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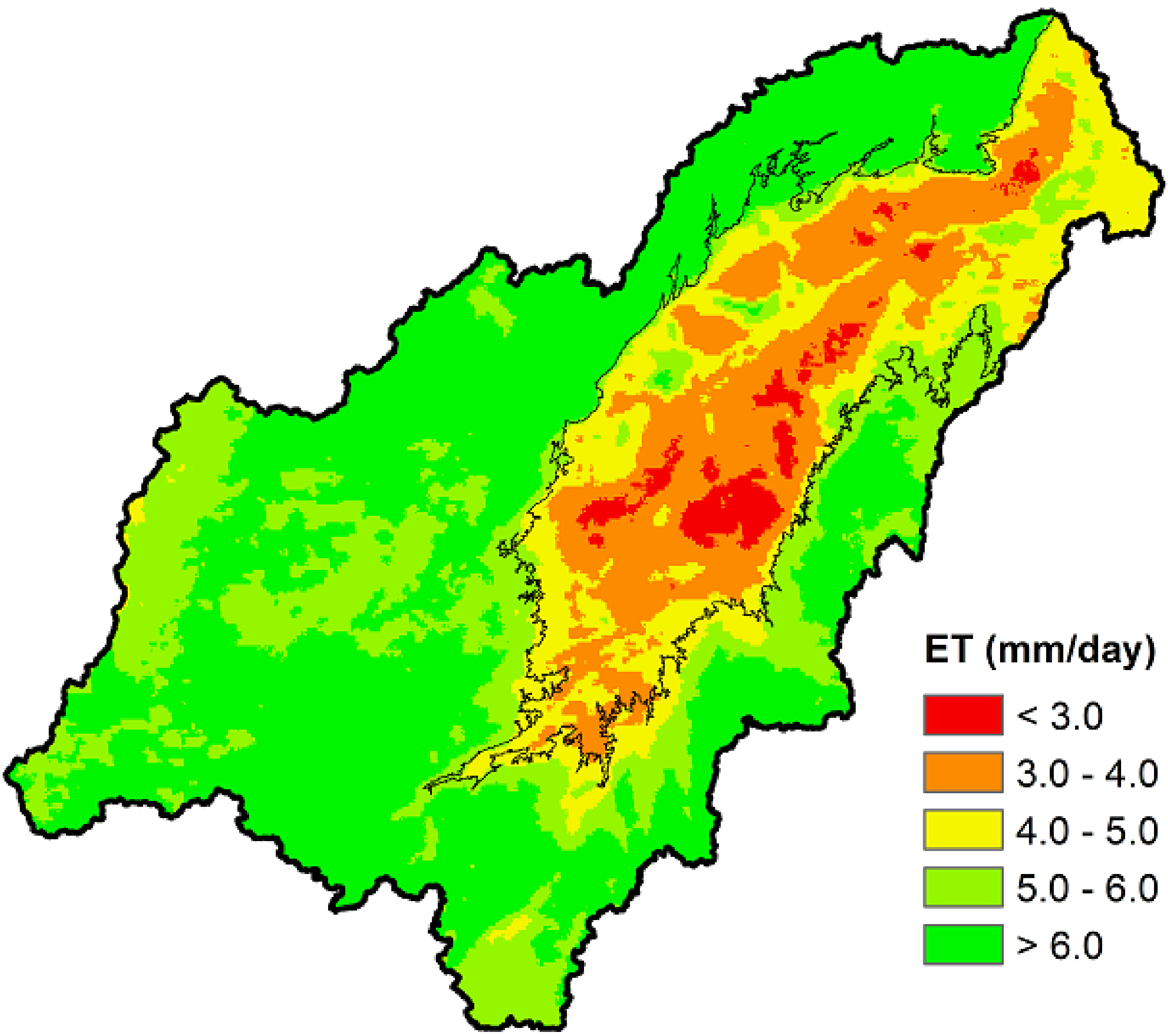
Modelling water resources despite data limitations in Tanzania's Kilombero Valley

William Senkondo



Doctoral Thesis in Physical Geography at Stockholm University, Sweden 2020

Modelling water resources despite data limitations in Tanzania's Kilombero Valley

William Senkondo

Academic dissertation for the Degree of Doctor of Philosophy in Physical Geography at Stockholm University to be publicly defended on Wednesday 29 April 2020 at 13.00 in De Geersalen, Geovetenskapens hus, Svante Arrhenius väg 14.

Abstract

Water is a vital resource for survival on the Earth. Sustainable management of water resources is therefore required for the wellbeing of present and future generations. A cornerstone of water resources management is scientific guidance supported by relevant data (in terms of quantity and quality). Most developing regions, where such guidance is crucial due to the intimate connection between natural resources and livelihoods, unfortunately face data limitations. This thesis aims to develop systematic approaches for informing water resources management in data limited regions. Specifically, this work targets Tanzania's Kilombero Valley (KV) basin as an exemplar of a data limited region undergoing social-economic development through expansion and intensification of agriculture and other water-related interventions. Through a synthesis of lessons learned from the ongoing evolution of hydrological modelling development for water resources management in the Eastern Africa, several promising approaches were identified that could potentially be robust despite data limitations across the region. Putting these approaches into practice, recession analysis based on non-continuous discharge data in conjunction with estimations of the actual evapotranspiration (ET) using remote sensing techniques provided a basis to improve process understanding and help characterize the hydrological systems in the KV basin. This understanding translated into more-informed parameter estimation and improved accuracy when integrated into the development of a hydrological modelling framework using the Soil and Water Assessment Tool (SWAT) model. The modeling framework established for KV has potential to be used as tool for estimating impacts of water resources management strategies relative to future anthropogenic pressures and climatic changes. What is even more promising, is the possibility to derive scientific guidance to assist water resources management in a data limited region through implementation of an integrated workflow which employs state-of-the-science approaches. The methodological framework for model development adopted in this thesis could be applied in any data limited region facing similar challenges as those of the KV basin.

Keywords: *Hydrological modelling, Recession analysis, Remote sensing, Water resources, Evapotranspiration, Transmissivity, SWAT model, Kilombero Valley.*

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To the believers of the
Light of the world

Abstract

Water is a vital resource for survival on the Earth. Sustainable management of water resources is therefore required for the wellbeing of present and future generations. A cornerstone of water resources management is scientific guidance supported by relevant data (in terms of quantity and quality). Most developing regions, where such guidance is crucial due to the intimate connection between natural resources and livelihoods, unfortunately face data limitations. This thesis aims to develop systematic approaches for informing water resources management in data limited regions. Specifically, this work targets Tanzania's Kilombero Valley (KV) basin as an exemplar of a data limited region undergoing social-economic development through expansion and intensification of agriculture and other water-related interventions. Through a synthesis of lessons learned from the ongoing evolution of hydrological modelling development for water resources management in the Eastern Africa, several promising approaches were identified that could potentially be robust despite data limitations across the region. Putting these approaches into practice, recession analysis based on non-continuous discharge data in conjunction with estimations of the actual evapotranspiration (ET) using remote sensing techniques provided a basis to improve process understanding and help characterize the hydrological systems in the KV basin. This understanding translated into more-informed parameter estimation and improved accuracy when integrated into the development of a hydrological modelling framework using the Soil and Water Assessment Tool (SWAT) model. The modeling framework established for KV has potential to be used as tool for estimating impacts of water resources management strategies relative to future anthropogenic pressures and climatic changes. What is even more promising, is the possibility to derive scientific guidance to assist water resources management in a data limited region through implementation of an integrated workflow which employs state-of-the-science approaches. The methodological framework for model development adopted in this thesis could be applied in any data limited region facing similar challenges as those of the KV basin.

Sammanfattning

Vatten är en av våra viktigaste och mest hotade naturresurser. Fortsatt välfärd för kommande generationer kräver därför en hållbar förvaltning av vattenresurserna. En grundpelare i förvaltningen är att den baseras på vetenskap tillsammans med relevant data vad gäller såväl kvantitet och som kvalitet av vatten. I många utvecklingsländer, som ofta kräver en effektiv resurshantering på grund av den starka kopplingen mellan naturresurser och försörjning, råder idag brist på relevanta data. Denna avhandling syftar till att utveckla systematiska strategier för att förbättra förvaltningen av vattenresurser i regioner med brist på vattenrelaterade data. Arbetet fokuserar på våtmarksområdet Kilombero Valley (KV) i Tanzania, ett för Afrika typiskt område med brist på relevant vatten-data och som dessutom just nu genomgår stor socio-ekonomisk förändring genom intensifiering av jordbruk och andra vattenrelaterade interventioner. Genom att sammanställa och analysera information om hydrologisk modellering och vattenresurshantering i östra Afrika, identifierades flera tillvägagångssätt som potentiellt kan användas i regionen trots databegränsningar. Resultaten visade att förståelsen för processerna och möjligheten att karakterisera hydrologin för KV förbättrades när man kombinerade recessionanalys baserad på icke-kontinuerliga flödesdata med beräkningar av den faktiska evapotranspirationen med hjälp av fjärranalys. Detta kunde sedan översättas till en förbättrad parameteruppskattning och noggrannhet i utvecklingen av ett hydrologiskt modelleringsramverk med hjälp av SWAT-modellen (Soil and Water Assessment Tool). Även om modelleringsramverket upprättats för KV finns en stor potential för mer generell användning för att uppskatta effekterna av vattenresurshanteringsstrategier relativt framtida klimatförändringar även på andra platser. Dessutom ger detta ramverk möjlighet att på ett mer vetenskapligt sätt vägleda vattenresurshanteringen i andra databegränsade områden genom att integrera ett arbetsflöde som använder toppmoderna metoder metoder med praktik.

Thesis content

This doctoral thesis consists of a comprehensive summary and four appended Papers. The Papers are referred to as Papers I–IV in the comprehensive summary. The published Papers are reprinted by prior permission from the copyright holder.

List of papers

I. **Senkondo, W.**, Tumbo, M., Lyon, S.W., 2018. On the evolution of hydrological modelling for water resources in Eastern Africa. *CAB Reviews* 13, 1-26. https://doi.org/10.1079/PAVSNNR201813028.

II. **Senkondo, W.**, Tuwa, J., Koutsouris, A., Tumbo, M., Lyon, S.W., 2017. Estimating aquifer transmissivity using the recession-curve-displacement method in Tanzania's Kilombero valley. *Water (Switzerland)* 9, 948. https://doi.org/10.3390/w9120948.

III. **Senkondo, W.**, Munishi, E.S., Tumbo, M., Nobert, J., Lyon, W.S., 2019. Comparing Remotely-Sensed Surface Energy Balance Evapotranspiration Estimates in Heterogeneous and Data-Limited Regions: A Case Study of Tanzania's Kilombero Valley. *Remote Sensing* 11, 1289. https://doi.org/10.3390/rs11111289.

IV. **Senkondo, W.**, Nobert, J., Munishi, E.S., Tumbo, M., and Lyon, 2020. On the potential of using satellite-based evapotranspiration estimates to constrain hydrological modeling in Tanzania's heterogeneous and data-limited Kilombero Valley. *Journal of Hydrology*, submitted.

Author and co-authorship

I. I led the writing, data collection and analysis. I designed study with the support of Lyon, S.W. and Tumbo, M., both of which helped with interpretation of results and contributed to the writing of the manuscript.

II. I led the writing, conceptualization and designing of the study with input from Lyon, S.W. I was responsible for compilation and analysis of hydrological data with regards to quality control. I also did the recession analysis and interpreted results with Lyon, S.W. Tuwa, J., Koutsouris, A., and Tumbo, M., all of which reviewed the manuscript and contributed to the writing of the manuscript.

III. I led the writing, conceived and designed the study in collaboration with Lyon, S.W. I conducted data collection, data analysis, and performed surface energy balance modelling. I interpreted modelling results together with Lyon, S.W. Munishi, E.S., Tumbo, M., and Nobert, J., all of which reviewed the manuscript and contributed to the writing of the manuscript.

IV. I led the writing, conceived and designed the study with input from Lyon, S.W. I analyzed hydrometeorological data in terms of quality control and performed hydrological modelling. Nobert, J., Munishi, E.S., and Tumbo, M. reviewed the manuscript and contributed to the writing of the manuscript.

Contents

Abbreviations and symbols

ET	Evapotranspiration
ENSO	El Niño–Southern Oscillation
G	Soil heat flux
GLEAM	Global Land Evaporation Amsterdam Model
GPCC	Global Precipitation Climatology Center
H	Sensible heat flux
IAHS	International Association of Hydrological Science
IOZM	Indian Ocean Zonal Mode
ITCZ	Intertropical Convergence Zone
KGE	Kling-Gupta Efficiency
KV	Kilombero Valley
LE	Latent heat flux
MODIS	MODerate Resolution Imaging Spectroradiometer
NSE	Nash-Sutcliffe Efficiency
PBIAS	Percent Bias
PUB	Prediction in Ungauged Basins
R^2	Coefficient of determination
RBWO	Rufiji Basin Water Office
RMSE	Root Mean Square Error
R_n	Net surface radiation
RSR	Ratio of RMSE to the standard deviation of observation
SAGCOT	Southern Agricultural Growth Corridor of Tanzania
SEB	Surface Energy Balance
SEBAL	Surface Energy Balance Algorithm for Land
SRTM	Shuttle Radar Topography Mission
SSEBop	operational Simplified Surface Energy Balance
S-SEBI	Simplified Surface Energy Balance Index
SUFI-2	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Programs
TAHMO	Trans-African HydroMeteorological Observatory
λ	Latent heat of vaporization
Λ	Evaporative fraction

1. Introduction

1.1 Background and Problem description

Water is a vital resource for life on Earth. For example, humans use water for domestic, agricultural, industrial, hydroelectric power generation, recreation, and navigation purposes. Additionally, when water circulates between the atmosphere, land, and the ocean it plays an integral role in regulating most biogeochemical cycles such as the carbon cycle, nitrogen cycle, phosphorus cycle, and sulfur cycle (Jacobson et al., 2000). Given the varied uses and roles of water, it is clear that management of water resources is of great importance especially in regions with considerable deterioration of water quality and lowered land productivity (Vörösmarty et al., 2010). Management is challenging given the constant movement of water from the atmosphere to land through precipitation, then from land to the ocean through runoff (or discharge/streamflow when flow is within a channel/river), and then from the ocean back to the atmosphere through evaporation.

Within this hydrologic cycle, water can also return to the atmosphere directly from the landscape through soil/water evaporation and/or transpiration from plants/vegetation. The combined flux from water evaporated from soil pores, surface of leaves, open water bodies (e.g. oceans and lakes), and water transpired from plants' leaves through stomata is denoted as evapotranspiration (ET) - one of the key components of the hydrological cycle accounting for around 60% of the average annual precipitation that falls on land globally (Oki and Kanae, 2006). The water not leaving the landscape through ET can either flow horizontally (overland flow) towards the water bodies, be stored in the unsaturated zone as soil moisture, or percolate into the saturated zone where it is stored as groundwater before making its way to the water bodies or other uses. These stored waters are often what human populations rely on as a manageable resource. Globally, more than 1.5 billion people rely on groundwater to meet their water demands (Alley et al., 2002). Groundwater also contributes a substantial amount of baseflow into perennial rivers especially during the dry season (Chen and Lee, 2003; Rorabaugh, 1964). Normally, groundwater is stored in geological formations known as aquifers (Abo and Merkel, 2015; Van Camp et al., 2013; Soupios et al., 2007; Theis, 1935) making accurate information on aquifer properties (e.g. transmissivity, hydraulic conductivity, and specific yield) and their associated hydrological processes across scales important for understanding, developing, and managing water resources.

However, water resources management can be inhibited by limitations of data (e.g. hydro-climatic data such as precipitation and streamflow). Studies show a remarkable decline in the global hydro-climatic observation network (e.g. degradation of the number of observation stations monitoring precipitation and streamflow) over recent decades (Becker et al., 2013; Hannah et al., 2011). Additionally, most historic observational records are discontinuous and contain significant number of erroneous (inconsistent) values. For example, Becker et al. (2013) conducted an inventory study to demonstrate global degradation of precipitation gauges based on the Global Precipitation Climatology Center (GPCC) database. They found a remarkable drop (73%) in the number of gauges between 2001 and 2011 compared to the drop (15%) in the number of gauges between 1991 and 2001 (Figure 1). Also, they discovered an uneven distribution of the rain gauge coverage across the global landmass, which leaves large parts of the globe uncovered. A similar trend has been reported for streamflow observations across the globe (Hannah et al., 2011), such that large parts of global hydrological basins are poorly gauged and/or ungauged (Hrachowitz et al., 2013).

The issue of data limitation looms large in developing regions such as those across much of the so called global-south as these are regions where water resources management could benefit the most from a clear scientific guidance backed-up with data. For example, Tanzania has approximately 0.9 million hectares of irrigable land spread across several river basins. Unfortunately, only 15% of these hectares are currently under irrigation, with more than 80% of these being under traditional (i.e. unlined ditches and canals) irrigation systems (http://www.tzdpg.or.tz/ accessed on 30 December 2019). Tanzania therefore has a great potential to boost her economy and improve food security through sustainable development of water resources targeting dryland irrigated agriculture to support year-round harvest by extending growing seasons beyond rain-fed periods. However, such development needs to be implemented in a manner that does not jeopardize other vital ecosystem services, which is challenging in the face of limited data upon which to build our understanding and base our decisions.

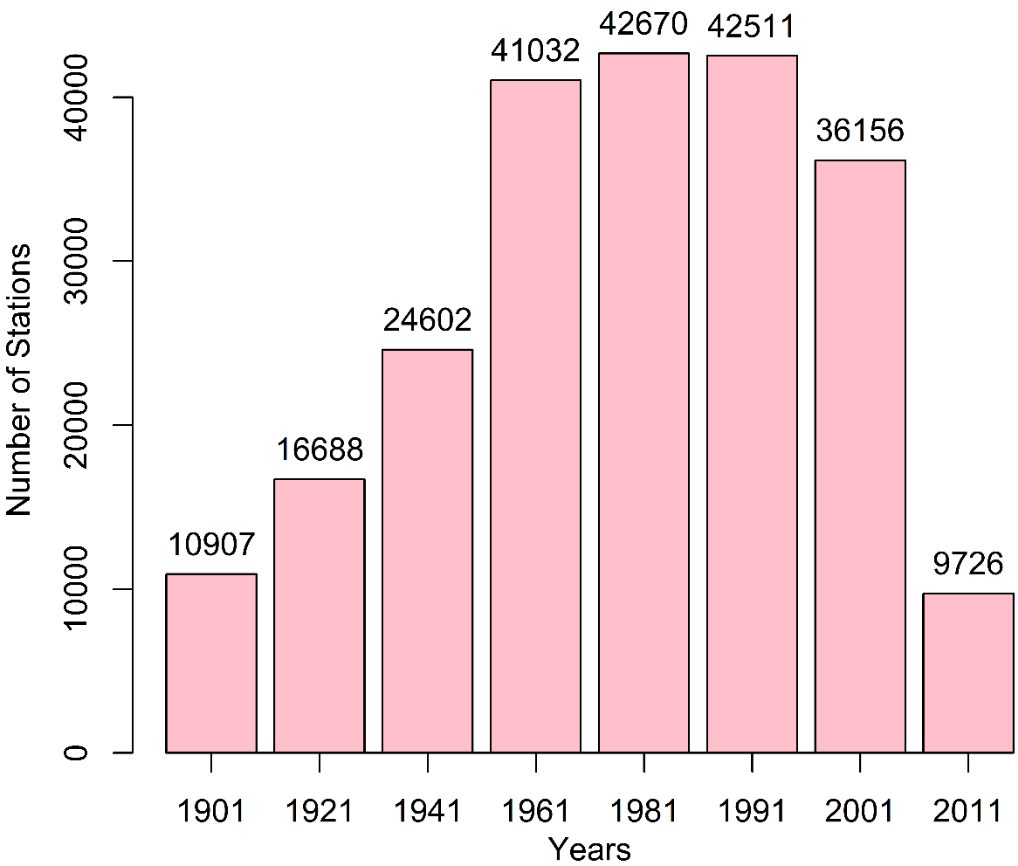

Figure 1: Number of rain gauges in the Global Precipitation Climatology Center (GPCC) database, extracted from 'Spatial distribution of the number of stations per $2.5^o \times 2.5^o$ *grid available for the July reanalyzes (Version 6)' in Becker et al. (2013). Number on top of each bar represents absolute number of stations in a given year.*

For Tanzania, this challenge prevails for the Kilombero Valley (KV) where the land and water that support a unique ecology and biodiversity are also suitable for development of dryland irrigated agriculture. KV contains unique populations of flora and fauna, which qualifies it to be designated as a Ramsar site of international importance (Mombo et al., 2011). For example, KV contains around 75% of the world’s wetland-dependent puku antelope (*Kobus vardonii*) highlighting the need for conservation and holistic planning around the valley’s wetlands and water resources. Recent developments also show an increasing trend in utilization of wetlands in the KV floodplain by local populations. Such developments have been triggered by several factors including increasing food demand due to population growth, degradation of upland soils in KV, and changes in government policy. The latter mainly started in 2010, when Tanzanian government launched the ‘Kilimo Kwanza’ (Agriculture First) policy which prioritizes agricultural development through agricultural expansion and intensification. In KV, this policy has been implemented under initiative known as the Southern Agricultural Growth Corridor of Tanzania (SAGCOT). This is an inclusive, multi-stakeholder partnership to improve agricultural productivity, food security as well as livelihoods in Tanzania through development of small-scale and large-scale agriculture over the coming 20 years.

Among other things, SAGCOT aims to minimize traditional reliance on rain-fed agriculture by expansion and modernization of irrigation schemes (SAGCOT, 2013). For example, SAGCOT aims to construct seven new irrigation schemes (36,387 ha), expand five existing irrigation schemes (6,029.5 ha), construction of three new hydropower stations (144, 248, and 358 MW, respectively) with reservoirs totaling 850 Million cubic meters in the KV. Additionally, Tanzanian Government has planned to construct a Stiegler’s Gorge dam downstream of the KV targeted for hydropower generation (2,100 MW) (Senkondo et al., 2018). It is apparent that efficiency, functionality and sustainability of the Stiegler’s Gorge dam (and much of SAGCOT in general) will depend on water resources management in the KV. Unfortunately, data scarcity is an obstacle for water resources management in the Kilombero Valley. The valley, like many developing regions globally, faces numerous data and monitoring challenges such as accessibility of river gauging stations (especially in the rainy season), limited number of trained monitoring staff, and insufficient equipment due to limited funds (Munishi-Kongo, 2013).

Despite these complexities and data issues, we still must implement state-of-the-science tools to inform policy and practice under current and estimated future scenarios. One common tool is a hydrological model. Hydrological models have been widely utilized as tools to explore the potential impacts of different water-related interventions on water resources. These interventions include human induced land use changes, such as agricultural expansion and intensification (Kiptala et al., 2014; Epelde et al., 2015), or deforestation (Siriwardena et al., 2006; Oliveira et al., 2015); human water usage, such as irrigation (Mutiga et al., 2010; Yalcin, 2019) or hydropower (Han et al., 2019; Wang et al., 2019); and climatic changes (Setegn et al., 2011; Bhatta et al., 2019). Different hydrological models ranging from simple linear models to complex physically-based models have been developed and utilized in different studies (e.g. Gumindoga et al., 2011; Tessema et al., 2014; Zhang et al., 2016). Amongst the most commonly used hydrological models are Systeme Hydrologique Europeen (SHE) model (Abbott et al., 1986), Hydrologiska Byråns Vattenbalansavdelning (HBV) model (Lindström et al., 1997), TOPographic driven MODEL (TOPMODEL) model (Beven and Kirkby, 1979), Variable Infiltration Capacity (VIC) model (Liang et al., 1994), and Soil and Water Assessment

Tool (SWAT) Model (Arnold et al., 1998). A common theme in modeling is to match model complexity with the question being asked and the data available for model development. For example, SWAT is a semi-distributed, physically-based, time-continuous hydrological model for simulation of hydrological and biophysical processes under a specified range of climate and management conditions. It has been used extensively across different watersheds in the world (e.g. in Immerzeel and Droogers, 2008; Dessu and Melesse, 2012; Abbaspour et al., 2015; Mwangi et al., 2016; Pradhan et al., 2020) primarily due to a combination of ease of use, largely available off-the-shelf datasets, and inherent flexibility with regards to process representation/interoperability.

Traditionally, hydrological modelling relies on a classical approach of rainfall-runoff curve-fitting, in which model calibration is based on the comparison between simulated and observed streamflow hydrographs for a single or limited number of locations, and model parameters are optimized in a 'trial and error' (manually) mode to achieve a desired response (Gupta et al., 1998). However, application of traditional hydrological modelling is mainly applicable in watersheds with natural flowing systems and good quality hydrometeorological observations, which is not a case in many remote hydrological basins, like those in developing countries where hydrometeorological monitoring networks are collapsing. This situation is even more problematic when such watersheds are also governed by human decisions (e.g. dams, dryland irrigation) and targeted for development, as any available observed streamflow data may not be representative of the natural characteristics of the system. Under such circumstance, hydrological variables (e.g. evapotranspiration and soil moisture) estimated using remote sensing techniques could provide suitable alternative targets for training or calibrating our modeling to help inform management decisions. One advantage of remotely-sensed datasets are the reasonably high temporal and spatial resolutions often available. For example, Moderate Resolution Imaging Spectroradiometer (MODIS) datasets (Justice et al., 2002; Myneni et al., 2002) have temporal resolutions ranging from one day to one year with spatial resolutions ranging from 250 m to 1,000 m. Landsat datasets have temporal resolutions of 16-day and spatial resolutions of 30 m. In the context of water resources management in data limited regions, remote sensing offers two partially overlapping areas of expertise – deriving hydrological variables (e.g. precipitation and evapotranspiration) by remote sensing techniques and use of remotely sensed data in parameterization/calibration of hydrological models. This thesis focuses on both of these two topics as well as on how to utilize them in combination with limited existing hydrometeorological data to derive useful information for water resources management in heterogeneous and data limited regions.

1.2 Thesis objectives

This thesis aims to develop state-of-science approaches that could be utilized in data limited regions to provide relevant and applicable scientific guidance for water resources assessment, planning, development, and management. The thesis mainly focuses on Tanzania's Kilombero Valley as a relevant regionally case study representing data limited regions targeted for rapid development. Specifically, the main objectives of this thesis are to:

A. Identify the gaps inhibiting the development and use of hydrological models to guide water resources management in data limited regions (Paper I).

B. Explore approaches that provide relevant information on aquifer characteristics and hydrological processes to bridge the gaps inhibiting hydrological modeling in data limited regions (Paper II, III).

C. Develop hydrological modeling capable of supporting water resources management across the Kilombero Valley of Tanzania (Paper IV).

These objectives have been addressed in Papers I – IV, based on the following structure:

1. Paper I addresses objective A by using a comprehensive review of literature on hydrology, water resources sciences, and hydrological modelling approaches. Paper I starts by exploring the gaps hindering the application of the current state-of-the-science to guide water management policy and practice in Tanzania's Kilombero Valley and then investigates potential solutions to bridge these gaps through a comprehensive review of case studies from other hydrological basins in Eastern Africa.

2. Paper II addresses objective B by using a combination of the Recession-Curve-Displacement Method, Master-Recession-Curve, and the instant recharge theory. Specifically, Paper II focuses on estimation of an aquifer's transmissivity and on a characterization of hydrological processes based on streamflow hydrograph when there are limited observation data available.

3. Paper III addresses objective B by comparing the daily actual evapotranspiration estimates derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) datasets using three different Surface Energy Balance (SEB) algorithms – Surface Energy Balance Algorithm for Land (SEBAL), operational Simplified Surface Energy Balance (SSEBop), and Simplified Surface Energy Balance Index (S-SEBI) to assess fluxes of water through the land surface across Kilombero Valley.

4. Paper IV addresses objective C by comparing hydrological modelling results derived using traditional modelling approach (i.e. calibrating hydrological model against observed streamflow data) to those derived by calibrating hydrological model against satellite-based actual evapotranspiration data. Specifically, a physically-based and semi-distributed Soil and Water Assessment Tool (SWAT) hydrological model is developed for the Kilombero Valley.

2. Study area and datasets

2.1 The Kilombero Valley basin (Papers I–IV)

The Kilombero Valley (KV) basin is a river basin with an area of approximately 34,000 km^2, defined by the river gauging station (1KB17) furthest downstream on the Kilombero River. KV is located in central Tanzania and situated between longitudes 34°33′E and 37°20′E, and between latitudes 7°39′S and 10°01′S (Figure 2). The KV basin is located in the upstream part of the Rufiji River Basin (RRB) and contributes about 66% of the average annual flow of the Rufiji River (McClain and Williams, 2016). The Udzungwa Mountains (2576 m above sea level) form the north-western border of the KV basin. These mountains are characterized by steep slopes and relatively dense forests. The Mahenge Mountains (1516 m above sea level) form the south-eastern border of the KV basin. These mountains rise gradually and eventually change to a steep escarpment. Tributaries originating in the Udzungwa and the Mahenge Mountains form the headwaters of the KV river system. These tributaries (e.g. Ruhuji, Mnyera, and Mpanga) join together to form the main Kilombero River which becomes a braided network in the valley's central floodplain.

A large part of the valley bottom (which lies around 270 m above sea level) is covered by the seasonal wetland (7,967 km^2) which was designated as a RAMSAR site in 2002 (www.ramsar.org accessed on 2 December 2019) due to its uniqueness in terms of ecology and biodiversity. This RAMSAR site contains 75% of the world population of wetland-dependent Puku antelope (*Kobus vardonii*), endemic species such as the Kilombero Weaver bird (*Ploceus burnieri*), and a large population of various types of water birds. In addition, the Udzungwa Mountains located north-west of the KV basin contain the Udzungwa Mountains national park. This park exhibits large biodiversity including several endemic species such as the Rufous-winged sunbird (*Cinnyris rufipennis*) and the primate Udzungwa red colobus (*Procolobus gordonorum*). Furthermore, the eastern part of the KV basin is part of the Selous Game Reserve, which is a world heritage site. This reserve contains significant populations of African elephant (*Loxodontha africana*), a large population of Nile Crocodile (*Crocodylus niloticus*), and black rhinoceros (*Diceros bicornis*). All these populations puts emphases on the need for conservation and holistic use of the Kilombero Valley wetland and its associated resources (Lyon et al., 2015).

Climatically, the Kilombero Valley (KV) basin experiences a subtropical climate with distinct rainy and dry seasons. The valley bottom is generally hot and humid with a long-term (1998–2010) average daily temperature of 24^{o}C and a long-term (1998–2010) average annual precipitation between 1200 mm and 1400 mm. The mountainous regions around the KV basin are considerably cooler and wetter with a long-term (1998–2010) average daily temperature of 17^{o}C and a long-term (1998–2010) average annual precipitation between 1500 mm and 2100 mm (Koutsouris et al., 2016). The seasonality of the KV basin is driven by the passing of the Intertropical Convergence Zone (ITCZ), first southward which corresponds to the short rains (between November and January) and then northward which corresponds to the long rains (between March and May). El Niño–Southern Oscillation (ENSO) and the Indian Ocean Zonal Mode (IOZM) have been correlated to the inter-annual variability of the short rains in the KV basin. Specific driver(s) of the inter-annual variability of the long rains in the KV basin is less well understood, though researchers have associated it with the internal chaotic atmospheric variations, which is based on weak relationships among ITCZ, ENSO, IOZM, and other patterns (Camberlin and Philippon, 2002). Variations in the large-scale climate patterns have been the main factor controlling the differentiation and timing of the rainy seasons (i.e. short and long rains) in the KV basin (Koutsouris et al., 2016).

Geologically, the KV basin is characterized by an asymmetrical rift valley depression which was formed by Pliocene faulting (Bonarius, 1975). The highlands of the KV basin are underlain by crystalline limestone, schists, gneisses, graphite, and their respective metamorphic versions. The lower parts of the KV basin are underlain by Karoo sediments (e.g. sandstones, conglomerates, and shales). Alluvial materials of recent age and non-alluvial sand-flats (Miombo plains) characterized the valley bottom (Beck, 1964). Rainwater infiltrated at a high altitude is the main source of groundwater recharge in the KV basin. Generally, groundwater recharge is mainly controlled by climate, geology and geomorphology (Senkondo et al., 2017). Groundwater water discharge contributes substantial amount to the streamflow especially during low flows (Burghof et al., 2018; Koutsouris and Lyon, 2018). The average annual streamflow in the KV basin is around 13.8 billion cubic meters (McClain and Williams, 2016).

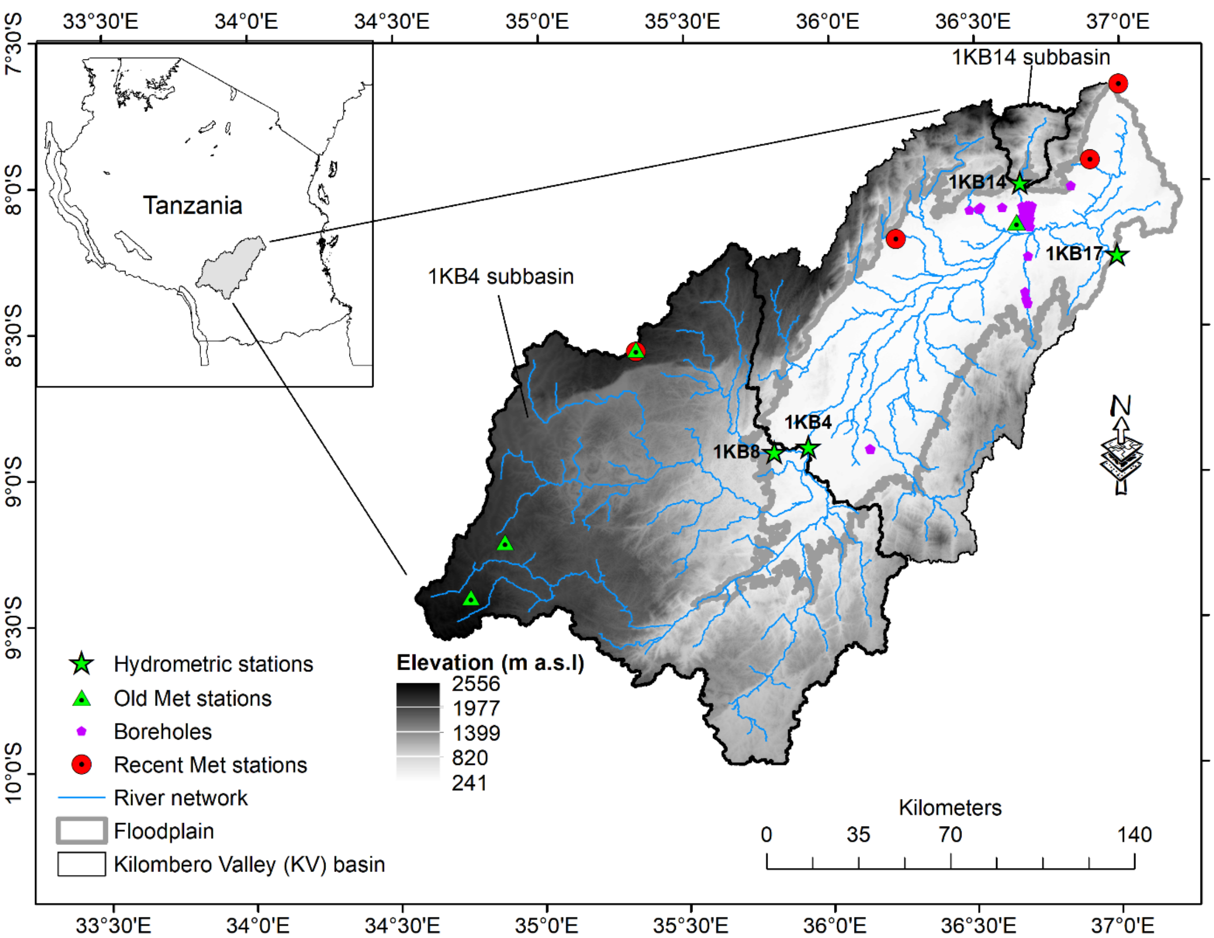

Figure 2: Location map of Kilombero Valley (KV) basin of central Tanzania. Old Met stations and Recent Met stations represent historical (1960s) and recent (2010s) meteorological stations.

2.2 Overview of datasets considered

A number of hydro-climatic, topographic, and biophysical (e.g. soil and land cover) data (Table 1) covering various spatiotemporal scales and of different levels of quality and consistency (mainly depending on their respective sources) have been utilized in this thesis (Papers II–IV) to address objectives B and C. Details on how a given dataset was preprocessed (e.g. quality control and how missing values were dealt in hydro-climatic data) can be found in respective Papers II–IV. An overview of each dataset utilized in this thesis has been provided below.

2.2.1 Observed streamflow and water level data

Observed daily streamflow data and their corresponding daily water levels (stage) data from four river gauging stations (Figure 2) – Kilombero River at Swero (1KB17), Kilombero River at Ifwema (1KB4), Mpanga River at Mpanga (1KB8), and Lumemo River at Kiburukutu (1KB14) – had been provided by the Rufiji Basin Water Office (RBWO). 1KB17 drains the entire Kilombero Valley (KV) basin. Streamflow and water levels data from 1KB17, 1KB4, and 1KB4 stations span from 1960 to 1982 and have been used in Paper II to address objective B. Streamflow data from 1KB17 and 1KB8 span from 1960 to 1966 had been used in Paper IV to calibrate and validate (respectively) the Soil and Water Assessment Tool (SWAT) hydrological model while addressing objective C. More details (e.g. quality control, treatment of missing values) on these datasets can be found in Papers II and IV.

2.2.2 Borehole and Pumping Test Data

Pumping test data from 38 boreholes located within the Kilombero Valley (KV) basin have been utilized in Paper II to validate (evaluate) streamflow-based aquifer transmissivities while addressing Objective B. The pumping test data included saturated thickness of the aquifer, aquifer hydraulic conductivity, aquifer transmissivity, borehole depth, and borehole elevation per each borehole. It is noteworthy that aquifer transmissivity (from pumping test data) was estimated using the Cooper-Jacob straight-line method (Cooper and Jacob, 1946) and the corresponding aquifer hydraulic conductivity was computed by dividing the aquifer transmissivity by the saturated thickness of aquifer. All borehole and pumping test data had been provided by the Rufiji Basin Water Office (RBWO). The reader is recommended to refer to Paper II for more details about these datasets.

2.2.3 Observed precipitation and other climatic data

Observed daily precipitation and other climatic data (e.g. maximum and minimum air temperature, wind speed, and relative humidity) were obtained from the Rufiji Basin Water Office (RBWO) for several gauging stations in the KV basin (Figure 2). Specific data that have been used in each part of this thesis vary depending on what was needed in addressing a given objective in terms of completeness of time series, temporal coverage, data quality, and vicinity to studied area. Readers are recommended to refer to Papers III and IV for specific details on these datasets.

2.2.4 Satellite-based and remotely-sensed data

This thesis utilized the Moderate Resolution Imaging Spectroradiometer (MODIS) Satellite Images in Paper III to estimate the daily actual evapotranspiration (ET) using Surface Energy Balance (SEB) models while addressing objective B. Four MODIS datasets – Land Surface Temperature and Emissivity (LST/EMM), Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and short-wave broadband surface albedo (BRDF-albedo) – have been considered. All these datasets were preprocessed (e.g. scaled, resampled, and corrected for invalid pixels) before being utilized in the SEB models. Readers are recommended to refer to Paper III on how preprocessing of these datasets was performed and for more details on these datasets. Additionally, the daily actual evapotranspiration estimates provided by the Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al., 2017) have been utilized in Paper IV to calibrate the Soil and Water Assessment Tool (SWAT) hydrological model while addressing objective C. It is noteworthy that unlike MODIS datasets which are derived mainly from the visible and thermal infrared bands (and thus affected by clouds), the GLEAM ET estimates are derived from microwave sensors.

Table 1: Various datasets used in this thesis. LST stands for Land Surface Temperature, m stands for meter, mm stands for millimeter, K stands for kelvin, [-] stands for dimensionless, NDVI stands for Normalized Difference Vegetation Index, RBWO stands for Rufiji Basin Water Office, NA stands for not applicable, and LAI stands for Leaf Area Index

Data	Properties and source				
	Spatial Resolution	Temporal Resolution	Units	Period of record	Source/url
Digital Elevation Model (DEM)	90 m	NA	m	NA	SRTM
Precipitation	Points	Daily	mm	1957-1966, 2001-2015	RBWO
Max and Min air temperature	Points	Daily	^{o}C	1957-1966, 2001-2015	RBWO
Relative humidity	Points	Daily	%	1957-1966, 2001-2015	RBWO
Wind speed	Points	Daily	m/s	1957-1966, 2001-2015	RBWO
Streamflow	Points	Daily	m^3/s	1960-1982	RBWO
Water level (stage)	Points	Daily	m	1960-1982	RBWO
Actual evapotranspiration	25 km	Daily	mm	2004-2015	https://www.gleam.eu/
LST/Emissivity	1 km	8-day	K	2005, 2010, 2015	https://lpdaac.usgs.gov/
NDVI	250 m	16-day	[-]	2005, 2010, 2015	https://lpdaac.usgs.gov/
LAI	500 m	8-day	[-]	2005, 2010, 2015	https://lpdaac.usgs.gov/
Albedo	500 m	Daily	[-]	2005, 2010, 2015	https://lpdaac.usgs.gov/
Land cover	300 m	NA	NA	2015	http://maps.elie.ucl.ac.be/
Soil	1 km	NA	NA	1998	http://www.fao.org/

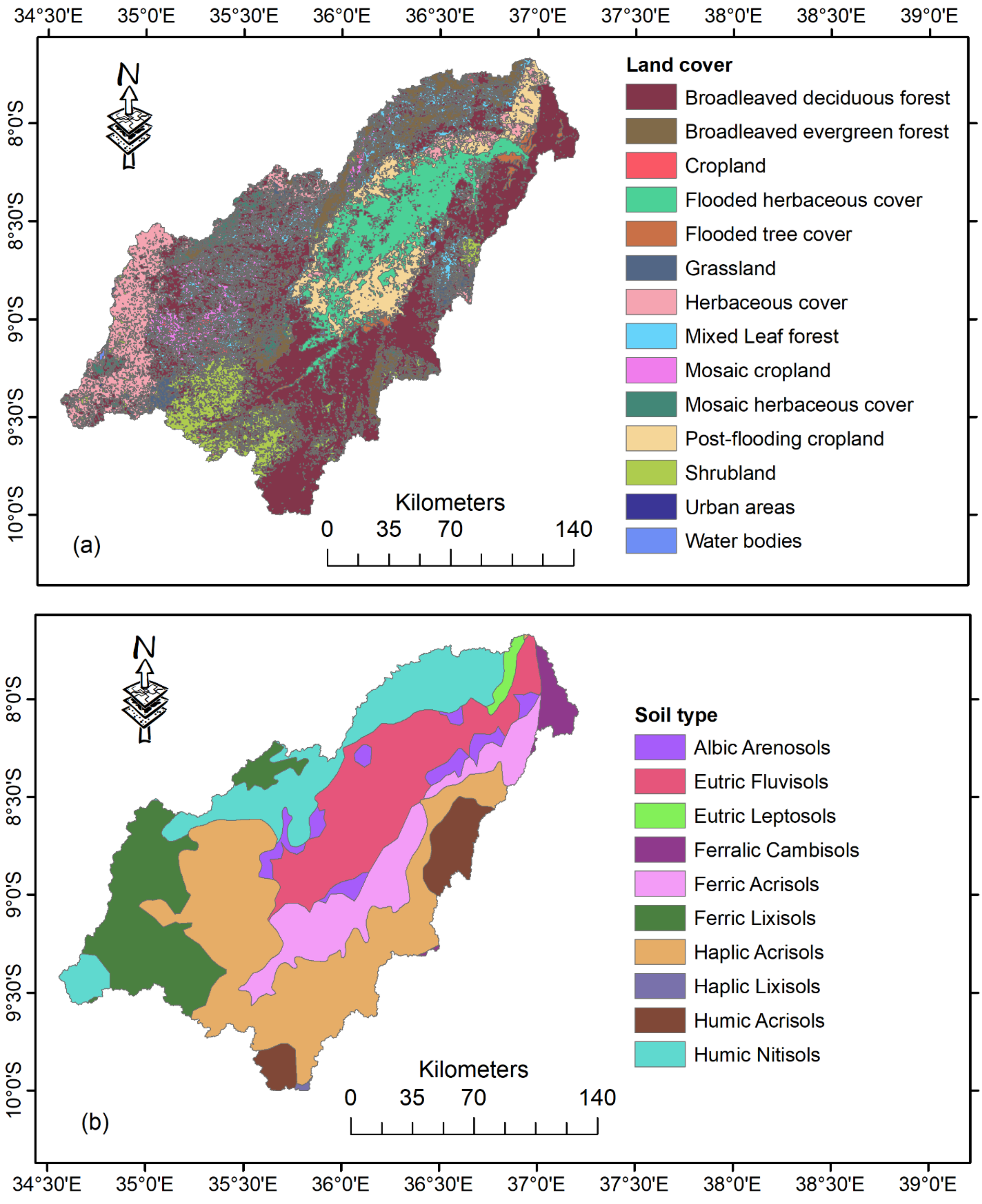

Figure 3: (a) Land use/cover map of the Kilombero Valley (KV) basin of central Tanzania for the year 2015 provided by the European Space Agency (ESA) Climate Change Initiative Land Cover project (CCI-LC project). (b) Soil map of the KV basin retrieved from the Harmonized World Soil Database (Dewitte et al., 2013).

2.2.5 Topographic, land use/cover, and soil data

A Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with a 90 m raster resolution has been utilized in this thesis to delineate catchments and to provide other landscape (topographic) information (e.g. surface slope and aspect). Land use/cover (LULC) map for the year 2015 provided by the European Space Agency (ESA) Climate Change Initiative Land Cover project (CCI-LC project) has been utilized in Papers III and IV of this thesis. This land use/cover map had spatial resolution of 300 m. Soil information was retrieved from the Harmonized World Soil Database (HWSD) (Dewitte et al., 2013) with the spatial resolution of 1 km. Forest and Acrisol are the main LULC and soil type, respectively, over the KV basin (Figure 3). These data (i.e. DEM, LULC, and soil) have been utilized in Papers III and IV to address objectives B and C, respectively.

3. Methods

3.1 Comprehensive literature review (Paper I)

An in-depth review of literature on hydrological modelling for water resources in Eastern Africa was conducted mainly to serve two purposes. First was to explore possible gaps that limit the application of traditional state-of-the-science approaches to inform water resources management policy and practice in the region. Second was to identify relevant solutions to bridge these gaps. Two complementary approaches (one for each purpose) were undertaken to accomplish the task.

3.1.1 Water resources and hydrological modelling in Kilombero Valley

This thesis considered the Kilombero Valley (KV) basin of central Tanzania as a real-world case study (providing context for the region of Eastern Africa) to explore water development issues currently faced. Emphasis was given to exploring implications of potential gaps in data and hydrological modelling scales. The main hypothesis was that these gaps would hinder the application of the currently available state-of-the-science to guide policy and practice on water management under the current and projected future scenarios. This hypothesis was tested through an in-depth literature review. The literature search was done within three peer-reviewed scientific citation databases – Web of Science, Science Direct, and Scopus – and one non-peer-reviewed database – International Water Management Institute (IWMI). Additionally, a literature search was conducted within several websites in Tanzania, such as websites of Tanzania Ministry of Water (http://www.maji.go.tz), Tanzania Ministry of Agriculture (http://www.kilimo.go.tz), and Southern Agriculture Corridor of Tanzania (http://www.sagcot.com), and within the website of the Food and Agricultural Organization (FAO; http://www.fao.org). The literature search was constrained to literature published before 31 December 2017. Several key words were specified during the search, such as 'Rufiji' OR 'Kilombero' AND 'hydrology', OR 'water resources' OR 'modelling' OR 'climate' OR 'agriculture' OR 'irrigation' OR 'hydropower'. These criteria returned over 200 pieces of literature, which were then reduced to 22 literatures after reviewing their respective abstracts. An in-depth review and meta-data analysis were conducted for these retained publications. Readers are recommended to refer to Paper I for more details on how in-depth review and meta-data analysis were performed.

3.1.2 Evolution of hydrological models in Eastern Africa

A systematic review of literature on modelling for hydrology and water resources in East Africa was conducted to explore potential recommendations on how to advance hydrological modelling in any hydrological basin facing challenges similar to those faced by the KV basin. The main motivation behind conducting this review was to distill applicable recommendations on how the current understanding of the practical application of hydrological models can be advanced in an efficient manner. A literature review for Eastern Africa was developed along similar lines as the case study above to enable the placement of the Kilombero Valley (KV) basin in its regional context. Geographical classification provided by the United Nations (UN; (https://unstats.un.org/unsd/methodology/m49/) was used to define and obtain the names of the mainland countries of Eastern Africa – Zimbabwe, United Republic of Tanzania, Burundi, Djibouti, Eritrea, Kenya, South Sudan, Ethiopia, Malawi, Mozambique, Somalia, Uganda, Rwanda, South Sudan, and Zambia. Additionally, the names of drainage basins within these countries provided by FAO (http://www.fao.org) and the names of the major rivers and lakes within these countries provided by the 'Google Earth' were included in the search terms within scientific citation databases – Web of Science, Science Direct, and Scopus. The following terms were used during the literature search: 'water resources' OR 'hydrology' OR 'hydrological' OR 'modelling' OR 'streamflow' OR 'runoff' OR 'land use' OR 'land cover' OR 'climate' AND (any of the specific country or drainage basin or river or lake names). The search was confined to publications published before 31 December 2017. More than 7,000 publications were obtained from these search criteria. Initial review of each abstract allowed this to be reduced to 169 publications, which were retained for in-depth review and meta-data analysis. Readers are recommended to refer to Paper I for more details on how the in-depth review and meta-data analysis have been performed.

3.2 Recession analysis for estimating aquifer transmissivity (Paper II)

The reliability of streamflow data, especially at low flows, is very important in a river basin targeted for dryland irrigation such as the Kilombero Valley (KV) basin. This is particularly true for the KV basin as most of the streamflow during the dry season originates from the drainage of groundwater aquifers as baseflow (Koutsouris and Lyon, 2018). It is noteworthy that groundwater is stored in a geological formation known as an aquifer, therefore information on aquifer characteristics such as aquifer transmissivity is important for water resources management as well as hydrologic model development. Therefore, this thesis performed recession analysis (i.e. analyzing the falling limb on a streamflow hydrograph) to estimate aquifer transmissivity using streamflow records. This has been done to serve two purposes. The first was to evaluate if streamflow-derived aquifer transmissivity is as good as borehole-derived (i.e. through pumping test) aquifer transmissivity. Assessing methods to derive transmissivity is important as most of the time streamflow data are readily available compared to borehole data. The second purpose was to provide initial insights on the quality and reliability of the streamflow data available in the KV basin for subsequent hydrological modelling in Paper IV.

Theoretically, this thesis used the recession-curve-displacement method combined with the master-recession-curve and an instantaneous recharge theory to estimate aquifer transmissivity from daily observed streamflow records. The recession-curve-displacement method is based on the following assumptions: aquifer is homogeneous; stream fully penetrates the aquifer and acts as a discharge boundary (sink) of the groundwater flow system; groundwater recharge is concurrent with the peaks in streamflow; groundwater recharge induces upward shift in the recession curve of streamflow hydrograph; and evapotranspiration and other riparian losses are negligible. Readers are recommended to refer to Paper II for a detailed theoretical development of the recession-curve-displacement method. Generally, the recession-curve-displacement method estimates aquifer transmissivity (*T*) using a functional definition provided in the Equation (1).

$$T = \frac{a^2 K (Q_2 - Q_1) Q_0}{2.3026 A h_0 Q_t} \tag{1}$$

where *T* is the aquifer transmissivity [L^2/T], *a* is distance from the stream to the groundwater divide [L], *K* is the recession index [T] per log cycle, h_0 is the instantaneous rise in the water table [L] at time t [T], Q_t is a streamflow at the peak at a time when the surface runoff recession has started [L^3], Q_1 and Q_2 are the hypothetical groundwater discharges extrapolated from the pre-event and the post-event streamflow recession respectively for a given critical time [L^3/T], and Q_0 is a streamflow at a beginning of surface runoff recession [L^3]. Demonstration of how to estimate h_0, Q_0, Q_1, Q_2, and Q_t is shown in Figure 4.

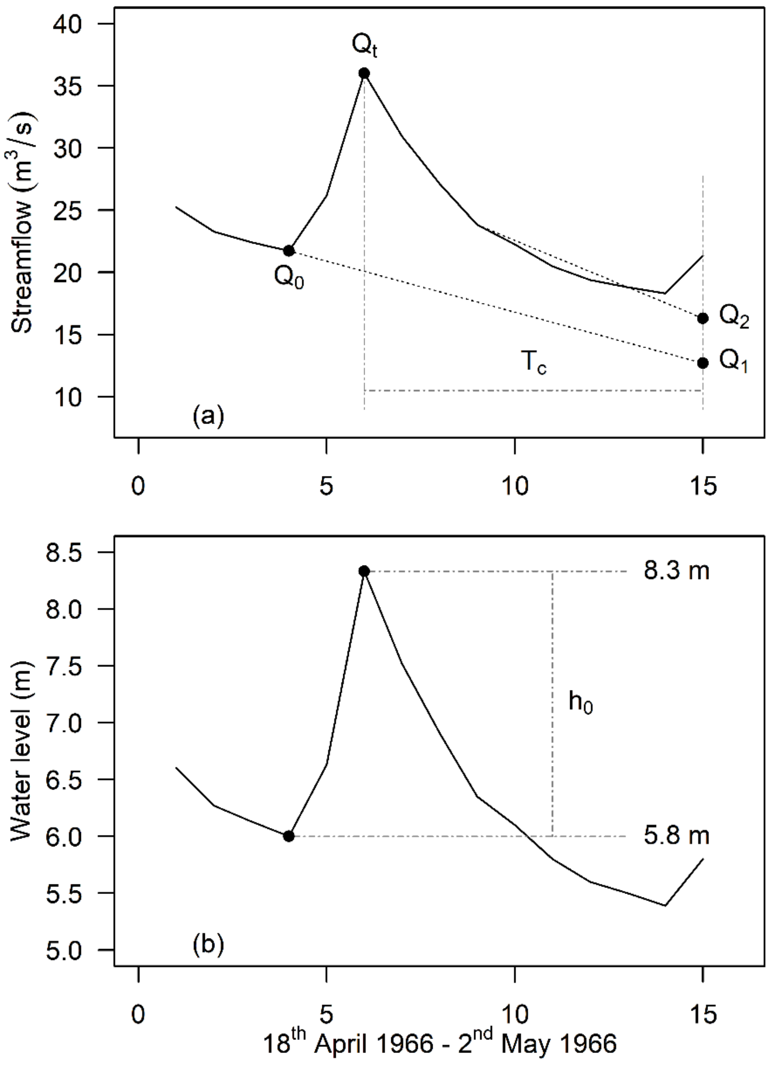

Figure 4: Schematic diagram demonstrating the recession-curve-displacement method at 1KB14 river gauging station within the Kilombero Valley basin where (a) demonstrates how to estimate Q_1 and Q_2 for the wet season recharge event occurring on 21st April 1966; (b) demonstrates estimation of h_0 for the same recharge event as in (a) above (Modified from Paper II: Senkondo et al. (2017)).

This thesis estimated T using streamflow records from three river gauging stations: 1KB17 which drains the entire KV basin, 1KB4 which drains upstream parts of the KV basin before Kilombero river enters a Ramsar site, and 1KB14 which drains a tributary of Kilombero river, namely the Lumemo river (Figure 2). Wet season (December–April) and dry season (May–November) aquifer transmissivities were computed for each station based on Equation (1). The medians of wet season T and dry season T for each gauging station were then compared with the median aquifer transmissivity estimated from the pumping tests across the KV basin. Basically, regional-scale aquifer transmissivity derived from streamflow records across the KV basin was compared to local-scale aquifer transmissivity derived from point measurements (i.e. pumping tests) across the KV basin. Readers are recommended to refer to Paper II for more details on how the comparison was made.

3.3 Surface Energy Balance (SEB) modelling (Paper III)

This thesis estimated spatiotemporal variations of the actual evapotranspiration (ET) in the KV basin using three independent Surface Energy Balance (SEB) models – Surface Energy Balance Algorithm for Land (SEBAL) model (Bastiaanssen et al., 1998), operational Simplified Surface Energy Balance (SSEBop) model (Senay et al., 2013), and Simplified Surface Energy Balance Index (S-SEBI) model (Roerink et al., 2000). In general, SEB models utilize remotely sensed land surface and atmospheric variables such as land surface temperature (T_s), vegetation indices (e.g. Normalized Difference Vegetation Index ($NDVI$)), albedo (α), and surface emissivity (ε) to estimate ET based on the surface energy balance equation:

$$LE = R_n - G - H \tag{2}$$

where LE is latent heat flux (W/m^2), R_n is net radiation (W/m^2), G is soil heat flux (W/m^2), and H is sensible heat flux (W/m^2). Generally, SEB models compute available energy ($AE = R_n - G$) and then partition it into H and LE. Details on how R_n and G are computed can be found in Allen et al. (2007). It is important to note that SEBAL and S-SEBI models compute instantaneous (i.e. at image acquisition time) AE, whereas SSEBop model computes daily AE directly.

Table 2: A summary of mathematical formulations used to estimate daily actual evapotranspiration (ET) in the data limited Kilombero Valley (KV) basin. All symbols and abbreviations have been defined in the main text.

Model (References)	Evaporative fraction (-)	Daily actual ET (mm)
SEBAL (Bastiaanssen et al., 1998)	$\Lambda = LE/(R_n - G)$	$(86400 \times \Lambda \times R_{n24})/\lambda$
S-SEBI (Roerink et al., 2000)	$\Lambda = (T_{hot} - T_s)/(T_{hot} - T_{cold})$	$(86400 \times \Lambda \times R_{n24})/\lambda$
	$T_{hot} = a_1 + b_1\alpha$	
	$T_{cold} = a_2 + b_2\alpha$	
	where a_1, a_2, b_1, and b_2 are regression coefficients	
SSEBop (Senay et al., 2013)	$ET_rF = (T_{hot} - T_s)/(T_{hot} - T_{cold})$	$ET_rF \times k_{max} \times ET_0$
	$T_{cold} = c \times T_{max}$	
	$T_{hot} = T_{cold} + dT$	
	$dT = (R_{n24} \times r_{ah})/(\rho_a \times c_p)$	

3.3.1 Overview of SEB models

The major difference among the three SEB models considered is how they utilize T_s to determine instantaneous H (only required in SEBAL model) and/or instantaneous evaporative fraction (only required in SEBAL and S-SEBI models) or daily evaporative fraction (only required in SSEBop model). For example, SEBAL model uses a heat transport equation, $H = \rho_{air} c_p dT / r_{ah}$ (where ρ_{air} is air density (kg/m^3), c_p is specific heat of air at constant pressure (J/kg/K), dT is near-surface temperature difference, and r_{ah} is aerodynamic resistance (s/m)) proposed by Farah and Bastiaanssen (2001) to determine instantaneous H. dT is derived from T_s using a linear relationship, $dT = a + bT_s$ (where a and b are correlation coefficients). To determine the two unknowns on the right hand side of the heat transport equation (i.e. dT and r_{ah}), a modeler has to select two anchor pixels (a hot pixel where $H = R_n - G$ and a cold pixel where $H = 0$) within an image and applies the Monin-Obukhov scheme (Monin and Obukhov, 1954) iteratively to correct the buoyancy effects (Allen et al., 2011). On the other hand, neither SSEBop nor S-SEBI requires calculation of H. Instead, SSEBop model utilizes a predetermined dT for each pixel on the image to estimate extreme temperatures at hypothetical hot (T_{hot}) and cold (T_{cold}) surfaces and then utilizes these to determine daily evaporative fraction (ET_rF) which is multiplied with the daily grass reference evapotranspiration (ET_0) to derive the daily actual ET (Table 2). S-SEBI model applies the same concept of T_{hot} and T_{cold} as in SSEBop model but assumes T_{hot} represents a hot edge (where $H = R_n - G$) and T_{cold} represents a cold edge (where $H = 0$). These two edges are derived using linear regression lines representing hot (for hot edge) and cold (for cold edge) surfaces from a $T_s \sim \alpha$ trapezoidal space (Roerink et al., 2000). Then the S-SEBI model utilizes these T_{hot} and T_{cold} to derive an instantaneous evaporative fraction (Λ) which multiplied with the daily average net radiation (R_{n24}) to estimate the daily actual ET (Table 2). A summary of differences in estimation of daily ET among three SEB models utilized in this thesis is given in Table 2.

3.3.2 SEB model implementations and comparisons

All three SEB models utilized in this thesis were coded and executed within the R programming environment. Due to the absence of locally estimated actual ET across the KV basin, ET estimates derived from the SEB models were compared to each other (i.e. model to model comparison) as well as to their ensemble mean (i.e. SEBAL ET vs. SSEBop ET, SEBAL ET vs. S-SEBI ET, SEBAL ET vs. ensemble mean ET, SSEBop ET vs. S-SEBI ET, SSEBop ET vs. ensemble mean ET, and S-SEBI ET vs. ensemble mean ET). Prior to model comparison, ET estimates from each SEB model were aggregated per each land cover (LC) class per each day of satellite overpass to evaluate how ET varied across land cover classes. Therefore, a single ET estimate was obtained per each LC class per each day of satellite overpass per each SEB model. Additionally, ET estimates from each model were aggregated per catchment boundary (three catchment boundaries were identified – the whole KV basin, the mountainous part of the KV basin, and the valley part of the KV basin) per each day of satellite overpass. Therefore, a single ET estimate was obtained per each catchment boundary per each day of satellite overpass per each SEB model. Model comparison was then done using two widely utilized model performance metrics – correlation coefficient (r) and Percent Bias ($PBIAS$). Additionally, two widely accepted nonparametric tests – Wilcoxon's test and Levene's test – were carried out to assess uncertainty in ET estimates. It is noteworthy that, 44 days of satellite overpasses (18, 14, and 12 days in 2005, 2010, and 2015 respectively) were utilized in this thesis. Readers are recommended to refer to Paper III for specific dates and more details on these 44 days of satellite overpasses.

3.4 Hydrological modelling (Paper IV)

This thesis utilized the Soil and Water Assessment Tool (SWAT) hydrological model (Arnold et al., 1998) to perform hydrological modelling for the Kilombero Valley (KV) basin. The overall aim was to evaluate the potential of using satellite-based evapotranspiration estimates to calibrate hydrological modelling in this heterogeneous and data limited basin. SWAT is a physically-based, process-oriented, continuous, and semi-distributed hydrological model for simulations of flow discharges, sediment yields, nutrients, pesticides, and plant uptakes on a daily or sub-daily basis. The model requires four main input data: Digital Elevation Model (DEM), land-use/cover map, soil map, and meteorological data (e.g. precipitation, minimum and maximum temperatures, and wind speed). Land management practices such as tillage, fertilization, and irrigation can also be incorporated into the model. Then SWAT model partitions the basin into sub-basins, which are derived from drainage networks generated from the DEM, and by specifying a threshold that defines the allowable minimum drainage area to form a stream. These sub-basins are further subdivided into Hydrologic Response Units (HRUs) which contain distinct combinations of land-use/cover classes, soil types, and slope classes.

Basically, SWAT model simulates hydrological processes (e.g. evapotranspiration, surface runoff, infiltration, lateral flow, percolation, and baseflow) within the land phase and/or channel phase. Most of the hydrological processes within the land phase are modeled at the HRU level and then summed up at sub-basin level to calculate the overall water balance (Equation 3) after integrating with meteorological data and the channel processes:

$$\Delta S = \sum_{i=1}^{N} (P - Q_{total} - ET - losses)_i \tag{3}$$

Where ΔS is the change in water storage (mm), i is an index, N is time in days, P is amount of precipitation (mm), Q_{total} is the total water yield (aggregated sum of the surface runoff, lateral flow, and return flow), ET is the evapotranspiration (mm), and $losses$ are the groundwater losses (mm). Readers are recommended to refer to Arnold et al. (1998) and Neitsch et al. (2011) for a detailed theoretical documentation and computations basis.

In this thesis, the surface runoff was computed using the Soil Conservation Service Curve Number (SCS-CN) method (USDA, 1972). Flow routing was carried out using the variable storage method equipped within the model. Potential evapotranspiration (PET) was computed using the Penman-Monteith method (Monteith, 1965). Generally, SWAT model simulates actual evaporation from soil (i.e. soil water evaporation) and from plants (i.e. canopy evaporation and transpiration) separately using a similar concept described in Ritchie (1972). The actual soil water evaporation is calculated using exponential functions of soil depth and available water content. The actual plant transpiration is reduced exponentially when soil water contents fall below field capacity (Neitsch et al., 2011). Therefore, the actual ET in SWAT refers to aggregated sum of the evaporation from the soil, canopy, as well as plant transpiration (Arnold et al., 2012).

3.4.1 SWAT model set-up and modelling scenarios

The Kilombero Valley (KV) basin was delineated using a 90 m resolution Digital Elevation Model (DEM) in ArcSWAT2012 (revision 664). The KV basin was discretized into 67 sub-basins, which were further subdivided into 912 hydrologic response units (HRUs). Specific details on land-use/cover map and soil map utilized in the SWAT model are given in Table 1. Observed meteorological data were then incorporated into the model and, after setting a spin-up period of three years, the model was run with default model parameters to provide the default scenario.

It is noteworthy that two sets of meteorological data (relatively old [1957–1966] data and relatively recent [2001–2015] data) were utilized separately to produce two default scenarios – one for the relatively old forcing data and another one for the relatively recent forcing data. Additionally, it is important to note that the SWAT model with relatively old data was run on a daily time step and that model setup with relatively recent data was run on monthly time step. Therefore, two models with similar model set-up (e.g. the same sub-basins and HRUs), but with different meteorological forcing data and temporal coverages were established – one with relatively old observed meteorological forcing data (hereafter $SWAT_{old}$ model) and another one with relatively recent observed meteorological forcing data (hereafter $SWAT_{new}$ model). The $SWAT_{old}$ model and the $SWAT_{new}$ model were then calibrated against observed daily discharge time series (i.e. traditional hydrological modelling) and satellite-based monthly actual evapotranspiration time series respectively. Both models were calibrated automatically using the Sequential Uncertainty Fitting (SUFI-2) module in SWAT Calibration and Uncertainty Programs (SWAT-CUP) interface (Abbaspour, 2015) by adopting calibration protocols recommended by Arnold et al. (2012) and Abbaspour et al. (2015).

Three modelling scenarios were undertaken for each model – default scenario, calibrated scenario, and transferred scenario. The default scenario represented model simulation results obtained using the default model parameters (i.e. un-calibrated model). The calibrated scenario represented model simulation obtained using the best possible calibrated set of model parameters obtained after calibrating the model in SWAT-CUP. The transferred scenario represented model simulation obtained using the best calibrated set of model parameters from another model (i.e. parameters from $SWAT_{old}$ model into $SWAT_{new}$ model, and vice versa). Therefore, for simplicity, these scenarios can be defined with respect to their base models (i.e. either $SWAT_{old}$ model or $SWAT_{new}$ model) as: default-$SWAT_{old}$, calibrated-$SWAT_{old}$, transferred-$SWAT_{old}$, default-$SWAT_{new}$, calibrated-$SWAT_{new}$, and transferred-$SWAT_{new}$ scenarios.

3.4.2. Automatic model calibration using SWAT-CUP

This thesis utilized the Sequential Uncertainty Fitting (SUFI-2) algorithm in SWAT-CUP to perform automatic calibration for both $SWAT_{old}$ and $SWAT_{new}$ models. SUFI-2 performs stochastic calibration (as opposed to deterministic calibration) such that uncertainty in model results is taken into consideration by propagating the parameter uncertainties. These parameter uncertainties account for all potential sources of uncertainties such as uncertainty in forcing data (e.g. precipitation), model structure, model parameters, and observed data (Abbaspour et al., 2007). This propagation of the parameter uncertainties leads to uncertainties in the model outputs, which are expressed as the 95% prediction uncertainty (95PPU). The 95PPU are computed at the 2.5% and 97.2% levels of the cumulative probability distribution of the model output generated by propagating parameter uncertainties using Latin Hypercube Sampling (LHS). It is important to note that unlike deterministic calibration approach where model output is represented by a single signal, in a stochastic calibration approach, model output is represented by an envelope of good solutions defined by the 95PPU, which is generated by certain ranges of a parameter. SUFI-2 utilizes two statistics – P-factor and R-factor – to quantify the fit between observation (expressed as a single signal) and simulation result (expressed as 95PPU). The P-factor represents the percentage of observations enveloped by the 95PPU whereas the R-factor represents the thickness of the 95PPU envelop. The P-factor ranges between 0 and 1. The R-factor ranges between 0 and infinity. A P-factor of 1 and a R-factor of 0 represent an ideal resolution (i.e. simulation result exactly corresponds to observation). The degree to which result is away from these ideal numbers is used to judge the robustness of the calibrated model. It is noteworthy that a relatively large P-factor can be obtained at the expense of a relatively large R-factor. Additionally, this thesis utilized the coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), percent bias ($PBIAS$), Kling-Gupta Efficiency (KGE), and the ratio of Root Mean Square Error ($RMSE$) to standard deviation of observation (RSR) metrics to further assess the goodness of fit between simulated result and observation. Respective formulas for each of these metrics can be found in Paper IV of this thesis. The KGE was used as the main objective function during model calibration within the SWAT-CUP interface. The objective function explains the difference between the observed and simulated values. The target (goal) was set to achieve a KGE value of at least 0.60. This targeted KGE value (0.60) was selected based on model calibration guidelines recommended by Gupta et al. (2009).

4. Results

4.1 Water resources developments and hydrological modelling in Kilombero Valley (Paper I)

The Kilombero Valley (KV) basin had four main sources of water abstractions identified – domestic, irrigation, industrial, and livestock uses. Irrigation consumed the largest amount of water abstracted annually (89%) in the KV basin. On the other hand, industrial uses consumed the least amount of water abstracted annually (0.5%) in the basin (Figure 5). Interestingly, the total amount of water abstracted annually in the KV basin (0.2 billion cubic meters) was only about 1% of the average annual flow (13.8 billion cubic meters) monitored at the outlet of the basin.

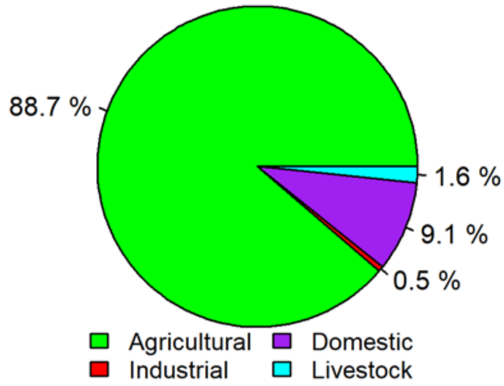

Figure 5: Percentages of water abstracted annually for different water uses in the Kilombero Valley (KV) basin. The total annual water abstractions in the KV basin was 202.85 million cubic meters. (Extracted from Table 3 in Paper I: Senkondo et al. (2018)).

Looking at the historical development of hydrological modelling for water resources in the KV basin, there was a remarkable shift in the how rainfall-runoff modelling was conducted in the basin. The shift was from application of simple linear relationships between rainfall and runoff, which was very common in the past modelling (e.g. Atwitye, 1999), to more complex physically based models, which has been common in the more recent modelling efforts (e.g. Leemhuis et al., 2017). However, all modelling studies conducted in the KV basin highlighted the issue of data (in terms of availability and quality) to be the main challenge they faced in their respective studies (e.g. Näschen et al., 2018; Yawson et al., 2005).

Several future water resources development plans such as construction of 7 new schemes of irrigation (36,387 ha), expansion of 5 existing irrigation schemes (6,029.5 ha), and construction of 3 new hydropower stations (750 MW) with a total reserving capacity of 850 Million Cubic Meters had been proposed in the basin. It is clear that scientific guidance will be needed to assess sustainability of these targeted development plans. One of the potential ways of providing such guidance is through implementation of hydrological modelling frameworks. However, most traditional ways of doing hydrological modelling rely on observed hydro-climatic data which are limited in the KV basin. To unfold how to tackle such data limitation challenges, solutions were sought from other modelling studies across the Eastern Africa as presented in the section below.

4.2 Hydrological modelling development in Eastern Africa (Paper I)

Results from the number of publications per countries (Figure 6) showed that about 50% of the reviewed publications (169) refer to modelling studies conducted in Ethiopia. About 10% of all 169 reviewed publications reported modelling studies undertaken in transboundary drainage basins (i.e. basin shared by more than one country). Around 75% of publications had been published within this current decade (2010s), compared to 20% in the 2000s and 5% before the year 2000. This positive trend suggested an increasing interest in the advancement of modelling in East Africa. More interestingly, no publications had reported hydrological modelling in Somalia, Djibouti, or Eritrea.

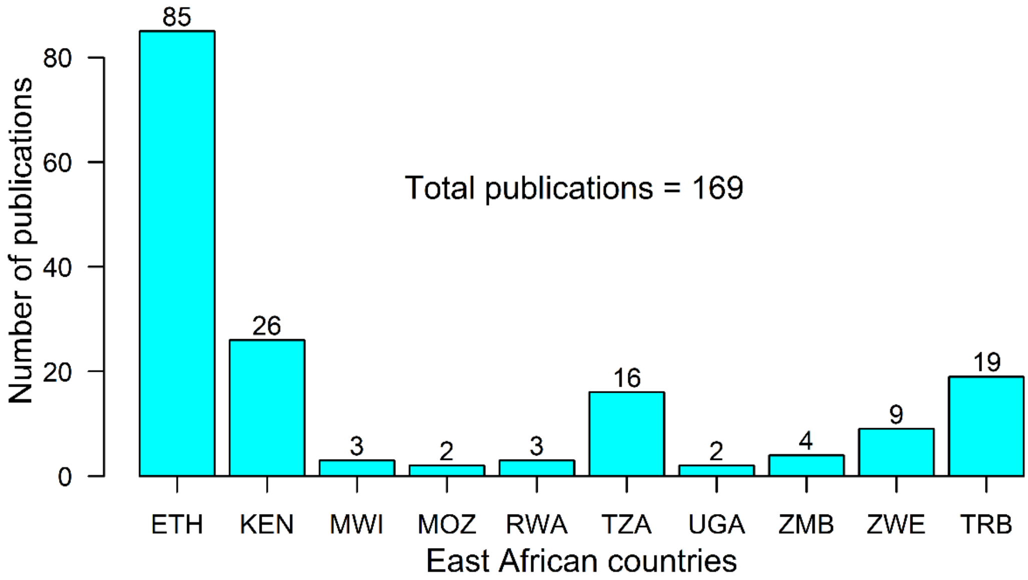

Figure 6: Number of publications (per countries) on the hydrological modelling in East Africa. The earliest publication had been published in 1991 and the latest publication had been published in 2017. ETH is Ethiopia, KEN is Kenya, MWI is Malawi, MOZ is Mozambique, RWA is Rwanda, TZA is Tanzania, UGA is Uganda, ZMB is Zambia, ZWE is Zimbabwe, and TRB is Transboundary. This figure was modified from Paper I: Senkondo et al. (2018).

When considering the distribution of hydrological modelling studies across spatial scales (Figure 7), most of studies (35%) had been conducted in the drainage basins covering sizes between 1,000 and 10,000 km^2. This could partly be attributed to the natural geological and geographical constraints occurring across the region such that average drainage sizes typically fall within this scale. It might also in part be attributed to the idea that many management activities (e.g. water resources planning) are conducted within this scale.

This thesis performed a meta-data analysis on the different model performance metrics – Coefficient of Determination (R^2), Percent Bias ($PBIAS$), and Nash-Sutcliffe Efficiency (NSE) – to investigate the robustness of Eastern Africa hydrological models for both calibration and validation periods. Before analysis, modelling studies were categorized into two groups – studies which followed 'traditional hydrological modelling' approaches and studies which went 'beyond traditional hydrological modelling' approaches. In the context of this thesis, 'Traditional hydrological modelling' was defined as the modelling approach which involved three features – model was set-up/established based on observed forcing data (e.g. observed precipitation), model was calibrated based on the properties/characteristics (e.g. soil properties) of the same drainage basin, and model performance was evaluated based on observed streamflow data (i.e. simulated discharge vs. observed discharge). On the other hand, the 'beyond traditional hydrological modelling' approach was defined as a modelling approach which deviated from any of the three features specified in the definition of the 'traditional hydrological modelling'.

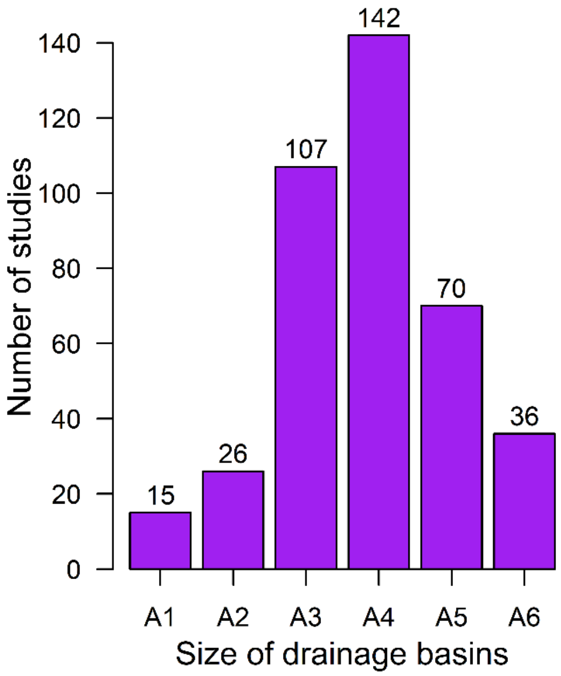

Figure 7: Distribution of number of hydrological modelling studies for water resources in East Africa per spatial scales. The number shown on top of every bar represents number of studies for that particular spatial scale. A1 < 10 km^2, 10 ≤ A2 < 100 km^2, 100 ≤ A3 < 1,000 km^2, 1,000 ≤ A4 < 10,000 km^2, 10,000 ≤ A5 < 100,000 km^2, and A6 >100,000 km^2. This Figure was modified from Paper I: Senkondo et al. (2018)

Six novel aspects that have been used by researchers in studies which went beyond traditional hydrological modelling could be broadly identified – alternative sources of forcing data such as satellite precipitation (e.g. in Koutsouris et al., 2017; Habib et al., 2014), transferability of model parameters (e.g. in Love et al., 2011; Kim and Kaluarachchi, 2008), the use of isotopes/tracers (e.g. in Tekleab et al., 2015; Munyaneza et al., 2014), the use of an alternative variable (apart from streamflow) to calibrate the model (e.g. in Abera et al., 2017; Jung et al., 2017), modification of conceptual model (i.e. model structure/code) to fit the local conditions (e.g. in Alemayehu et al., 2017; Kiptala et al., 2014), and application of uncertainty approaches/principles (e.g. in Knoche et al., 2014; Tumbo and Hughes, 2015).

Comparison of model performance metrics between traditional hydrological modelling and beyond traditional hydrological modelling approaches showed that the medians of R^2, $PBIAS$, and NSE for the beyond traditional hydrological modelling were as good as their corresponding values for the traditional hydrological modelling (Figure 8). This outcome is promising as it showed how application of additional novel approaches could help to improve hydrological modelling for water resources in East Africa despite data limitations. This seems to be a positive response to the global efforts on how to improve hydrological modelling in data limited regions (e.g. Sivapalan et al., 2003; Hrachowitz et al., 2013). It also serves as inspiration for potential approaches to advance modelling in the KV basin, which is the emphasis of the remainder of this thesis.

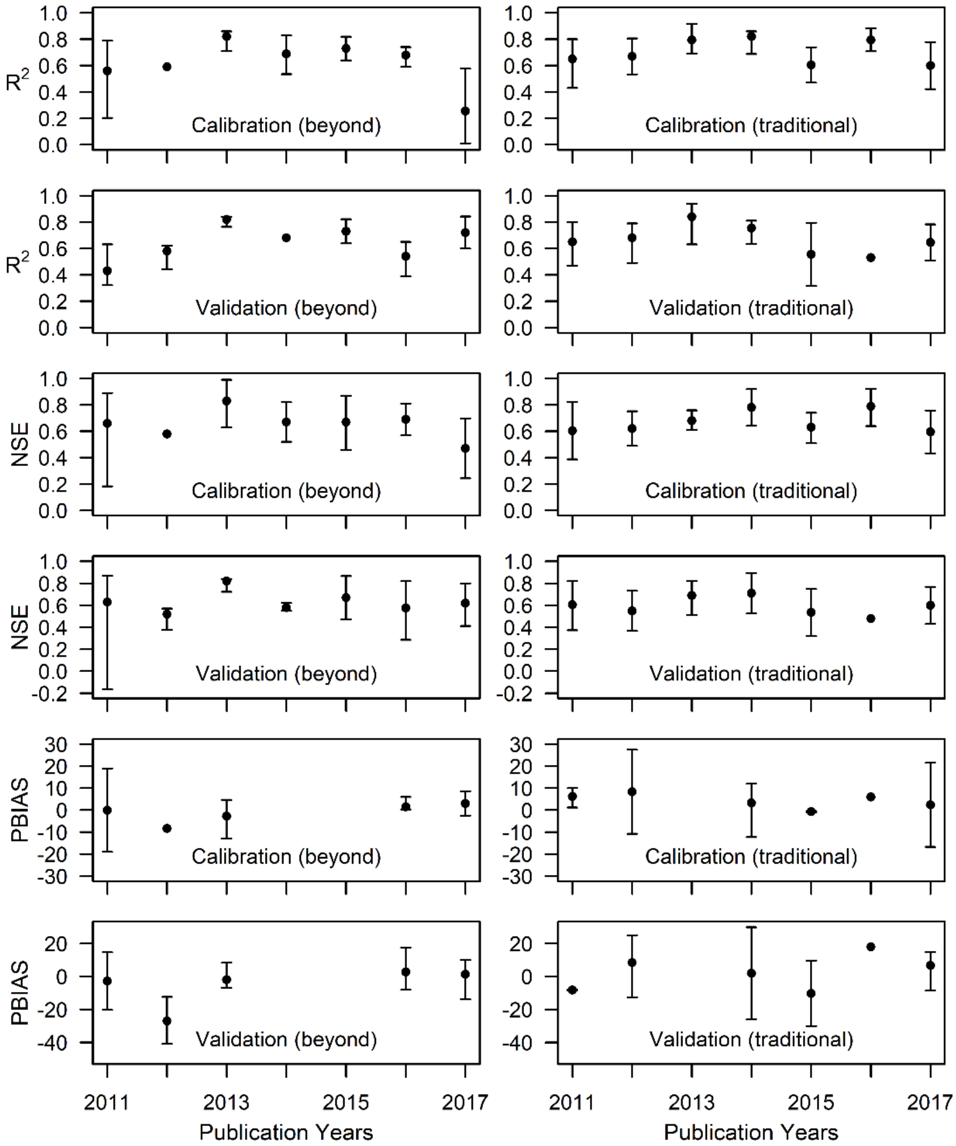

Figure 8: Model performance metrics for hydrological models evaluated using daily streamflow time series for drainage basins in East Africa. Filled circles represent the median values, error bars represent differences between median values and standard deviation values (note: minimum values were used whenever the lower limits were greater than the minimum values, and the maximum values were used whenever the upper limits were greater than the maximum values); (traditional) stands for studies which conducted traditional hydrological modelling, (beyond) stands for studies which conducted approaches beyond traditional hydrological modelling. This figure was modified from Paper I: Senkondo et al. (2018).

4.3 Information on aquifer processes and characteristics in Kilombero Valley (Paper II)

This thesis compared aquifer transmissivity (*T*) derived from point measurements using pumping tests (i.e. the more local-scale *T* estimates) to *T* derived from streamflow records (i.e. the more regional-scale *T* estimates) across the Kilombero Valley (KV) basin (Table 3). The local-scale *T* values from pumping-test (borehole) ranged between 0.01 and 11.65 m^2/min with a median *T* value of 0.18 m^2/min. The regional-scale *T* values derived from streamflow for three catchments ranged from 0.01 to 7.93 m^2/min for the wet season, and from 0.01 to 10.60 m^2/min for the dry season. Interestingly, the median *T* value of 0.18 m^2/min from the local-scale is quite similar to the wet-season regional-scale median *T* values from 1KB17 (0.14 m^2/min) and 1KB4 (0.16 m^2/min). However, this local-scale median *T* value (0.18 m^2/min) was almost 3 times larger than the wet-season regional-scale median *T* value (0.05 m^2/min) for the 1KB14 (Table 3). During the dry season, all the regional-scale median *T* values increased and were about 3 times larger than the local-scale median *T* value derived from the pumping-test (Table 3). Based on these results, the local-scale and regional-scale *T* values were similar under certain conditions such as during the wet season.

No significant relationships (with exception to hydraulic conductivity which showed strong linear relationship) were found between pumping test-derived T values and other parameters (Figure 9). This could partly be attributed to the geological heterogeneities that exist in the KV basin. This finding (heterogeneity) was supported by significant spatiotemporal variations in the K values across three catchments in the KV basin (Table 4). It is worth noting that the relative rankings and magnitudes of the median K values across the catchments (Table 4) were similar to those found by Lyon et al. (2015), signifying consistency and provides confidence in utilizing the full potential range of T values obtained by the recession-curve-displacement method to constrain aquifer parameterization when developing models to inform management as demonstrated in the Paper IV. These results highlight not only the role of process understanding in model development as seen in Paper I of this thesis, but also reflect significant implications for methodology selection for estimation of parameters pertaining to pollutant and contaminant spreading within the groundwater.

Table 3: Summary of borehole-derived and streamflow-derived aquifer T values estimated from pumping tests and streamflow records, respectively, across the Kilombero Valley (KV) basin. Number of events depends on the number of groundwater recharge events analyzed in the recession-curve-displacement method. 'na' stands for not applicable.

Parameter	Borehole	Catchment ID 1KB17		1KB4		1KB14	
Season	na	Wet	Dry	Wet	Dry	Wet	Dry
Number of boreholes/events [-]	27	13	14	24	6	53	23
Minimum *T* (m^2/min)	0.01	0.02	0.04	0.01	0.24	0.01	0.01
Median *T* (m^2/min)	0.18	0.14	0.66	0.16	0.70	0.05	0.51
Maximum *T* (m^2/min)	11.65	7.93	10.60	1.91	1.46	0.97	9.59
Average *T* (m^2/min)	2.48	1.18	2.40	0.31	0.73	0.12	1.16
Standard Deviation *T* (m^2/min)	3.50	2.31	3.64	0.47	0.50	0.17	2.07

Table 4: Statistical summary of recession index (K) across three catchments in the Kilombero Valley basin for dry (May to November) and wet (December to April) seasons. Extracted form Paper II (Senkondo et al., 2017).

Parameter	Catchment ID 1KB17		1KB14		1KB4	
Season	Dry	Wet	Dry	Wet	Dry	Wet
Total events	8	6	8	7	8	5
Minimum *K* (days)	40	58	38	17	40	43
Median *K* (days)	63	80	79	44	193	89
Maximum *K* (days)	100	128	112	72	288	249
Mean *K* (days)	67	88	76	44	180	136
Standard Deviation *K* (days)	18	27	27	20	87	93

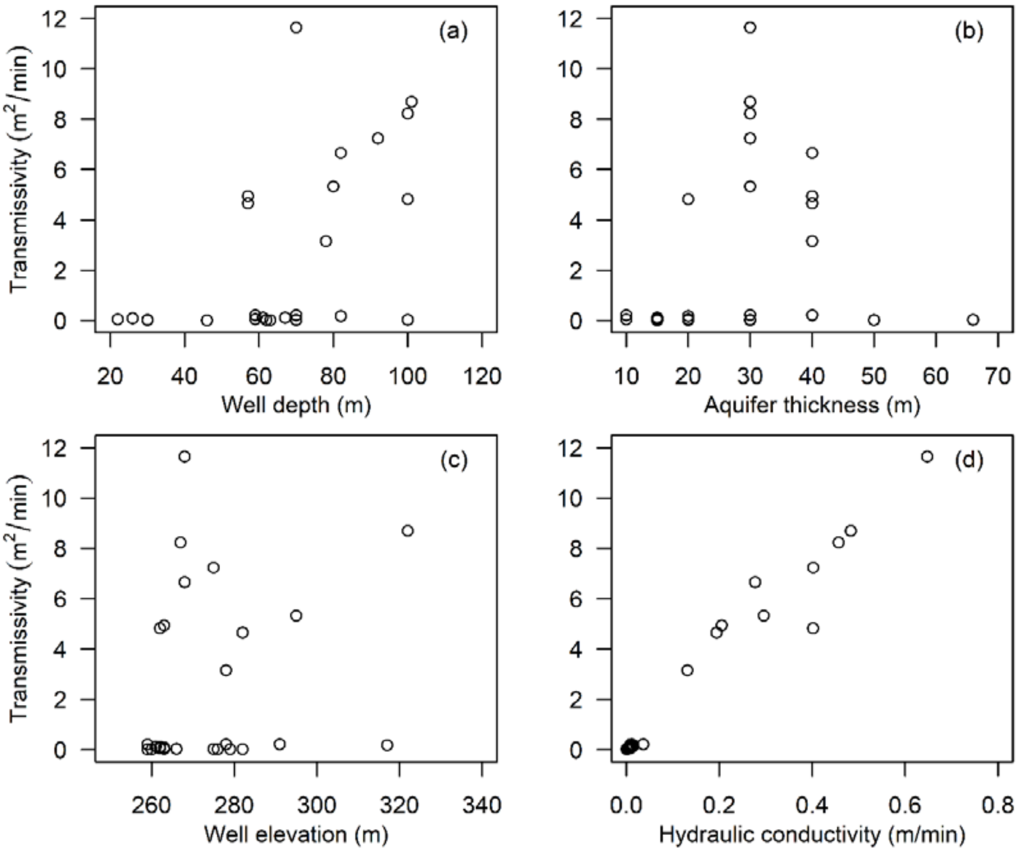

Figure 9: Relationships between pumping test-derived aquifer T estimates and: (a) Well depth, (b) Thickness of aquifer, (c) Well elevation, and (d) Hydraulic conductivity of aquifer. Modified from Paper II (Senkondo et al., 2017).

4.4 Satellite-based daily actual evapotranspiration estimates (Paper III)

Broadleaved evergreen forest and mosaic herbaceous cover had the highest average daily actual ET across all the SEB models considered (Table 5). Analysis indicating the highest ET for the mosaic herbaceous cover was expected due to the fact that this land cover class contained relatively large proportions of Miombo woodland, which normally maintains high ET rates throughout the year due to its nature of maintaining green leaves up to some few weeks before onset of the rainfall (Munishi-Kongo, 2013). On the other hand, the highest ET rates being shown over the broadleaved evergreen forest could in part be attributed to the availability of relatively high moisture content received by this land cover class from the dense network of streams draining the Udzungwa and Mbarika (in Mahenge) mountains where most of the broadleaved evergreen forests were located.

Another interesting trend was the relatively low ET estimates across all the SEB models for all land cover classes located within the floodplain (wetland-valley) which included flooded herbaceous cover, post-flooding cropland, and flooded tree cover. This trend could in part be attributed to the relatively low soil moisture content over the wetland-valley during the dry season (most of satellite overpasses used in this thesis were from the dry season) as supported by findings from Mombo et al. (2011). Additionally, all the SEB models estimated relatively high ET rates for cropland. This might partly be attributed to an ongoing dryland irrigation practiced in the KV basin. All these results suggest the capability of the SEB models to capture real-life processes and to develop reliable ET estimates.

More interesting, all the SEB models together with their ensemble mean managed to capture the two distinct ET patterns – ET pattern over the mountain-forests and ET pattern over the wetland-valley (Figure 10) – as reported by Munishi-Kongo (2013). When considering the temporal dynamics of daily actual evapotranspiration (ET) across the KV basin, all the SEB models as well as their ensemble mean captured similar ET patterns (Figure 11).

Table 5: The average daily actual evapotranspiration (ET) estimates derived from 25 MODIS satellite overpasses using three independent Surface Energy Balance (SEB) models as well as their ensemble mean across land cover classes in the Kilombero Valley (KV) basin. SEBAL represents the Surface Energy Balance Algorithm for Land, SSEBop represents the Operational Simplified Surface Energy Balance Algorithm, S-SEBI represents the Simplified Surface Energy Balance Index, and Ensemble mean represent the mean of daily actual ET estimates computed from the three SEB models (SEBAL, SSEBop, and S-SEBI).

Land cover classes	Models			
	SEBAL	SSEBop	S-SEBI	Ensemble mean
Cropland	6.3	6.4	6.4	6.4
Herbaceous cover	5.6	5.6	5.7	5.6
Post-flooding cropland	3.5	3.1	3.8	3.5
Mosaic cropland	6.2	6.3	6.2	6.2
Broadleaved evergreen forest	6.7	7.0	6.9	6.9
Broadleaved deciduous forest	5.8	5.6	5.8	5.7
Mixed Leaf forest	6.4	6.5	6.4	6.4
Mosaic herbaceous cover	6.8	7.1	6.9	6.9
Shrubland	6.5	6.6	6.5	6.5
Grassland	6.3	6.3	6.3	6.3
Flooded tree cover	4.6	4.0	4.6	4.4
Flooded herbaceous cover	3.7	3.0	3.8	3.5
Urban areas	5.1	5.2	5.3	5.2
Water bodies	5.9	5.4	5.7	5.6

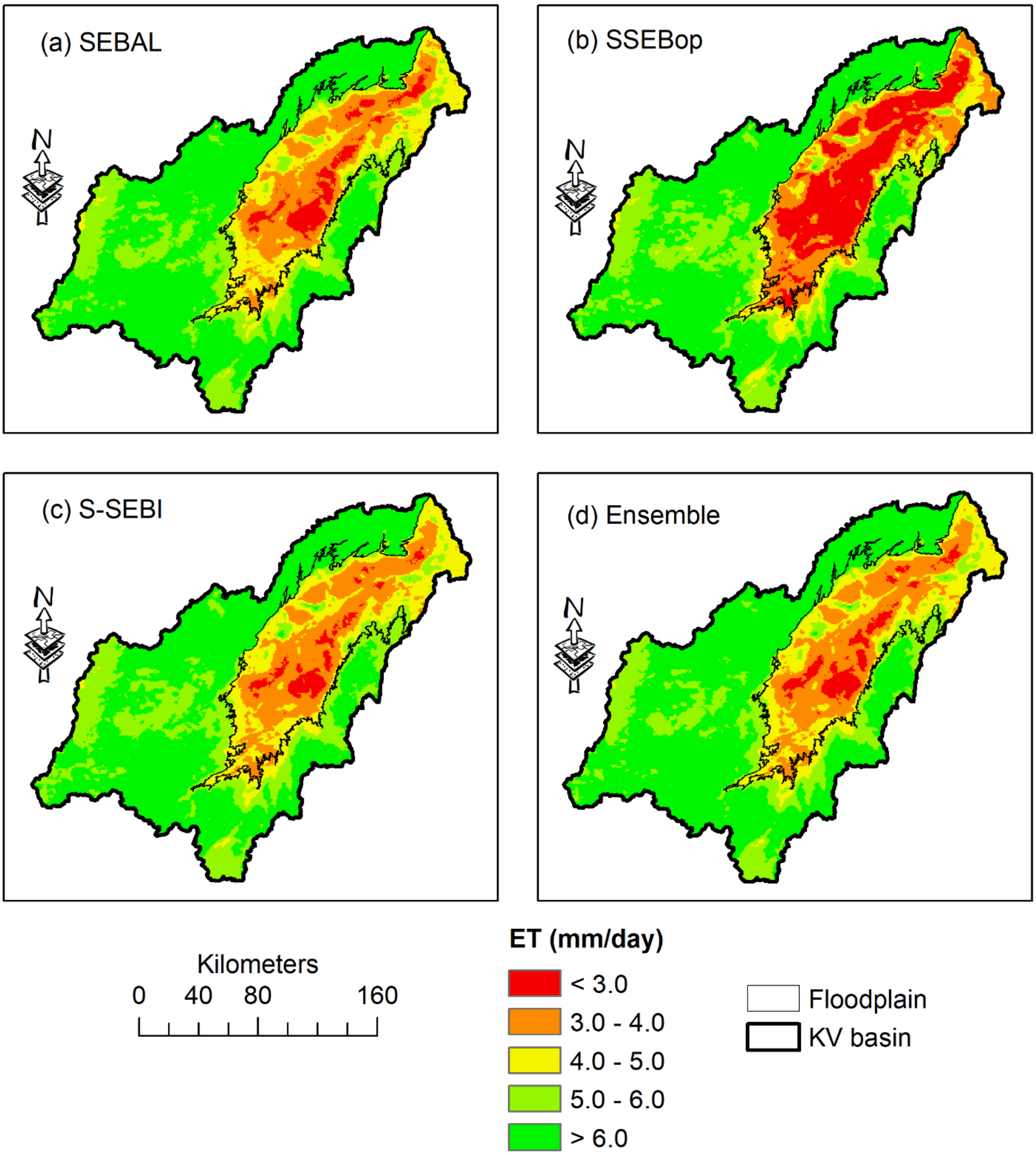

Figure 10: Spatial patterns of long-term average daily actual evapotranspiration (ET) across Kilombero Valley (KV) derived from 25 MODIS satellite overpasses using: (a) Surface Energy Balance Algorithm for Land (SEBAL) model, (b) operational Simplified Surface Energy Balance (SSEBop) model, (c) Simplified Surface Energy Balance Index (S-SEBI) model, and (d) the ensemble mean of the three models. Modified from Paper III (Senkondo et al., 2019).

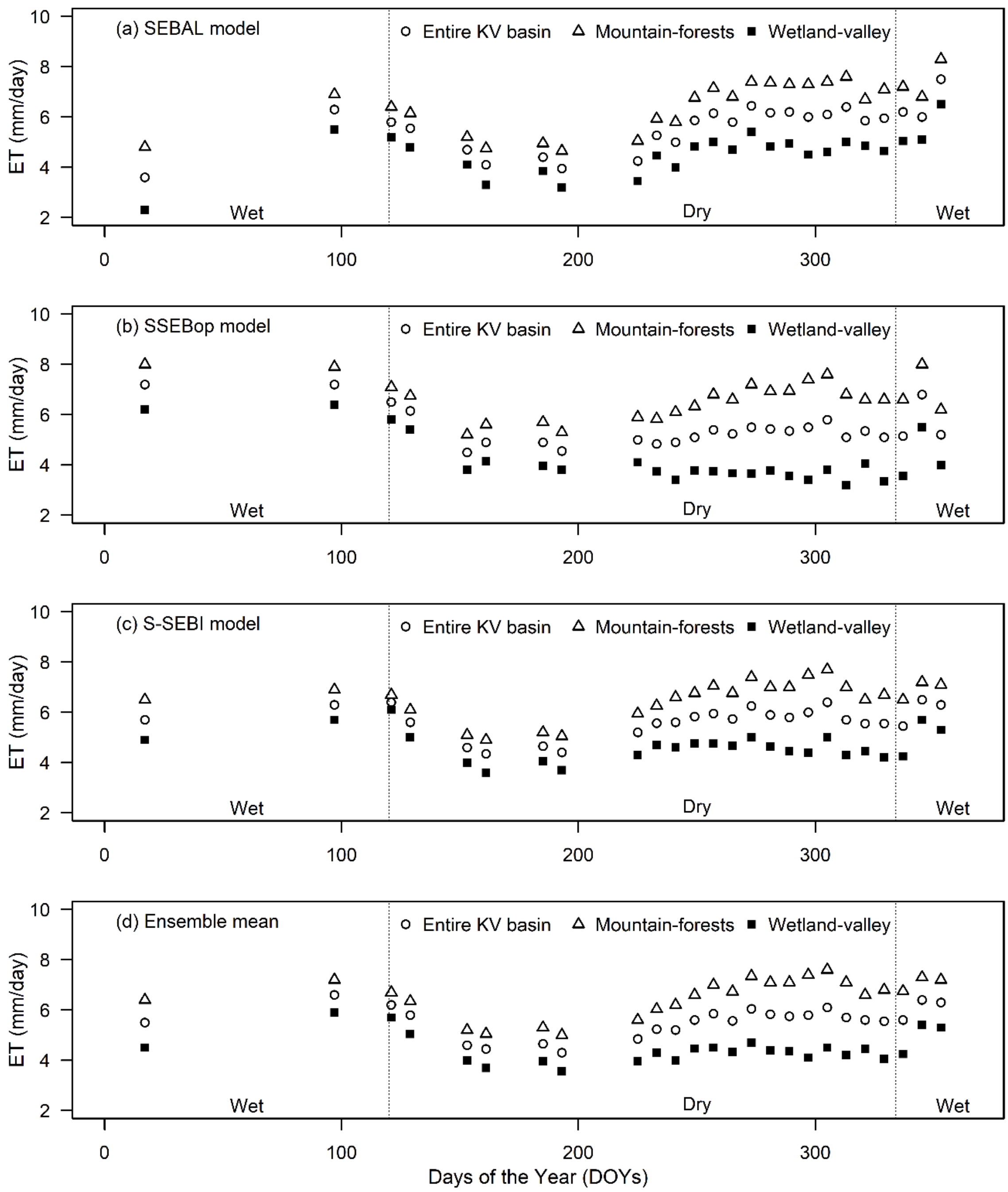

Figure 11: Temporal dynamics of the daily actual evapotranspiration (ET) over the entire Kilombero Valley (KV) basin, Mountain-forests within KV basin, and Wetland-valley within KV basin for 25 days of the year with MODIS satellite overpasses. The vertical dashed lines represent the interface between wet-season (Wet) and dry-season (Dry). (a) Actual ET estimates computed using the SEBAL model, (b) Actual ET estimates computed using the SSEBop model, (c) Actual ET estimates computed using the S-SEBI model, and (d) Actual ET estimates for the ensemble mean of the SEBAL, SSEBop, and S-SEBI models. Note: This Figure utilized composites of daily results from three separate years (2005, 2010, and 2015). This Figure was modified from Paper III: Senkondo et al. (2019).

A closer look at the ET patterns shows that SEBAL and SSEBop models had larger variations of actual ET compared to the others. Generally, there was no sharp interface between wet-season and dry-season ET estimates regardless of the spatial scales considered (i.e. neither for the entire KV basin nor the mountain-forests or wetland-valley).

4.5 Hydrological modelling (Paper IV)

4.5.1 Traditional hydrological modelling approach

The streamflow simulation for the calibrated scenario of the $SWAT_{old}$ model managed to capture the main streamflow dynamics (Figure 12 (a)). This is supported by reasonably good model performance metrics (e.g. KGE = 0.91, and NSE = 0.83) as depicted in Figure 12 (b). It is interesting to note that the recession periods for the calibrated scenario of the $SWAT_{old}$ model were represented reasonably well. This suggests the potentiality of the calibrated $SWAT_{old}$ model to be used to estimate minimum reference flow for the KV basin, which is a promising tool for water resources planning, development, and management. Further exploration shows that the calibrated $SWAT_{old}$ model underestimated some of the peak flows (e.g. 1960, 1962, and 1963; Figure 12 (a)). Similar trends were also observed by Näschen et al. (2018), who applied the SWAT model in the KV basin using forcing data derived from the Coordinated Regional Downscaling Experiment (CORDEX) Africa (Gutowski et al., 2016) regional climate models.

The hydrograph of the default scenario of the $SWAT_{old}$ model did not manage to capture streamflow dynamics. It underestimated the recession periods (i.e. the dry seasons) and overestimated the peak flows (Figure 12 (a)). Poor performance of the default scenario using SWAT with uncalibrated parameters had been reported almost in all modelling studies (e.g. Alemayehu et al., 2017; Chanzi, 2017) which applied the SWAT model to perform hydrological modelling in the tropical regions. This might partly be attributed to irrelevant default values (i.e. not applicable in the tropical regions) of input model parameters specified in the default database of the SWAT (Notter et al., 2012; Alemayehu et al., 2017) for the hydrological processes of the region. Also, it might be attributed to a basic assumption that hydrological models developed for temperate climates might not always be suitable for tropical regions with distinct periods of wet and dry seasons (Lyon et al., 2015), which would be consistent with the variations in aquifer properties estimated in Paper II of this thesis and highlights the role of process understanding in model development as seen in Paper I of this thesis. This signifies the usability of automatic calibration algorithms such as SUFI-2 (Abbaspour et al., 2007) in SWAT-CUP (Abbaspour, 2015), with capability of performing model parameters sensitivity analysis prior to model calibration as demonstrated in Paper IV of this thesis. Model parameters sensitivity analysis enables the modeler to pick the most sensitive parameters for model calibration, which to some extent reduces the problem of 'equifinality' in the final set of calibrated model parameters (Savenije, 2001; Beven, 2006; McDonnell et al., 2007).

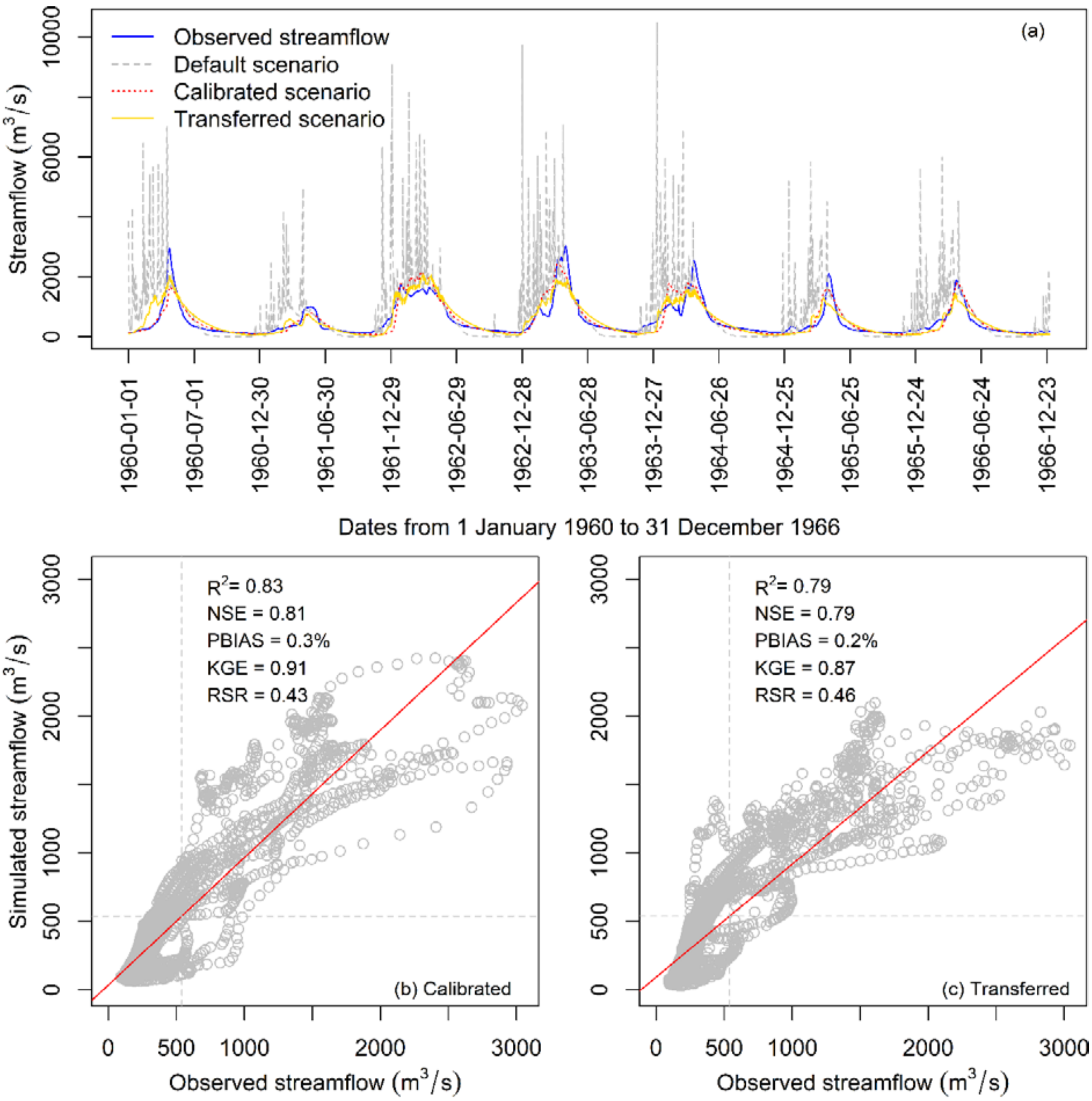

Figure 12: Hydrological modeling results across the Kilombero Valley basin of central Tanzania derived from the Soil and Water Assessment Tool (SWAT) model developed using historical (1957-1966) observed meteorological data, and then calibrated traditionally using historical (1960- 1966) observed streamflow time series ($SWAT_{old}$ model). (a) Daily hydrographs for the observed streamflow, default scenario, calibrated scenario, and the transferred scenario, (b) Scatter plot of the simulated streamflow for the calibrated scenario versus observed streamflow, (c) Scatter plot of the simulated streamflow for the transferred scenario versus observed streamflow. The solid red lines in the scatter plots represent regression line for the fitted data points, and the dashed lines represent arithmetic means of simulated streamflow (horizontal dashed lines) and observed streamflow (vertical dashed lines). R^2 stands for coefficient of determination, NSE stands for Nash-Sutcliff Efficiency, PBIAS stands for percent bias, KGE stands for Kling-Gupta Efficiency, and RSR stands for the ratio of root mean square error to standard deviation of observation.

4.5.2 Beyond traditional hydrological modelling

The monthly evapotranspiration (ET) hydrograph for the calibrated scenario of the $SWAT_{new}$ model managed to capture the general seasonality of the monthly GLEAM ET (Figure 13 (a)).

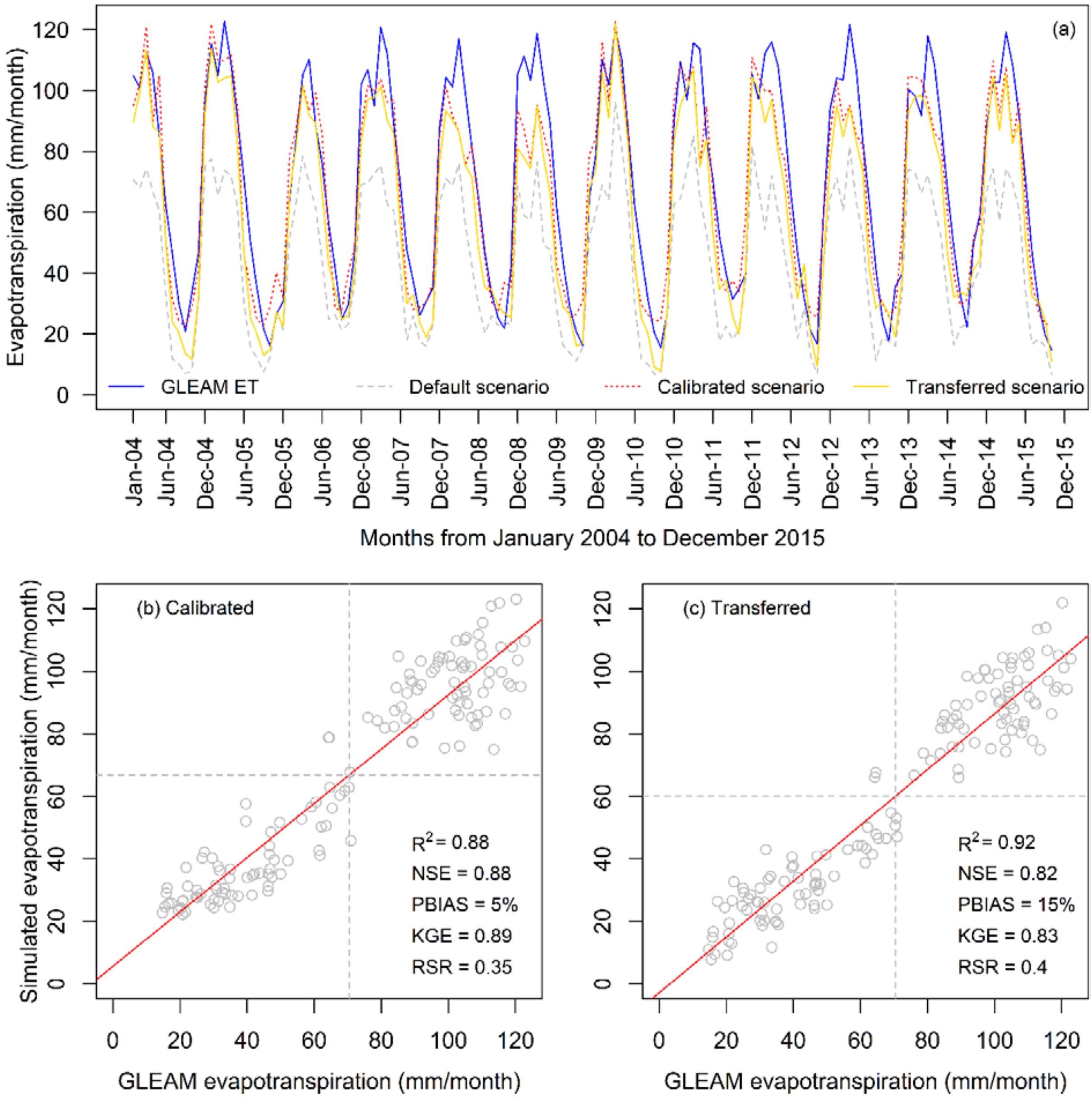

Figure 13: Hydrological modeling results across the Kilombero Valley basin of central Tanzania derived from the Soil and Water Assessment Tool (SWAT) model developed using recent (2001–2015) observed meteorological data, and then calibrated using recent (2004–2015) satellite-based actual evapotranspiration (ET) time series ($SWAT_{new}$ model). (a) Monthly hydrographs for the satellite-based actual ET derived by the Global Land Evaporation Amsterdam Model (GLEAM), default scenario, calibrated scenario, and the transferred scenario, (b) Scatter plot of the simulated ET for the calibrated scenario versus GLEAM ET, (c) Scatter plot of the simulated ET for the transferred scenario versus GLEAM ET. The solid red lines in the scatter plots represent regression line for the fitted data points, and the dashed lines represent arithmetic means of simulated ET (horizontal dashed lines) and GLEAM ET (vertical dashed lines). R^2 stands for coefficient of determination, NSE stands for Nash-Sutcliff Efficiency, PBIAS stands for percent bias, KGE stands for Kling-Gupta Efficiency, and RSR stands for the ratio of root mean square error to standard deviation of observation.

The GLEAM ET had been used as observed actual ET in this scenario. This was mainly due to absence of in-situ estimates of ET in the KV basin, and the promising modelling results obtained by other researchers which utilized remote sensed ET to calibrate/parameterize hydrological models in similar watersheds across Eastern Africa as presented in Paper I of this current thesis. Good performance of the calibrated scenario of the $SWAT_{new}$ model was also supported by the reasonably good statistical metrics (e.g. R^2 = 0.88 and $PBIAS$ = 5%) shown in Figure 13 (b).

While the calibrated scenario of the $SWAT_{new}$ model managed to capture the recession periods of the GLEAM ET reasonably well, the model underestimated the peaks (Figure 13 (a)). This might partly be attributed by the limitation in the observed input meteorological forcing data and the general tendency of the satellite-based ET estimates to overestimate the actual ET. The former is supported by the lower recession values and peaks values in the default scenario of the $SWAT_{new}$ model compared to the GLEAM ET (Figure 13(a)). The latter is supported by different modelling studies which utilized satellite-based ET time series (e.g. Immerzeel and Droogers, 2008; Alemayehu et al., 2017; Ha et al., 2018; Odusanya et al., 2019).

This study also tested the potential of transferring calibrated model parameters between $SWAT_{old}$ and $SWAT_{new}$ models (i.e. temporal transferability). As mentioned in the preceding section, the main objective of this temporal transferability approach was to evaluate robustness of these models prior to any applications as tools for simulations of past and/or future scenarios of water-related interventions. The transferred scenario of the $SWAT_{old}$ model seemed to be comparable to the calibrated scenario of the $SWAT_{old}$ model (Figure 12). This particular result is promising as it shows the applicability of the satellite-based ET time series in the calibration of a hydrological model, especially in data limited watersheds like the KV basin. It is noteworthy that the transferred scenario of the $SWAT_{old}$ model was derived using a set of model parameters obtained (without alteration) from the calibrated $SWAT_{new}$ model. The latter (i.e. $SWAT_{new}$ model) was calibrated using the time series of the satellite-based GLEAM ET. Similar promising results were obtained for the transferred scenario of the $SWAT_{new}$ model (Figure 13). The transferred scenario of the $SWAT_{new}$ model was derived using a set of model parameters obtained (without alteration) from the calibrated $SWAT_{old}$ model.

It is interesting to note that the transferred scenario of the $SWAT_{new}$ model had managed to capture the general seasonality of the GLEAM ET slightly better (R^2 = 0.92) than the calibrated scenario (R^2 = 0.88). However, both of these results (i.e. R^2 values) would be considered as very good performance under the model classification system recommended by Moriasi et al. (2007). It is noteworthy that transferring temporal parameters between different time periods can be precarious considering inter-decadal shifts in climatology (Shrestha et al., 2007; Zhang et al., 2013). Even so, considering changes in both land use and climate in the KV basin between 1960s and 2010s, reasonably good model results were obtained for the transferred scenarios in this thesis. Such a results garner confidence in utilizing the calibrated $SWAT_{new}$ model for water resources planning, development, and management in this heterogeneous and data limited KV basin. For example, as a tool for hindcasting previous impacts of water-related interventions in the basin on streamflow during periods of missing observations to help inform future strategies.

5. Discussion

5.1 Impacts of data availability and quality

Clearly, as is often the case, data availability and quality affect studies in this thesis. Some of previous hydrological modelling works in the Kilombero Valley (KV) basin utilized filtered and processed data as an attempt to bypass this influence (e.g. Yawson et al., 2005). However, the approaches considered in this thesis, to a large extent, allow us to avoid some of potential influence of limitations in data. For example, the recession technique utilized in Paper II requires only short periods of streamflow data corresponding to recession part of streamflow hydrograph and can leverage consistency across multiple years. This minimizes the potential influence of long periods of missing values in the streamflow data. The ease of the recession-curve-displacement method as an exploratory process as considered in Paper II of this thesis offers a clear benefit for data-limited and/or data-poor regions like KV basin. However, care must be taken because the recession-curve-displacement method, like many other recession techniques, is based on a simplified theory which might be too simple to describe the regional flows in more complex and dynamic catchment systems. This makes identification of all the impacts of quality of data, real shifts in the hydrological processes within a landscape, and limitations inherent in the general theory of recession-curve-displacement method somewhat unclear.

For example, Lyon et al. (2015) applied a recession technique to derive characteristic drainage times across the entire KV basin and its sub-catchments. That work found limitations in data to be one of the factors affecting their results. Lyon et al. (2015) proposed hydrological tracer studies as one alternative to illuminate and quantify mechanisms behind the patterns of characteristic drainage time values in the region. That proposal was later carried out by Koutsouris and Lyon (2018), who utilized a limited amount of water chemistry and stable water isotope information to perform end-member mixing analysis (EMMA) in one of the sub-catchments (Kiburubutu catchment) of the KV basin. They found a considerable delay in the commencement of overland flows in the basin from the onset of the rainy season. They attributed this with existence of a considerable wetting-up period before overland flow occurs for example associated with swelling of clay to seal off cracks and macros pores. This suggestion is in line with findings obtained in this thesis through hydrological modelling in Paper IV. Therefore, regardless of data limitations, recession technique considered in Paper II of this thesis, provided potential process and conceptual insights which could be used to constrain model development as demonstrated in the Paper IV of this thesis.

Another interesting impact of data availability can be seen in Paper III of this thesis. In this Paper the aim was to couple remote sensing with three Surface Energy Balance (SEB) models – SEBAL model (Bastiaanssen et al., 1998), SSEBop model (Senay et al., 2013), and S-SEBI model (Roerink et al., 2000) – to assess spatiotemporal variations of the actual evapotranspiration (ET) estimates in the Kilombero Valley (KV) basin. Although various proxies had been used to evaluate the validity of the ET estimates obtained from the SEB models, the absence of ET observations (or even fundamental energy balance components) in the KV basin to compare with means the SEB estimates remain uncertain. This highlights the importance of projects like those conducted by the Trans-African HydroMeteorological Observatory (TAHMO), which aims to develop, operate, and maintain a vast monitoring network of weather stations across Africa (see TAHMO's mission statement at https://tahmo.org/). Such efforts are particularly useful owing to the fact that agricultural development, climate monitoring, and many other hydro-meteorological applications depend on current and historical weather data.

Furthermore, lack of recent streamflow observations (in the era of satellite observations) in the KV basin, constrained direct evaluation of the $SWAT_{new}$ model in the Paper IV of this current thesis. Instead, evaluation was done indirectly using historical streamflow data covering the period from 1960 to 1966 assuming a parameter transferability approach. Singh et al. (2014) and Wu et al. (2009) have demonstrated an alternative way of bridging the gaps in historical streamflow records using Artificial Neural Networks (ANN). Promising results from their respective studies suggest the possibility of using ANN to construct time series of streamflow which could then be utilized into hydrological models for projections of different water-related scenarios. However, ANN is an emerging field, therefore, care must be taken when such approach is utilized to provide information for long-term water resources management as it has only reported to provide promising results in short-term forecasting of streamflow using limited streamflow observations (e.g. Meng et al., 2019; Vilanova et al., 2019; Tan et al., 2018; Prasad et al., 2017).

5.2 Implications for model development

The findings of the recession analysis (Paper II) showed that any future hydrological modeling in the Kilombero Valley (KV) basin should be able to consider seasonal shifts in flow pathways. Similarly, the results of actual evapotranspiration estimates based on Surface Energy Balance algorithms (Paper III) indicated that any future hydrological modelling in the KV basin should be able to partition the watershed to represent the mountainous and the valley landscapes separately if the whole KV basin is to be modelled. Furthermore, the results of Paper III indicated that any modeling conceptualization should be able to take into consideration different types of land use/cover classes across the basin. These findings formed the basis for selection of the Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998) considered in the Paper IV of this thesis.

Another important aspect of the SWAT model is its ability to simulate spatiotemporal dynamics of the actual evapotranspiration (ET) in addition to classical simulation of streamflow, which is not common in most of rainfall-runoff models (e.g. HBV and HEC-HMS models). In SWAT model, topographical information (stored in DEM) and land use/cover classes are dealt with during formation of Hydrological Response Units (HRUs), which represent unique combination of topography, land-use, soil, and management practices (Neitsch et al., 2011). Ability of the model to represent different hydrological features in the landscape (i.e. hydrological landscapes), is considered to be one of the important aspects towards development of robust model with capacity to simulate dominant hydrological processes in the watershed (Savenije, 2010). For example, to enhance parameter identification and calibration of the Spatial Tools for River Basin Environmental Analysis and Management (STREAM) model, Kiptala et al. (2014) identified and included three hydrological landscapes – hillslope, wetlands, and snowmelt – when modelling streamflow in a heterogeneous, data-limited, and highly utilized Pangani river basin (shared between Tanzania and Kenya) in Eastern Africa. What should be emphasized here is that this inclusion of different hydrological landscapes into the modelling framework does not inherently imply increased model complexity. For example, Collick et al. (2009) developed a simple, semi-distributed hydrological model for mountainous watershed in Ethiopia using a water balance method that divides a catchment into different zones that become active given different amounts of cumulative rainfall after the commencement of the rainy season. Such simple but robust modelling can provide a relevant tool for water resources management and conservation activities in the watershed (Asfaw and Neka, 2017; Zimale et al., 2017).

Often, hydrological models focus on natural processes and fail to consider anthropogenic manipulations, such as, irrigated agriculture and reservoirs. Calibrating hydrological model using modified streamflow data may lead to incorrect model parameterization and high uncertainty in the calibrated model outputs, which limits the abilities of such model in scenarios analysis for water use planning and management. To buffer against such inherent limitations, this current thesis developed an innovative approach whereby satellite-based actual evapotranspiration (ET) was used to calibrate the SWAT model (Paper IV). This is very advantageous (especially in the case of KV basin) because satellite-based ET implicitly accounts for supplementary irrigation (i.e. blue water) occurring in the landscape. Generally, the use of remotely sensed data in hydrological modelling has been possible in the recent decades owing to the advancement in remote sensing algorithms and availability of satellite images with reasonably good spatiotemporal accuracies (Schultz, 1993; Norman et al., 1995; Pauwels et al., 2001; Su, 2002). For example, calibration of the SWAT model based on the satellite-based ET time series considered in Paper IV of this thesis enabled the model to account for spatiotemporal dynamics in patterns of evaporative depletion which influence the hydrologic response of the catchment. In arid and semi-arid savannah regions, for example, ET accounts for more than 90% of the water use in watersheds (Kiptala et al., 2013). Since ET accounts for such a large flux of water, it makes accurate information on the spatiotemporal variability in ET rates important for planners and water managers responsible for water resources planning, development, allocation, and management in these watersheds. Therefore, a hydrological modelling framework which constrains information on ET estimates like that adopted in Paper IV of this thesis is a potentially useful tool for sustainable resource management especially for data-limited regions like that of the KV basin.

5.3 Scientific guidance to inform water resources management

Despite all the challenges facing water resources management in a data limited regions, relevant state-of-the-science approaches (Figure 14) can still be utilized to synthesize scientific guidance to assist water managers, policy makers, and planners to make informed decisions regarding planning, development, and management of water resources for the benefit of both present and future generations. This thesis provides clues on how such information could be generated through a novel workflow. More specifically, comprehensive lessons learned from other data limited regions (Paper I) could be used in targeted approaches such as recession analysis (Paper II) and Surface Energy Balance (SEB) modelling (Paper III) to better inform the choice and calibration of hydrological model (Paper IV). The subsequent hydrological model could then be used as a relevant tool for water resources scenario analysis. It is noteworthy that, implementation of this workflow requires the integration of remote sensing, geographical information system (GIS), and multiple global databases for – development of model parameters, analysis, and visualization of the outputs – as demonstrated in this thesis.

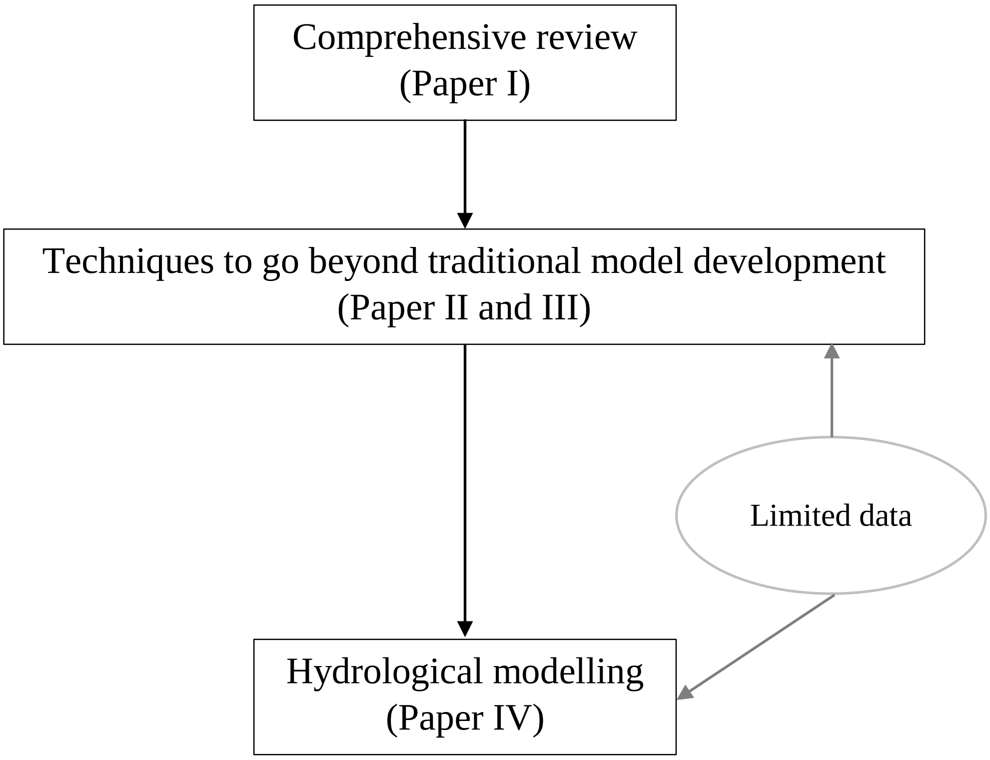

Figure 14: Methodology for provision of scientific guidance to assist water resources management in data limited Tanzania’s Kilombero Valley (KV) basin as implemented in this thesis.

Such a workflow is promising considering an increased pressure on water resources brought by agricultural expansion and intensification, demographic growth, climate change, and other water-related interventions, which necessitate development of sustainable plans regarding water resources management regardless of existing status of data availability of a region.

5.4 Implications for future research

The work in this thesis has several possible implications for future research or application across the KV. For example, the calibrated SWAT model developed in Paper IV has potential to be utilized in predicting the hydrological impacts of changes in both land use/cover and climate in the KV basin. Currently, there are increased concerns (globally) by public and political groups about the impacts of climate and land use changes on water resources. Different studies on the hydrological effects of climate and land use/cover changes at both global and local scales have reported significant feedback effects brought about by changes on hydrological processes (e.g. Adhikari et al., 2017; Chen et al., 2020; Guo et al., 2020). Such outcomes underline the importance of having a baseline assessment in the KV basin which is currently targeted for rapid social-economic development with emphasize in expansion and intensification of agriculture. One of advantage of using the calibrated SWAT model of Paper IV to predict such changes in climate and land use/cover on the water resources of KV basin, is its ability to estimate uncertainties of the impacts of these changes (using the SWAT-CUP program). This could be translated into risk for decision makers.

The SEBAL model developed in Paper III of this thesis could also be used to derive information on the water productivity (expressed as a net return per unit of water consumed) of different land, water and other ecosystems in the KV basin. Being expressed either economically/socially ($/m^3) or biophysically (kg/m^3), water productivity can be used as an indicator in water resources management of the basin. It can be used to provide an optimal water allocation to different water uses in the basin. The SEBAL model developed in Paper III could be used to compute gridded biomass production in both agricultural and natural landscapes which could then be converted into crop yield, amount of sequestered carbon, and economic water productivity. Mapping water productivity across the KV basin would help water managers to know specific areas which need improvement. Such improvement (of water productivity) could enhance production of more food, better livelihoods, more income, and an improved ecosystem services with less water. For example, Kiptala et al. (2018) estimated the spatial water productivity for different land use/cover classes in the Upper Pangani River Basin (shared between Tanzania and Kenya) based on MODIS images and the SEBAL model. They found a strong correlation between biomass production and economic water productivity. Additionally, they identified areas for improvement, and trade-offs in river basin. Specific details on how to improve water productivity can be seen in Molden et al. (2010) and Zwart et al. (2010).

Another important research area to be considered is the assessment of water quality in the KV basin. As it had been highlighted in Paper I of this thesis, a combination of driving forces (e.g. irrigation, industries, and energy production) are increasing pressure on water resources in KV basin. These not only affect water resources in terms of quantity as shown throughout this thesis, but also could affect water quality. For example, Nitrates and Phosphorus transported from croplands through overland flow and return flow from the irrigation canals (Alavaisha et al., 2019) into the river network affect water quality. The SWAT model developed in Paper IV of this thesis has module for water quality modelling, therefore, offers a great potential to be used for water quality modelling in the KV basin. However, no measured water quality data exist in the KV basin for model calibration, therefore, water quality monitoring (e.g. nitrate concentrations) would need to be undertaken (e.g. monthly for three consecutive years) in a few points (specific number to be decided after a preliminary survey) prior to any modelling effort. However, such effort would depend on availability of resources.

6. Conclusion

The modelling presented in this thesis was coupled with limited observed hydrometeorological variables (e.g. streamflow and precipitation) and remotely sensed actual evapotranspiration estimates to achieve a reasonable degree of robustness based on model performance metrics. Such robustness gives confidence for its use as a tool for quantification and assessment of different water-related scenarios, such as, land-use/cover change, climate change, and human water-use change (e.g. irrigation) in the Kilombero Valley (KV) basin. Moreover, a methodological workflow could be outlined applicable for any other data limited basin with similar hydrological settings. It is clear, however, that the lack of historical and recent hydrometeorological observations still remains a stumbling block to assess sustainable management of water resources particularly with regards to KV basin. For example, the absence of overlap between historical streamflow observations and the remote sensing-based observations implies uncertainty around the validation of results from the SWAT model based on a temporal transferability approach. Although some techniques are less impacted by missing data, such as the recession analysis technique applied in this thesis, our ability to increase knowledge about watershed properties and process is still affected by data quality, which can still make results uncertain. All these challenges highlight the importance of supporting ongoing efforts which aim to collect new and better (in terms of quantity, quality, and spatiotemporal coverages) hydrometeorological data or attempt to push beyond traditional hydrological modelling.

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