflow and water chemistry data

Observed daily rain gauge and streamflow data were obtained from the Rufiji Water Basin Office (RWBO) for several locations across KDB (Figure 1; Table 2). The specific gauges that were used in each part of this study vary depending on the requirements of that study with regards to requirements of completeness of time series, vicinity to studied area and temporal overlap with large scale and field data (Table 2). Rainfall at each location was measured with a standard weighing bucket system. Streamflow was monitored manually by RWBO at each gauging location using a staffing to record stage and established rating curves to compute discharge. Only daily discharge values reported by RWBO were consider in this thesis.

Discontinuous weekly samples of both surface water and groundwater were taken for chemical analysis of cation and stable water isotope composition. Anion analysis was omitted due to combination of cost issues and lab difficulties. The sampling was conducted over the course of one hydrological year covering October 2013 through October 2014 (Table 2). The sampling locations (Figure 1) were chosen based on availability, initial system understanding from previous studies (Lyon et al., 2015) and field visits.

Methods

Methods considered in this thesis range from statistical methods, field-based empirical methods and hydrological modelling. This range of methods reflects to some extent the fundamental issue often faced in data limited environments. Namely, how can we begin to synthesize knowledge based on incomplete information? Combined, these methods provide a framework for catchment characterization relevant in data limited regions to start addressing this question and the practical objectives of this thesis.

Assessment of Global Precipitation Datasets (GPDs) (Paper I)

GPD precipitation estimates are often evaluated based on comparison to rain gauge data. This method is, unfortunately, not viable in regions where there are no or limited amount of rain gauges. When there are no ‘true’ datasets for evaluation, strengths and weaknesses can still be gleaned from an intercomparison between products. This was the approach adopted as a starting point in this thesis. First, GPD area averaged time series were constructed by rescaling each GPD product (Table 1) to a common spatial resolution of 0.25°x0.25° using a bi-cubic resampling method (mpimet.mpg.de/cdo) (Paper I). Then, to aid the intercomparison of GPDs, one GPD need to be selected as a point of reference for intercomparison. Here, that was done by determining the ‘best centered’ GPD in an iterative (or in a one-at-a-time cross validation) fashion where each GPD was used as a potential reference for evaluating all the other GPDs using the complete time series as well as wet and dry period months only. Then the GPD that most consistently ranked high in performance with regards to correlation coefficient (CC), root mean square error (RMSE), bias (BIAS) and Nash-Sutcliffe coefficient of efficiency (NS) and R2 was chosen as the reference dataset. CC measures spatial or temporal pattern similarity, RMSE measures absolute mean difference between estimated and observed values, BIAS measures systematic overestimation or underestimation of estimated values compared to observed values, NS measures the performance of an estimated time series to represent the observed time series relative to a reference mean, R2 is the coefficient of determination measuring the proportion of the variance of one variable that can be explained by another variable. See Paper I for the mathematical description of CC, RMSE, BIAS and NS. In this study TRMMv7 showed to be best centered and is henceforth used as a common reference point for evaluation of the other GPDs. From the basis of this reference dataset, the eval-
ulation of each GPD was conducted using five different statistical performance estimates: standard deviation (SD), CC, RMSE, BIAS and NS.

Recession analysis for estimating characteristic drainage time scale and evapotranspiration (Paper II)

The quality of streamflow data was initially assessed based on the amount of missing data (Paper II). In addition, an evaporation estimation derived from recession analysis using the available streamflow data was implemented to provide potential insights into the quality of the streamflow data available in KVDB (Paper II). At its core, recession analysis is based on linear groundwater theory (following a Boussinesq-type equation) commonly used for modelling gravity-driven flow through a porous medium. Similar to the approach of Zecharias and Brutsaert (1998), evapotranspiration ($E$) can then be estimated by exploiting its potential relationship with catchment drainage time scale ($K$):

$$y + E = -K \frac{dy}{dt}$$

where $y$ is the average specific discharge during the time period $dt$ and $dy/dt$ is the change in specific discharge over the time period $dt$. Across KVDB, observed streamflow recessions (namely day to day changes in streamflow during periods of falling hydrographs) were used to empirically define $dt$ and $dy/dt$ for each sub-catchment with sufficient data availability. $K$ in Eq. (2) then represents the intercept of a straight line in log-log space and determined by a fitted line for the lower envelope of plotted observations of $dy/dt$ against $y$. $K$ was first estimated independently by setting $E$ in Equation 2 to zero. $E$ was then calibrated for each sub-catchment assuming that the monthly average value of $K$ should fall within an expected range of 45 ±15 days based on literature values (Brutsaert, 2008). This provides a simple model for monthly $E$ derived from the assumption of a constant catchment drainage time scale.

The long term monthly averages of $E$ estimates made via this recession style model were then compared to estimates from the Moderate Resolution Imaging Spectroradiometer (MODIS) evapotranspiration product. In the context of this thesis, this recession-style analysis provides an initial screening for assessing streamflow data and potentially some insight regarding the variability with which water flows through a landscape.

Stream water samples were taken at three locations sampling the outlet of KC as well as the inlet and outlet of Kilombero Wetland (Figure 3). Geographic sources of water, or end-members (EM), were sampled as: deep ground water (dGW), soil water (SW) and overland flow (OF). Samples representing dGW were taken from water pumped by a municipal well located on the valley floor. The water was drawn from bedrock at a depth of 70 m below the ground level. Samples representing SW were pumped from a shallow well also located on the valley floor. The pump draws water from the soil at a depth of 15 m. Finally, the water representing OF was taken from a naturally flooded area used for growing paddy rice. While OF was taken from flowing flood water it is assumed to be representative for both flood water and superficial pathways. The groundwater table on the valley floor of KV is on average found at 6 m depth, discounting flood areas (Hemlin-Söderberg, 2014).

Stable water isotopes were sampled in 2 ml glass vials, with a PTFE/Silicone/PTFE lid, that were rinsed three times before sampling. As with the anion water samples, water samples were stored non-refrigerated for up to 3 months before being moved to cold storage. Analysis was then performed using Cavity Ring Down Spectroscopy within an Isotope Water Analyser L2140-i from Picarro at Stockholm University, Department of Geological Sciences. Resulting stable water isotope compositions were normalized using Standard Light Antarctic Precipitation (SLAP) and Vienna Standard Mean Ocean Water (VSMOW). The normalized concentrations were reported as per mil deviation from VSMOW ($\delta D$ and $\delta^{18}O$).
End-member mixing analysis in a generalized likelihood uncertainty estimation framework (Paper III)

The ability to garner catchment process understanding in data limited regions was investigated using tracer analysis for hydrograph separation. Precipitation in a catchment is partitioned and routed through a range of vertical and lateral flow pathways allowing water to be partitioned among different storages (e.g. deep and shallow groundwater) within the landscape. During its flow through the landscape, water is affected by its surrounding material causing it to change in chemical solute composition. If the water chemistry in the various storages are different enough, the stream water, which integrates across these storages, leaving the landscape will have a unique chemical signature depending on the amount of water released from each type of storage at a given time. By measuring the chemical composition of stream water and water storages, often referred to as end-members (EMs), one can determine the contributing fraction of each EM to the stream water (i.e. the stream’s source water apportionment) using a mass balance approach. This method is built upon assumptions that (1) tracers are conservative and mix linearly; (2) end-member (EM) chemical signatures are spatially and temporally homogenous; and (3) EM chemical signatures are sufficiently different from each other to be distinguished (Hooper, 2003).

This idea of backtracking the stream water to different sources was first developed to trace the fraction of ‘new rainwater’ in the streamflow as the river responded to rain events (Sklash et al., 1976) and then further developed into End-Member Mixing Analysis (EMMA) to trace from where in a catchment water was derived (Christophersen et al., 1990, Hooper et al., 1990). These concepts were recently further developed to account for uncertainty impacts by combining EMMA with the Generalized Likelihood Uncertainty Estimation (GLUE) framework developed by Beven and Binley (1992), creating G-EMMA (Delsman et al., 2013). The GLUE-framework explicitly accounts for uncertainties in the EMMA methodology and measurements by recognizing that model parameters may compensate for each other and that a range of different parameter sets may result in an equally likely result (Beven and Binley, 1992). To explore the full range of uncertainty in the source water contribution estimates G-EMMA uses a Monte Carlo approach where a large number of model realizations of source water apportionment (108 model runs in our case) are solved for each time step.

In the context of this thesis and in reference to G-EMMA, the procedure for one model realization for one time step can be summarized as: (1) randomly select a subset of the available EMs, tracer solutes and EM fractions in stream water, (2) randomly select solute concentrations within a given range of the measured value for each solute and EM, (3) use the solute concentrations and assumed EM fractions to estimate stream water tracer concentrations, (4) compare estimated and measured stream water tracer concentrations and assign a likelihood rating based on measurement uncertainty. Model realizations that render a sufficient likelihood rating are retained while non-accepted model realizations are discarded. For G-EMMA one mixing model can be described in matrix notation as in Delsman et al. (2013):

\[ \ln B = x_n \]

for each iteration \( n \), if \( b \) and \( c \) are the number of EMs and tracers considered in that iteration, respectively, then \( \ln \) is a vector of EMs fractions with length \( b \), \( B \) is the \( b \) by \( c \) matrix of EMs concentrations and \( x_n \) is a vector of stream water sample tracer concentrations with length \( c \).

Applying G-EMMA in Kilombero Valley (Paper III)

For application of G-EMMA to the water chemistry data collected in KVDB (Table 2), up to 14 separate tracers (namely, Al, Ba, Ca, Cu, Fe, Mg, Na, S, Si, Sr, Zn, Zr, δD, δ18O) were used with an individual randomly selected subset of these ranging from 3 to 14 tracers for each mixing model. Cations were sampled in 12 ml polystyrene vials. Due to the remoteness of the location samples were stored up to three months before cold storage, filtering and acidifi-
cation were available. The samples were then analyzed using inductively coupled plasma (ICP) spectroanalysis with a Thermo iCAP 6500 DUO, run with an internal standard (NIST 1640a). The lack of in-field filtering and acidification introduce a source of uncertainty in the chemical analysis results for, mainly, Al, Fe, Si and Zr due to their tendency to bind to in-stream particles. To decrease the particle load influence these elements were corrected for by normalizing concentrations using Ti concentrations ($C_{Ti}$) using:

\[
\frac{C_{sol}}{C_{Ti}} = Z_{norm}
\]

where $C_{sol}$ is the tracer measurement of a sample prior to correction and $Z_{corr}$ is the Ti-normalized value (Boës et al., 2011).

Based on a preliminary investigation of the effect of a more constrained set of solutes as tracers (to assess the risk of including non-conservative tracers) a minimal assumption approach was adopted since reducing the number of tracers had no significant impact. As such, all tracers stated above were included in order to showcase the full range of uncertainty and thereby allow for robust analysis of EM contributions.

**Statistical downscaling using quantile mapping (Paper IV)**

To investigate the potential to use the GPDs from Paper I for bridging precipitation data gaps at local water resource management-relevant scales, statistical downscaling of GPDs in the KVDB region was explored (Paper IV). The impact of downscaling method was assessed via the ability to estimate streamflow within a hydrological model building on process insights from Paper II and Paper III. The performance of streamflow simulations driven by downscaled precipitation estimates was compared to the performance of streamflow simulations using the non-downscaled GPD products (see following section).

In general, downscaling may be required for using GPDs at smaller catchment scales due to the coarse spatial resolution of GPDs and their tendency to contain systematic errors (e.g. Dinku et al., 2008; Li et al., 2013a; Romilly and Gebremichael, 2011). Statistical downscaling aims to overcome these discrepancies by relating statistical patterns of local precipitation measurements (predictands) to the large scale GPDs (predictors). Statistical downscaling can be used either as a method to increase the spatial resolution of the relatively coarse GPDs or, as in this case, as a method for localizing and correcting for small scale variations of the downscaled variable. Two separate methods for statistical downscaling of GPDs were evaluated based on streamflow simulation results: Quantile Mapping (QM) was used for the GPDs with daily resolution (CMORPH, CFSR, ERA-i, MERRA and TRMMv7) and Daily Percentages (DP) was used for the GPDs with monthly resolution (CRU, GPCC and UDEL).

Quantile Mapping (QM) has previously been readily evaluated in a range of environments with favorable results (Dobler and Ahrens, 2008; Piani et al., 2010; Themeßl et al., 2011). QM corrects for both bias and variability errors by correcting the cumulative density function ($cdf$) of estimated precipitation based on the observed $cdf$. Since this study aims to downscale historical estimated precipitation records, an empirical cumulative density function ($ecdf$) was used for downscaling. Using $ecdf$ for QM was also specifically recommended in KV by Lindborg (2016) who concluded that using $ecdf$ rather than, for example gamma distribution, would reduce the inability to represent both wet and dry period distributions as well as ENSO variability. Furthermore, considering the limited available data, the QM downscaling was here applied to the spatial average of precipitation time series rather than the common point to pixel approach (e.g. Themeßl et al., 2011). Following the notation in Themeßl (2011), QM is defined as:

\[
Y_{w,d}^{val} = edf_w^{obs,cat}^{-1}\left(edf_w^{mod,cat}(X_{w,d}^{val})\right)
\]
where $X$ is the original GPD estimate and $Y$ is the downscaled value of that estimate. The $\text{ecdf}$ is constructed from the estimates within a calibration period ($\text{cal}$) consisting of a moving 61-day window ($\omega$) centered on the value ($\text{val}$) of a specific day of the study period ($d$). The $\text{ecdf}$ is constructed based on either observed data ($\text{obs}$) or modeled data ($\text{mod}$) to conduct the specific downscaling.

**Statistical downscaling using daily percentages (Paper IV)**

The interpolated GPDs (CRU, GPCC and UDEL) were only available at a monthly temporal resolution. To construct daily time series for these products the daily average of monthly totals were assigned to each day within a specific month. As such, there was no variability in precipitation within a month. This constructed daily time series is then considered as the equivalent of daily non-downscaled estimates. Due to the lack of variability within a specific month of the constructed daily time series QM could not be applied. Rather, daily downscaled data were calculated based on daily percentages (DP) of monthly total rainfall on each specific day within a month calculated from the rain gauge nearest to each catchment as:

$$Y_{d,j} = X_j^{p_dj/p_j}$$

where $Y$ is the downscaled precipitation estimate for a specific day $d$ within the month $j$, $X$ is the GPD total precipitation and $p$ is observed total precipitation.

**Using downscaled GPDs to model streamflow at the catchment scale (Paper IV)**

The results from Paper II and III were used as a basis for conceptualizing a hydro-climatic model framework in a manner consistent with the catchment-scale processes in KV. The HBV (Hydrologiska Byråns Vattenbalansavdelning) model (Lindström et al., 1997) in the version HBV-light (Seibert and Vis, 2012) was selected as the base model for this purpose because of its pragmatic approach to representing hydrology (Figure 4). Further, the HBV model has utility for investigating the effect of downsampling GPDs on streamflow modelling in data limited environments due to its parsimonious data requirements (Knoche et al., 2014). For this study, streamflow was simulated in the HBV model at a daily time step in two sub-catchments (MC and KC) using downscaled and non-downscaled GPDs as precipitation input. Simulated streamflow was then compared to observed streamflow records for evaluation of model performance. The ability of using HBV-light to provide a consistent hydro-climatic modelling framework for improving downscaling was then also investigated by using it as an explicit downscaling tool with streamflow observations as the predictor variable (Paper IV).

HBV-light (Lindström et al., 1997; Seibert and Vis, 2012) can be described as a catchment-scale, semi-distributed rainfall-runoff model. It simulates runoff based on rainfall using mathematical conceptual descriptions to represent hydrological processes. The smaller parameter set considered in HBV-light is advantageous for hydro-climatological evaluations of datasets since parameter incommensurability and uncertainty tends to increase with model complexity (Beven, 2006). In environments without snowfall, such as in KV, data inputs are limited to precipitation and potential evapotranspiration ($ET_p$). Streamflow is then used for evaluation of model performance. In HBV-light precipitation estimations are routed through three routines for simulating streamflow (Paper IV). First, a soil moisture routine partitions the input precipitation into actual evapotranspiration, groundwater recharge and soil moisture storage. Second, a groundwater routine generates outflow and shifts in groundwater level based on the recharge from the soil moisture routine. The outflow response is non-linear based on three linear response functions with thresholds for peak, intermediate and baseflow conditions. Peak flows are determined based on the storage of an upper groundwater box, intermediate
flows are determined based on a second recession coefficient for the upper groundwater box, baseflow is determined by storage in the lower groundwater box which has percolated from the upper groundwater box. Third, a triangular weighting function transforms the generated runoff into simulated streamflow (see paper Paper IV for a more detailed description).

The simulated streamflow is then evaluated against observed streamflow. In this thesis, the evaluation was done using LogReff as an objective function. LogReff is a measure similar to NS but gives extra weight to low values compared to that of NS (see paper IV for the mathematical definition). The resulting simulation performances were then characterized based on the LogReff value where above 0.7 was considered as “good” performance, LogReff between 0.5 and 0.7 was considered as “fair” performance and LogReff below 0.5 was considered as “poor”. While inherently subjective in nature, these definitions served as a qualitative performance scale to aid interpretation of the results.

Using a hydrological model to explicitly downscale GPDs to the catchment scale (Paper IV)

The ability to use HBV-light to compensate for GPDs precipitation bias by parameterization (e.g. Dawdy and Bergmann, 1969) as a downscaling technique was also explored. This was done by allowing HBV-light to calibrate a time-invariant bias correction factor as a multiplier for precipitation joint with the rest of its parameters. By introducing a parameter that allows HBV-light to directly adjust the amount of precipitation input, the precipitation estimates of a GPD are localized based on streamflow observations. It should be noted, though, that the correction factor is not directly related to the overestimation or underestimation of precipitation. Rather, it adds a degree of freedom for the hydrological model to autocorrect its parameterization to better represent streamflow. As such, this approach (i.e. where a hydrological model developed based on best available process understanding at the catchment scale is used to downscale large-scale precipitation products) aims to provide a consistent hydro-climatic modelling framework within which, for example, the impact of future development and water management scenarios or climatic projections could be evaluated.

Results summary

Assessment of Global Precipitation Datasets (GPDs) (Paper I)

The estimated mean annual precipitation for the period of 1998-2010 spanned between 969 mm/yr (CMORPH) and 1446 mm/yr (MERRA) depending on GPDs considered. All GPDs showed a clear seasonal signal in the climatology (Figure 5) with between 75% (MERRA) and 92% (CMORPH) of the precipitation falling during the wet period (December to April). During the dry period (June to October) all GPDs except for CRU and CMORPH tended to overestimate the precipitation relative to TRMMv7 product, with TRMMv7 chosen as reference. On a month by month comparison of the climatological mean the main difference among the GPDs was found in the timing of the peak of precipitation in the climatology curve, which may occur either in January (CMORPH), April (UDEL) or March (the remaining GPDs). Furthermore, estimates of long term monthly precipitation had a smaller difference between the highest and lowest GPD precipitation estimate during the first half of the wet period (the short rains from November–January) than during the second half (the long rains from March–May) with a peak occurring in April (Figure 5). The general overestimation or underestimation of precipitation (relative to TRMMv7) during the wet and dry period did not appear to be a function of the type of GPD considered (Figure 5).
Statistical comparisons of the estimated precipitation time series showed that all GPDs had high correlation coefficients (CC) when whole time series were compared to TRMMv7 (Table 3). The CC values ranged between 0.92 and 0.98 for CFSR and the ensemble mean respectively. The ensemble mean of all GPDs and GPCC had lower RMSEs than the other GPD products (Table 3). If the wet and dry periods are considered separately, the CC decreases to an average of 0.74 and 0.46 for the wet and dry period respectively. During the wet period the GPDs generally differed with regards to all performance measures. Similar to when the whole time series is considered, the ensemble mean of the GPDs and GPCC generally performed well while CFSR had a lower CC (0.64), larger RMSE (70 mm). The generally good performance of the ensemble mean is an effect of TRMMv7 being selected as a reference on the basis of being best centered. The generally good performance of GPCC is likely due to TRMMv7 not being completely independent from GPCC as GPCC is used for bias correction of the TRMMv7 product. During the dry period the GPDs also differed with regards to all performance measures with CMORPH and the ensemble mean of all GPDs generally performing well while MERRA and CRU performed poorly relative to TRMMv7 (Table 3).

Table 3. Summary of performance statistics on temporal data series derived from global precipitation products (GPDs) relative to the TRMMv7 product. The wet period is defined here as December through April and the dry period is defined here as June through October. The two best values (highest for CC and NS, lowest for RMSE and closest to zero for BIAS) are marked in bold.

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</table>
A spatial comparison of long term annual averages revealed large differences in precipitation patterns among the GPDs considered in KVDB, both when compared visually (Figure 6) and on a pixel by pixel comparison. The two satellite products (TRMMv7 and CMORPH) showed similar precipitation pattern with higher precipitation in the southeastern part of KVDB compared to the northwestern. The three interpolated products (CRU, GPCC and UDEL) also showed similarities to each other in that they all demonstrated distinct high precipitation areas in the eastern part of KVDB. The three reanalysis products (CFSR, ERA-i and MERRA) varied in spatial precipitation pattern both compared to each other and the other GPDs. CFSR showcased an extreme spatial variation with precipitation amounts that were not present in any of the other precipitation products. MERRA had an inverse spatial relation to the satellite and interpolated products with a high precipitation area estimated along the escarpment in the northern part of KVDB, likely indicating a strong elevation forcing impact in the reanalysis. ERA-i had a small spatial variation with precipitation amounts compared to the other GPDs. All three reanalysis products had a low spatial correlation compared to TRMMv7 with R2 values ranging from an negative relationship of 0.39 (MERRA) to a positive relationship of 0.32 (ERA-i) (Figure 6). The interpolated products had R2 values ranging from 0.50 (UDEL) to 0.62 (GPCC). The other satellite product included in this study, CMORPH, had the highest spatial correlation with an R2 value of 0.75.

Figure 6. Spatial pattern of long term annual precipitation estimates for global precipitation datasets (GPDs), based on the 1998-2010 period. The delineation for Kilombero Valley Drainage Basin (KVDB) is shown with a solid black line. R² values are relative to TRMMv7. Modified from Paper 1.
Assessment of streamflow data for catchment characterization (Paper II)

From a basic assessment of streamflow data, there were considerable missing periods and gaps across almost all sub-catchment in KVDB (Table 4). On average the amount of missing streamflow data per total length of record available was 18% with up to 36% for S2 and as low as 3% for S5. The gauge at the outlet of KVDB had 15% missing streamflow data during the period 1960 to 1982. Looking more into detail into the missing data reveals that the wet season and high flow conditions are overrepresented with regards to missing data (Paper IV). This is not overly surprising considering the manual staff gauge readings used by RWBO and that many of the gauges are difficult to access during flooding.

The characteristic drainage time scales (K) estimated via recession analysis for the smaller catchments averaged 160 days when using all available data, 52 days during wet season conditions and 199 days during dry season conditions (Table 4). For the larger catchments K had an average of 257 days when using all available data, 180 days during the wet season conditions and 343 days during the dry season conditions. Many of the catchments thus had K-values that were far outside the constant value of 45 ±15 days the suggested in Brutsaert et al. (2008). At most, just the smaller catchments during the wet period conditions had K values consistent with such a range.

In order to calibrate the K values to match the literature value of 45 days, the estimated E values were consistently lower than those estimated from MODIS at the catchment scale (Figure 7). Furthermore, most catchments showed a systematic relationship between recession analysis calibrated E values and MODIS derived E estimates when plotted against each other (Figure 7). Seasonality (wet versus dry) in this relationship appeared more consistent (linear) for the larger catchments relative to the smaller catchments (Figure 7). Disagreements between these independently estimated E values could be assumed to be due to some combination of (1) deficiencies in either the streamflow data or the MODIS product available, (2) limitations in the real-world applicability of the linear groundwater theory, (3) seasonal shifts in hydrology across various scales in KVDB, or (4) non-validity of K as 45±15 days as a universal constant. The occurrence of seasonal hydrological shifts within KVDB was further investigated using end-member mixing analysis (Paper III) in order to get a better understanding of the presence of each of these three limitations.

Table 4. Summary of daily time series statistics and characteristic drainage time scale (K) for catchments included in recession analysis (Paper II).

<table>
<thead>
<tr>
<th>Catchment ID</th>
<th>L1 (KVDB)</th>
<th>L2</th>
<th>L3</th>
<th>L4 (MC)</th>
<th>S1 (KC)</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time series length (yr)</td>
<td>25</td>
<td>28</td>
<td>28</td>
<td>52</td>
<td>45</td>
<td>28</td>
<td>30</td>
<td>35</td>
<td>18</td>
</tr>
<tr>
<td>Missing data (%)</td>
<td>15</td>
<td>0*</td>
<td>0*</td>
<td>27</td>
<td>23</td>
<td>36</td>
<td>4</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td>Annual K-value (days)</td>
<td>154</td>
<td>286</td>
<td>400</td>
<td>189</td>
<td>97</td>
<td>435</td>
<td>61</td>
<td>137</td>
<td>70</td>
</tr>
<tr>
<td>Wet season K-value (days)</td>
<td>201</td>
<td>318</td>
<td>146</td>
<td>57</td>
<td>47</td>
<td>73</td>
<td>47</td>
<td>54</td>
<td>40</td>
</tr>
<tr>
<td>Dry season K-value (days)</td>
<td>146</td>
<td>293</td>
<td>576</td>
<td>358</td>
<td>157</td>
<td>485</td>
<td>66</td>
<td>214</td>
<td>75</td>
</tr>
</tbody>
</table>

*Time series with gaps filled based on simulations (Yawson et al., 2005)
Assessment of source contribution to streamflow (Paper III)

The streamflow separation into EM source water showed a clear seasonal shift in KC flow pathways throughout a hydrological year (Figure 8). Though there are large uncertainties in all estimations of EM contributions to streamflow some tendencies can still be seen if the median of all behavioral models are taken into consideration. First, the contribution of overland flow (OF) was estimated to be low during the dry period and the first mode of the rainy period (Figure 8). Based on the median estimation of behavioral models OF then increased up to a maximum of 28% in March during the wet period. Second, soil water (SW) showed a similar pattern as OF with a low contribution during the dry period and then a distinct increase occurring in the wet period (simultaneously occurring with the increase of OF contribution to streamflow). The highest contribution of SW to streamflow was estimated to 67% based on the median estimation. Baseflow (BF) had an initial high contribution up to 87% of the streamflow considering the median of behavioral models during the dry period. This relatively high contribution was then displaced in late February by the increase in OF and SW contributions. Deep ground water (dGW) had a consistently low to non-existing contribution to the streamflow throughout the year.
Using downscaled GPDs to model streamflow at the catchment scale (Paper IV)

The comparison of simulated and observed streamflow in KC generally had higher LogReff values compared to that of MC, with a larger number of simulations that can be considered as fair (LogReff values between 0.5 and 0.7) (Table 5; Paper IV). The simulations also generally showed similar impacts from the downsampling on the streamflow simulation performance in both catchments. Model performance was reduced when precipitation input was first downscaled with QM and generally improved when downscaled with DP. Calibrations based on the DP downscaled GPDs, namely, the monthly resolution CRU, GPCC and UDEL products, exhibited LogReff values of 0.51, 0.51 and 0.56, respectively. These simulations could thus be considered as fair with regards to model performance.

The streamflow simulations for MC showed that most streamflow simulations had poor performance (LogReff < 0.5) when calibrated based on non-downscaled GPDs at a daily time step (Table 5). The exceptions were ERA-i and the ensemble mean of GPDs which had LogReff values of 0.53 and 0.55, respectively, making these fair performances under the defined classification system. Simulation performances (LogReff values) further decreased for all GPDs when input precipitation was derived from QM downscaled GPDs prior to the model calibration. Calibrations using monthly products as precipitation input increased HBV model performance when it was calibrated using DP downscaled GPDs compared to their non-downscaled counterparts. However, model performance overall was still considered as poor.
Table 5. Performance measures as LogReff values, comparing simulated and observed stream flow. Simulated streamflows are based on calibrations using non-downscaled or downscaled global precipitation datasets as input.

<table>
<thead>
<tr>
<th>Catchment</th>
<th>Non-Downscaled (LogReff)</th>
<th>Downscaled performance (LogReff)</th>
<th>Change in downscaled performance (Δ LogReff)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily (GDPs)</td>
<td>QM</td>
<td>DP</td>
</tr>
<tr>
<td>CFSR</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CMORPH</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERA-i</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>MERRA</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRMM+7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ensemble</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rain gauge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRU</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GPCC</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UDDEL</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Good > 0.70
- Fair > 0.50
- Poor < 0.50
- Increase > 0
- Decrease > 0

The streamflow simulation did not manage to capture all streamflow dynamics (and thus resulted in the low LogReff value). First, the recession periods during the dry seasons were often poorly represented, approximated by a horizontal lines. The HBV model did however manage to capture the recession period in some calibrations (Paper IV). Second, peak flows tended to exceed that of the observed streamflow. While peak flows often occur during periods of missing data the peaks of the simulated specific discharge are at around 7 mm/day. These simulated peak flows exceed the entire streamflow record of close to 40 years where specific discharge is at a maximum of 3 mm/day. The hydrographs from calibrated streamflow simulations using QM downscaled data as precipitation input had little connection to the streamflow processes seen in MC (Figure 9). The model appeared to release stored excess water during missing data periods (which does not affect the resulting LogReff value) to optimize calibration and then approximates streamflow as a near straight line. The effect of the poor streamflow representation is seen in the low LogReff value (0.05).
Using a hydrological model to explicitly downscale GPDs to the catchment scale (Paper IV)

The downscaling using a model integrated bias correction factor (ModB) as a multiplier improved the LogReff values for all calibrated stream flow simulations compared to the non-downscaled counterparts in both MC and KC (Table 5). Calibrated streamflow simulations for KC achieved fair results with regards to LogReff value when calibrated based on ModB downscaled GPD data for all GPDs except CFRS (Table 5). The highest LogReff value was obtained by the calibration based on ModB downscaled MERRA data (LogReff 0.68). For both MC and KC, all calibrations based combined QM and ModB or DP and ModB downscaling achieved LogReff values considered as “fair”, ranging from 0.51 (CMORPH) to 0.63 (UDEL). In general the calibrations based on GPDs downscaled using a combined method rendered equal or lower LogReff values compared to only ModB downscaled GPDs (Table 5).

For the MC calibration based on rain gauge data improved considerably from when ModB was applied compared to the original calibration. Performance increased from a LogReff value of 0.12 using the original data to LogReff 0.45 using ModB, but still rendered what is here considered as poor results under the assigned classification system. Calibrations based on ModB downscaled GPD data only rendered fair results (LogReff 0.5 to 0.7) for ERA-i, MER-
RA, TRMMv7 and the ensemble mean. Out of these the calibration based on MERRA had the highest LogReff value of 0.61. Combining the QM and ModB downscaling approach generated streamflow simulations with higher LogReff values than the non-downscaled counterparts in all cases except for when using the ensemble mean as precipitation input. However this approach also decreased the simulation performance compared to only using ModB as a downscaling technique when calibrated based on MERRA or the ensemble mean. The calibration using downscaled MERRA data, for example, decreased the LogReff value from 0.68 to 0.53 (Table 5). For all monthly products (CRU, GPCC and UDEL) the combined DP and ModB downscaling improved LogReff values compared to their non-downscaled counterparts. However, only the calibration based on DP and ModB downscaled UDEL data achieved a LogReff value (0.52) that is here considered as fair (Table 5).

A comparison of the hydrograph of the observed and calibrated streamflow simulation using ModB downscaled MERRA data (Figure 9) showed that the general seasonality was well captured. Similarly to the calibrations based on non-downscaled data the recession period during dry season appeared to be problematic. Furthermore, the simulation also appeared to not being able to capture the daily variations of observed streamflow. On the other hand, simulated peak flows were of a similar magnitude as the observed streamflow with peaks up to 2.5 mm/day. The hydrograph based on the calibration using ModB and QM downscaled MERRA data had some features that were similar to that of the hydrograph based on the calibration using QM downscaled MERRA data. More specifically, the peak flows were similar but of a smaller magnitude for the hydrograph based on the calibration using QM downscaled MERRA data. The general features seen in these simulated hydrographs were representative for most streamflow simulations using GPDs as input, with inability to capture the dry period recession period and large peaks during missing data periods. There were, however, streamflow simulations where these deficiencies were not present (Paper IV).

**Synthesizing data across spatiotemporal scales within a coherent hydro-climatological modeling framework for Tanzania’s Kilombero Valley**

In spite of all challenges entailed by working in a data limited regions, catchment processes understanding could be obtained in this thesis based on limited streamflow and hydrochemical data when experimental design and a strong signal to noise ratio were leveraged. A synthesis of information based on analysis methods using widely disparate data inputs also rendered a synthesis of process understanding. As such, this thesis constitutes a first iteration of a generalized workflow for building up catchment and data understanding, enabling water resource management (Figure 10). More specifically, the theoretical understanding of catchment flow processes garnered by the recession analysis (Paper II) and auxiliary data in the form of water chemistry data could be used in the G-EMMA (Paper III) to inform the choice of hydrological model. This, together with the lessons learned from the investigations of the utility of GPDs in data limited regions (Paper I), provided the pieces for building a consistent hydrological modelling framework (Paper IV) that can be used for hydrological/water resource scenario analysis (Figure 10). This approach of synthesizing across spatiotemporal scales and assessment techniques to build a consistent framework is promising considering that ongoing agricultural intensification climate change require development of sustainable water management plans regardless of initial data availability of a region.
Hydro-climatic data at the scale of Kilombero Valley

The intercomparison of eight GPDs and the ensemble mean in KVDB revealed that there were large differences both spatially and temporally between the investigated products. While all products managed to capture the general seasonality the difference in precipitation climatology increased at a sub-seasonal time scale. For example, the timing of the peak precipitation month as well as the onset of the dry season varied depending on the product. The difference in long term monthly averages increased as the wet season progressed. The impaired performance at higher temporal resolutions seen here is in concert with previous studies (Decker et al., 2012; Dinku et al., 2011; Zambrano-Bigiarini et al., 2017). From a management perspective these differences between the GPDs may have large impacts if used to inform water management and agricultural practices as they affect the ability to project the onset of the rainy period and, with it, the growing season. The differences in annual totals may also impact long term water management decisions considering that it affects the amount of water believed to be available.

The spatial comparison of GPD precipitation fields revealed that there are large differences between the products (Figure 6; Paper I). Though expected from a physical perspective, neither of the satellite (TRMMv7 and CMORPH) products appeared to capture orographic precipitation as an effect of Mahenge Escarpment. The inability of satellite products using PMW and/or IR to capture orographic precipitation due to low ice scattering and warm cloud top precipitation is a known limitation (e.g. Dinku et al., 2008; Cattani et al., 2016) and appears to be a limitation in KV as well. The interpolated products all had a high precipitation area in the eastern part of the catchment and a smooth gradient in the precipitation field. A closer look at the gauges used to construct, for example, GPCC shows that the high precipitation area coincides with the only available rain gauge in the region. The impact of that single gauge on precipitation estimates thus likely extend beyond its actual measurement footprint.

All three reanalysis products performed poorly with regards to the spatial patterns when compared to TRMMv7. CFSR showed that it has an extreme variance in the long term annual precipitation averages (Figure 6). Both the maximum precipitation and the minimum precipitation were outside the range that is normally found in the other GPDs and historical rain gauge observations. MERRA had an inverted relationship in precipitation pattern compared to TRMMv7 with a strong orographic precipitation effect. Though orographic precipitation tends
to be underrepresented in satellite products the low performance (LogReff value) of the streamflow model calibration based on non-downscaled MERRA data (Paper IV) indicates that MERRA overestimates the orographic effect of Mahenge Escarpment. As seen in (Decker et al., 2012), MERRA’s usage of coupled land-atmosphere reanalysis model and assimilation of satellite rain rates does not inherently mean precipitation estimation accuracy. One possible explanation for inability of reanalysis products (CFSR, ERA-i and MERRA) to model precipitation in KV may be the complex interaction of large scale climate systems that affect the inter-annual variability of the long rains (March-May) which are the main precipitation months (Camberlin and Philippon, 2002; Sun et al., 1999).

In general, considering the relatively high coherence of the GPD time series in concert with the low coherence of the spatial precipitation fields, it appears as KVDB (34 000 km2) approaches the lower limit of spatial scale where GPDs are relevant without downscaling. Similarly to Worqlul et al. (2014), this is in part attributed to the lack of precipitation gauges for either interpolation or bias correction of satellite and reanalysis products (see following discussion). The results also highlight the importance of matching spatial and temporal scale with the region of interest and aim the implementation of GPDs. The effect of this can be seen in the widely disparate conclusion regarding the applicability of GPDs across the range of studies that previously been conducted (e.g. Thiemig et al., 2012; Liu et al., 2015; Worqlul et al., 2014). Even so, each investigation of GPD performance adds to the knowledge base of when, where and in what form a specific GPD may be suitable.

Shifting focus to the movement of water through the landscape, when the streamflow data were used for estimating the characteristic drainage timescales (K) in KVDB and its sub-catchments the resulting estimates fell well outside of the range of expected values for catchments globally (Table 4). Though several aspects of the analysis contributed to this, the missing data did appear to be part of the explanation as the K-values tended to increase with the amount of missing data (Table 4; Paper II). To what extent the inability for the K-values to conform to expected values were due to missing data is, however, difficult to discern. Part of the explanation could also be contributed to the methodology’s underlying simplified representation of the catchment, to seasonal shifts in catchment flow processes or non-validity K of 45±15 days as a universal constant. Support for the impact of seasonality was seen when calibrated E was plotted against MODIS derived E estimates (Figure 8). Furthermore, previous studies have also shown that catchments do not always conform to a K of 45±15 days. For example, Carrillo et al. (2011) found catchments ranging between 20 to 83 days.

Similarly to the GPD intercomparison (Paper I) the results highlight the need to take seasonality into consideration when choosing modelling approach for streamflow simulations (Paper I, II). The results from the recession analysis may provide guidance both with regards to further investigations of seasonal flow pathways shifts (such as in Paper III) and future modelling framework (such as in Paper IV). Similar to the conclusion of, for example, Carrillo et al. (2011), Gupta et al. (2008) and Yawson et al (2005) modelling efforts in data limited regions, such as KV, must balance the need for being data parsimonious (considering the limited input data availability) while still being sufficiently complex to capture streamflow generation processes seen in complementary analysis.

**Building process understanding in data limited regions**

The comparison of calibrated E and MODIS derived E (Paper II) indicated that there may be a seasonal shift in hydrological processes generating streamflow. This was further investigated by applying G-EMMA in KC. The results from the G-EMMA showed large uncertainties in EM contributions to the streamflow. For several of the EMs the 5-95 percentiles implied contributions ranging from 0% to almost 100% during parts of the year. The uncertainty bounds found here when considering the interquartile range were still however in line with the range found in other similar studies (Bazemore et al., 1994; Genereux, 1998). There were several aspects contributing to the uncertainty seen in the EM contribution estimates both with re-
gards to analytical uncertainty (i.e. lab measurement uncertainty) and conceptual uncertainty (i.e. identified EMs to include and where to sample the EMs) (Delsman et al., 2013; Durand and Juan Torres, 1996). Further, several studies have argued that EMMA should be limited to catchments smaller than about 1 km² (e.g. Burns et al., 2001). KC is on two orders of magnitude larger than that with its 500 km². Even so, EMMA have previously been successfully applied at catchment scales up to 2 000 km² (Barthold et al., 2011; St Amour et al., 2005). As such KV can be considered well within the range EMMA. The remoteness and inaccessibility of the catchment also likely affected the uncertainty ranges since explicit sampling of EMs within the catchment was not possible. Based on the results from Soulsby et al. (2003) and St Amour et al. (2005) these two factors are expected to some extent be offset by the relative homogeneity of KC as well as a strong signal to noise ratio stemming from the seasonality and EM chemistries. The boundaries of the underlying assumptions EMMA are often pushed when applied to hydrological systems (Hooper et al., 1990, Soulsby et al., 2003) and this study is no exception. Robust conclusions may still be made by embracing existing uncertainties and explicitly take them into account in the analysis of the results.

The indication of a shift in hydrological processes and how water interacts with the landscape seen in Paper II both with regards to K-values and calibrated \(E\) could also potentially be seen in Paper III. OF and SW, for example, had a low contribution during the dry season and then increased their contribution during the second mode of the rainy season. The delayed OF and SW response compared the onset of the rainy period with regards to contributions indicated that there was a requirement of wetting up the catchment before the upper layers were activated as flow pathways. This supports the results in Paper II that showed that there was a dominant vertical flux of water in the dry season that is then overtaken by horizontal fluxes during the wet season. Finally, the dGW did not show any strong presence in the stream water throughout the sampled year. At the outlet of KC there were no evidence of mountain recharge supporting streamflow, rather it appears as the underlying granulitic gneiss bedrock functions an impermeable foundation to the soil aquifer. Finally, it should be noted that several authors have argued that results from EMMA should only be used for qualitative understanding of a catchment (Inamdar et al., 2013; Soulsby et al., 2003; Uhlenbrook and Hoeg, 2003) and in the constraint of model development. The large uncertainties seen in the results support this sentiment and constrain the use of these results to the conceptualization of the hydrological model implemented in Paper IV.

Towards an coherent hydro-climatic modelling framework

The results of the recession analysis and G-EMMA (Paper II, III) indicated that a model framework for streamflow simulation of KVDB needs to be able to take seasonal shifts in flow pathways by activation of quicker flow paths during wet season into consideration (i.e. a threshold in hydrological response). Furthermore, it should also be able to partition the catchment in order to represent the hillslopes and valley separately if the entire KVDB is to be modelled. Based on these results and the need for limited data input the HBV model was chosen. The rainfall-runoff models for MC and KC were both implemented and conceptualized based on these findings (Figure 8; Paper III). Even so, the calibrated streamflow simulations based on rain gauge data only achieved a \(LogReff\) value of 0.12 in MC and 0.52 in KC. Exchanging rain gauge data with non-downscaled GPD data generally improved simulations in MC (Paper IV). The results in KC were mixed as some GPD driven model performances increased while others decreased relative to calibration based on rain gauge data. As such, GPDs can be used as precipitation input as is for hydrological modelling at a daily time step with moderate results if care is taken when choosing GPD (Paper IV). Previous results GPD performance for hydrological modelling in ungauged basins have also shown that GPDs render streamflow simulation results comparable or better than hydrological models using rain gauge data (e.g. Xue et al., 2013; Lauri et al., 2014).
The QM downscaling of precipitation input data decreased model performance for almost all calibrations regardless of the GPD (Paper IV). This is not surprising with regards to MC considering the low model performance when the HBV model was calibrated using the rain gauge data. The calibrations using downscaled data also decreased the calibrated simulation performances in KC. The QM deterioration of the precipitation data can in part be contributed to the fact that only one gauge was available for the downscaling. The use of one gauge presents a commensurability problem since it is then assumed that the frequency distribution of the rain gauge was representative for the larger area (Duetthmann et al., 2013). Previous studies have shown that QM introduces an inflation of variability if rain gauge coverage is not at a spatial scale equal to the downscaled product (e.g. Maraun 2014). According to Maraun (2014) the issue is particularly prevalent in areas where localized convective rainfall is common (such as KVDB – Paper I). Furthermore there is also a mismatch in determinants of variability since large scale variability depends on, for example, large-scale climate circulation patterns while rain gauge variability depends on local scale parameters such as, for example, topography (Maurer et al., 2015). This introduces errors in the downscaling since the deterministic QM is assumed to correct the large scale variability based on local variability. The monthly products performed poorly when calibrated using non-downscaled monthly GPDs. Interestingly the DP downscaling generally produced better results than QM downscaling, especially in KC. Duetthmann et al. (2013) argued that correcting for precipitation amounts is more robust method for localization of precipitation data (as long as there is a rudimentary representation of the temporal dynamics). Comparing the results of QM and DP downscaling with regards to streamflow simulations supports this notion.

When the downscaling of GPD precipitation estimates were internalized into the HBV model, by using a bias correction factor as parameter in the ModB approach, the streamflow simulation performance improved for all calibrations independent on the GPD considered. Combining ModB with QM generally resulted in calibrations that increased the LogReff values of calibrated streamflow simulations compared to non-downscaled and QM downscaled counterparts. In contrast, the combined ModB and QM downscaling did not render higher LogReff values than the ModB only downscaled counterparts. The deterioration of the streamflow simulation capacity when using QM and ModB for downscaling shows that QM downscaling with a single gauge may also introduce frequency errors that could not be corrected by the ModB downscaling. This may indicate a mismatch in source of variability between GPD and rain gauge time series. Similar to Maurer et al. (2015) this highlights that one also needs to consider temporal precipitation distribution of a rain gauge relative to the catchment when implementing QM downscaling. The location of a rain gauge relative to, for example, topography may thus be more important than vicinity. This sentiment is similar to that of PUB (Sivapalan, 2003) where one aspect of advancing of streamflow modelling in ungauged basins would be based on extrapolating catchment parameters from a gauged basin to an ungauged basin based on catchment similarity and regionalization concepts.

While GPDs to some extent can replace observed data in data limited regions there is clearly still a need for an increased precipitation monitoring for bias correction of GPDs or construction of GPDs. This can be seen in the large differences in both spatial and temporal precipitation estimates (Paper I) as well as the model performances of the streamflow simulations (Paper IV). Furthermore, streamflow observations also continue to be relevant considering the need for evaluation of hydrological models and/or GPDs. As such, the ‘paradox of ungauged basins’ (Bonell et al., 2006) likely remains. Seibert and Beven (2009) sum up this paradox nicely in stating that that transferring parameters is precarious if the transferred parameter has not previously been rigorously tested in several catchments. Similarly, and as seen in Paper I and IV, the accuracy in precipitation estimates in one region does not necessarily transfer to another regions (e.g. Maidment et al., 2013; Dinku et al., 2007; Romilly and Gebremichael, 2011; Zhang et al., 2012; Habib et al., 2012) – especially not when considering data limited regions. However, by leveraging local process understanding (Paper II and Paper III) within development and application of a hydrological model can still to some extent offset or at least
identify impacts of such a transfer. The same holds true when transferring parameters to different time periods considering both inter-decadal shifts in climatology (Lindborg, 2016; Zhang et al., 2012) and shifts in input for constructing GPDs (e.g. Becker et al., 2013). Even so, considering current changes in both land use and climate in areas such as KV, the information gained through hydrological modelling based on a framework similar to what has been presented across this thesis garners hope in its potential ability to be utilized for water resource planning – as long as the uncertainties are adhered to for minimizing risk.

Reflections and future research

Closing streamflow and precipitation data gaps

The lack of recent streamflow observations remains problematic particularly with regards to KVDB where the historical record (ending in 1981) has only limited overlap with the satellite era (beginning in 1979). While there are methods, such as the recession analysis used in Paper III, that are less affected by data gaps (but of course affected by data quality) the lack of observed data constrains development of scientific studies already at the conceptualization stage. For example, the applicability of methods dependent on interpolated or remotely sensed data such as, for example, calibration of hydrological models based on saturation area extent (e.g. Ambroise et al., 1996; Birkel et al., 2009) or inclusion of remotely sensed gravity fields to inform ground water storage amount (Tangdamrongsub et al., 2015) remain uncertain without data for evaluation. This also highlights the importance of projects such as TAHMO (www.tahmo.org) which focuses on increasing the monitoring network of either streamflow or precipitation. An emerging field that shows promise for overcoming data gaps in historical records is streamflow or precipitation simulation based on artificial neural networks. Previous studies have shown promising results in short term forecasting using limited streamflow or rain gauge data (Singh et al., 2014; Wu et al., 2009). Artificial neural networks could potentially be used for streamflow hindcasting to construct streamflow time series which in turn could be assimilated into hydrological models for projections and land use or streamflow scenarios.

Integrated framework for social and ecological modelling of water resources

The interaction between people and resources can be quite complex (and quite informative). Integration of “soft” data available from people in the landscape could be a promising way forward to better understanding the biophysical landscape. For example, single actions of individuals may propagate across spatiotemporal scales to cause resource collapse (Cash et al., 2006; Peters et al., 2007). Improved understanding of social-ecological systems (SES) and their transgressional nature has the potential to diminish the risk for degraded ecosystems due to resource utilization. An underlying assumption of agent-based modelling is often that stakeholders make rational decisions. There is, however, a push towards more complex behavior models to better reflect human behavior (Schlüter et al., 2017). Participatory response analysis (PRA) can be used for informing the choice of behavioral models from models outlined in Schlüter et al. (2017). By allowing human-environment relationships, as well policy maker-stakeholder relationships to inform water resources management scenarios, its impact on the biophysical sphere can be estimated. Clearly, the key here is to align the complexity of the models with the scales of information available to allow for advancement in resource management and allocations.

The modelling framework presented in this thesis, using the HBV model (Bergström, 1976, Seibert and Vis, 2016) driven by GPDs could, for example, be coupled to human behavior, ecosystem and resilience modelling. Change in hydrological regime affects both water and nutrient flows with potentially adverse effects on socio-ecological systems. The hydrological
regime can thus be used as an indicator for tipping points to investigate cross-scale interconnectivity of a SES where land use and climate change scenarios drive precipitation input and evapotranspiration changes. Relevant for the overall social-ecological health of KVDB, bifurcation analysis can be used to identify said tipping points and, in extension, assess resilience (Tamba and Lemmon, 2014; Troost et al., 2007). By allowing for dynamic input where model output at a specific time step subsequently informs the human behavioral model at the next time step could allow for simulating adaptation strategies to changes in the hydro-ecological regime. Of course, uncertainties are inherent in all models. For example, several behavioral models are likely needed to fully represent the complex nature of human behavior. Parameter dimensionality of the model could be decreased by constraining the behavioral models to stylized scenarios (or by aligning them with the model framework developed within this thesis). As such, a coupled behavior-hydrological-bifurcation model appropriately constructed and constrained could provide a coherent platform for SES-analysis.

Why would this be needed? Efforts to showcase the effect of different management scenarios on SES resilience are paramount for enabling adaptive governance capable of managing sustainable resource utilization. By quantifying human-resource interactions across scales advancements in our understanding of the processes that drive social-ecological systems can be made and thereby allowing for improved access and allocation of resources to where they are most needed to improve rural livelihoods. This gets to the heart of the improving our understanding in more and more remote (and in particular data limited) regions to allow for the management of less and less available resources.

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