Climate change effects on drought, freshwater availability and hydro-power generation in an African environment – observations and projections for the Lake Malawi and Shire River Basins in Malawi

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by

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Abstract

The work is designed to investigate the impacts and sensitivity of climate change on water resources, droughts and hydropower production in Malawi, the South-Eastern region which is highly vulnerable to climate change. It is observed that rainfall is decreasing and temperature is increasing which calls for the understanding of what these changes may impact the water resources, drought occurrences and hydropower generation in the region. The study is conducted in the Greater Lake Malawi Basin (Lake Malawi and Shire River Basins) and is divided into three projects. The first study is assessing the variability and trends of both meteorological and hydrological droughts from 1970-2013 in Lake Malawi and Shire River basins using the standardized precipitation index (SPI) and standardized precipitation and evaporation Index (SPEI) for meteorological droughts and the lake level change index (LLCI) for hydrological droughts. And later the relationship of the meteorological and hydrological droughts is established.

While the second study extends the drought analysis into the future by examining the potential future meteorological water balance and associated drought characteristics such as the drought intensity (DI), drought months (DM), and drought events (DE) in the Greater Lake Malawi Basin. The sensitivity of drought to changes of rainfall and temperature is also assessed using the scenario-neutral approach. The climate change projections from 20 Coordinated Regional Climate Downscaling Experiment (CORDEX) models for Africa based on two scenarios (RCP4.5 and RCP8.5) for the periods 2021–2050 and 2071–2100 are used. The study also investigates the effect of bias-correction (i.e., empirical quantile mapping) on the ability of the climate model ensemble in reproducing observed drought characteristics as compared to raw climate projections.

The sensitivity of key hydrologic variables and hydropower generation to climate change in Lake Malawi and Shire River basins is assessed in third study. The study adapts the mesoscale Hydrological Model (mHM) which is applied separately in the Upper Lake Malawi and Shire River basins. A particular Lake Malawi model, which focuses on reservoir routing and lake water balance, has been developed and is interlinked between the two basins. Similar to second study, the scenario-neutral approach is also applied to determine the sensitivity of climate change on water resources more particularly Lake Malawi level and Shire River flow which later helps to estimate the hydropower production susceptibility.

Results suggest that meteorological droughts are increasing due to a decrease in precipitation which is exacerbated by an increase in temperature (potential evapotranspiration). The hydrological system of Lake Malawi seems to have a >24-month memory towards

meteorological conditions since the 36-months SPEI can predict hydrological droughts ten-months in advance. The study has found the critical lake level that would trigger hydrological drought to be 474.1 m.a.s.l.

Despite the differences in the internal structures and uncertainties that exist among the climate models, they all agree on an increase of meteorological droughts in the future in terms of higher DI and longer events (DM). DI is projected to increase between +25% and +50% during 2021-2050 and between +131% and +388% during 2071-2100. This translates into +3 to +5, and +7 to +8 more drought months per year during both periods, respectively. With longer lasting drought events, DE is decreasing. Projected droughts based on RCP8.5 are 1.7 times more severe than droughts based on RCP4.5.

It is also found that an annual temperature increase of 1°C decreases mean lake level and outflow by 0.3 m and 17%, respectively, signifying the importance of intensified evaporation for Lake Malawi's water budget. Meanwhile, a +5% (-5%) deviation in annual rainfall changes mean lake level by +0.7 m (-0.6 m). The combined effects of temperature increase and rainfall decrease result in significantly lower flows on Shire River. The hydrological river regime may change from perennial to seasonal with the combination of annual temperature increase and precipitation decrease beyond 1.5°C (3.5°C) and -20% (-15%). The study further projects a reduction in annual hydropower production between 1% (RCP8.5) and 2.5% (RCP4.5) during 2021–2050 and between 5% (RCP4.5) and 24% (RCP8.5) during 2071–2100.

The findings are later linked to global policies more particularly the United Nations Framework Convention on Climate Change (UNFCCC)'s Paris Agreement and the United Nations (UN)'s Sustainable Development Goals (SDGs), and how the failure to adhere the restriction of temperature increase below the global limit of 1.5°C will affect drought and the water resources in Malawi consequently impact the hydropower production. As a result, the achievement of most of the SDGs will be compromised.

The results show that it is of great importance that a further development of hydro energy on the Shire River should take into account the effects of climate change. The information generation is important for decision making more especially supporting the climate action required to fight against climate change. The frequency of extreme climate events due to climate change has reached the climate emergency as saving lives and livelihoods require urgent action.

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List of Abbreviations

CMIP3 (5 or 6)	Coupled Model Inter-comparison Project 3 (5 or 6)
COP	Conference of Parties
CORDEX	CO-ordinated Regional climate Downscaling Experiment
CRU	Climatic Research Unit
CV	Coefficient of Variation
DCCMS	Department of Climate Change and Meteorological Services
DD	Drought Duration
DDS	Dynamical Dimensioned Search
DE	Drought Events
DI	Drought Intensity
DM	Drought Months
DoDMA	Department of Disaster Management Affairs
DS	Drought Severity
DWR	Department of Water Resources
ENSO	El Niño Southern Oscillation
EQM	Empirical Quantile Mapping
ESCOM	Electricity Supply Commission
FAO	Food and Agriculture Organisation
GCMs	Global Climate Models
GDP	Gross Domestic Product
GHGs	Greenhouse gases
GOM	Government of Malawi
GPCC	Global Precipitation Climatology Centre
GLMB	Greater Lake Malawi Basin
HBV model	Hydrologiska Byrans Vattenavdelning model
HPP	Hydropower Production
IDW	Inverse Distance Weighting
IPCC	Intergovernmental Panel on Climate Change
KGE	Kling-Gupta Efficiency
LAM	Limited Area Models

LLCI	Lake Level Change Index
LMB	Lake Malawi Basin
LMM	Lake Malawi Model
MFHPP	Maximum Flow for Hydropower Production
mHM	Mesoscale Hydrological Model
MK test	Mann-Kendall test
MWB	Meteorological Water Balance
NDCs	Nationally Determined Contributions
NOL	No Outflow Level
PET	Potential Evapotranspiration
RCMS	Regional Climate Models
RCPs 2.6 (4.5 or 6 or 8.5)	Representative Concentration Pathway 2.6 (4.5, 6 OR 8.5)
RMSE	Root Mean Square Error
SD	Standard Deviation
SDG	Sustainable Development Goals
SPEI	Standardised Precipitation and Evapotranspiration Index
SPI	Standardised Precipitation Index
SRB	Shire River Basin
SRM	Shire River Basin Model
UFZ	Helmholtz Centre for Environmental Research
ULMBM	Upper Lake Malawi Basin Model
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
WMO	World Meteorological organisatio

I Introduction

1. Background and motivation

Climate change is likely to intensify the hydrological cycle (Hagemann et al., 2013) and this will probably lead to increased hydro-climatological extremes, and in turn, hydrological extremes like droughts and floods might change accordingly (Bates et al., 2008). There are though regional differences in the impacts of climate change on the hydrological cycle due to the regionally different landscape characteristics and the spatial variability of the changing climate. These hydrological impacts of climate change will have consequences on flood- and drought hazards in general, but also for the seasonal water availability and the use of water for human purposes such as hydropower.

Hydropower is one of the renewable energy sources that is recommended in the climate change era as it contributes towards the mitigation of greenhouse gases (GHGs) by enhancing the avoidance of the GHGs emissions (Berga, 2016). However, it is also the energy that can highly be affected by the changing climate as it usually relies on river flows (Berga, 2016; Kumar et al., 2011). As 16% of the world's electricity is hydro-based (Berga, 2016), the most countries in Southern Africa such as Malawi and Zambia have over 90% of their electricity derived from hydropower (Conway et al., 2017). However, Southern Africa region is highly ranked as vulnerable to climate change (Shukla et al., 2019) as the river streamflow is decreasing (Kumar et al., 2011; Kusangaya et al., 2014) and pose a threat to the generation.

In Malawi, hydropower contributes to 99% of electricity production and out of which 98% is generated on Shire River alone. The Shire River is the only outlet of Lake Malawi, and any lake level fluctuations affect the electricity production downstream (ESCOM, n.d.a). For instance, during the low flow seasons of 2014 to 2016, the production dropped by almost half due to the lower lake levels that were attributed to the shortage of rainfall (ESCOM, n.d.a). This increased the frequency of power cuts, and according to the World Bank (2011), the country loses more than 6% of its annual gross domestic product (GDP) due to the failure to meet the electricity demand.

In addition to the low flows which affect the hydropower production, floods are a relevant natural hazard that threatens life and goods and also impacts hydropower production in the Shire River Basin (SRB). In 2015, a 500-year-flood affected the hydropower production and transmission which took almost 14 days to restore. The damage on electricity alone was estimated to cost MWK 151 million (USD 347 000) and the losses that came along with this damage were at around MWK 306 million (USD 704 000) (GOM, 2015). Therefore, the understanding of the impacts of climate change on the evolution of both droughts and floods in Malawi is paramount.

Climate change is evident in Malawi and some of the indicators that are being felt by subsistence farmers are delayed and unpredictable rainfall onset, warming temperatures and increased frequency of prolonged dry spells (Nkomwa et al., 2014). It is noted that between 1961 and 2015 the temperature has been increasing while the rainfall is decreasing in Malawi (Ngongondo et al., 2015; Zuzani et al., 2019), and the projected temperature indicates the increase of up to 5 degrees by 2090 (McSweeney et al., 2010). While rainfall projections do not agree in the direction of change, as the changes range from –5.4% to +24.6% by 2050 (Umesh & Pouyan, 2016). The impacts of these changes are likely to reverse the social and economic development in the sub-Saharan Africa that will impede the progress of achieving the Millennium Development Goals (Brown, 2011) or the successor the 17 Sustainable Development Goals (SDGs).

Fig. I-1 is showing the summary of climate related reports and studies conducted in Malawi between 1980 and 2020. In total, there are 86 studies that were analysed and the figure consists of words that appear as part of the objectives of the studies, the size of the word indicates its frequency across the reports, which is later expressed as the percentage of the total studies.

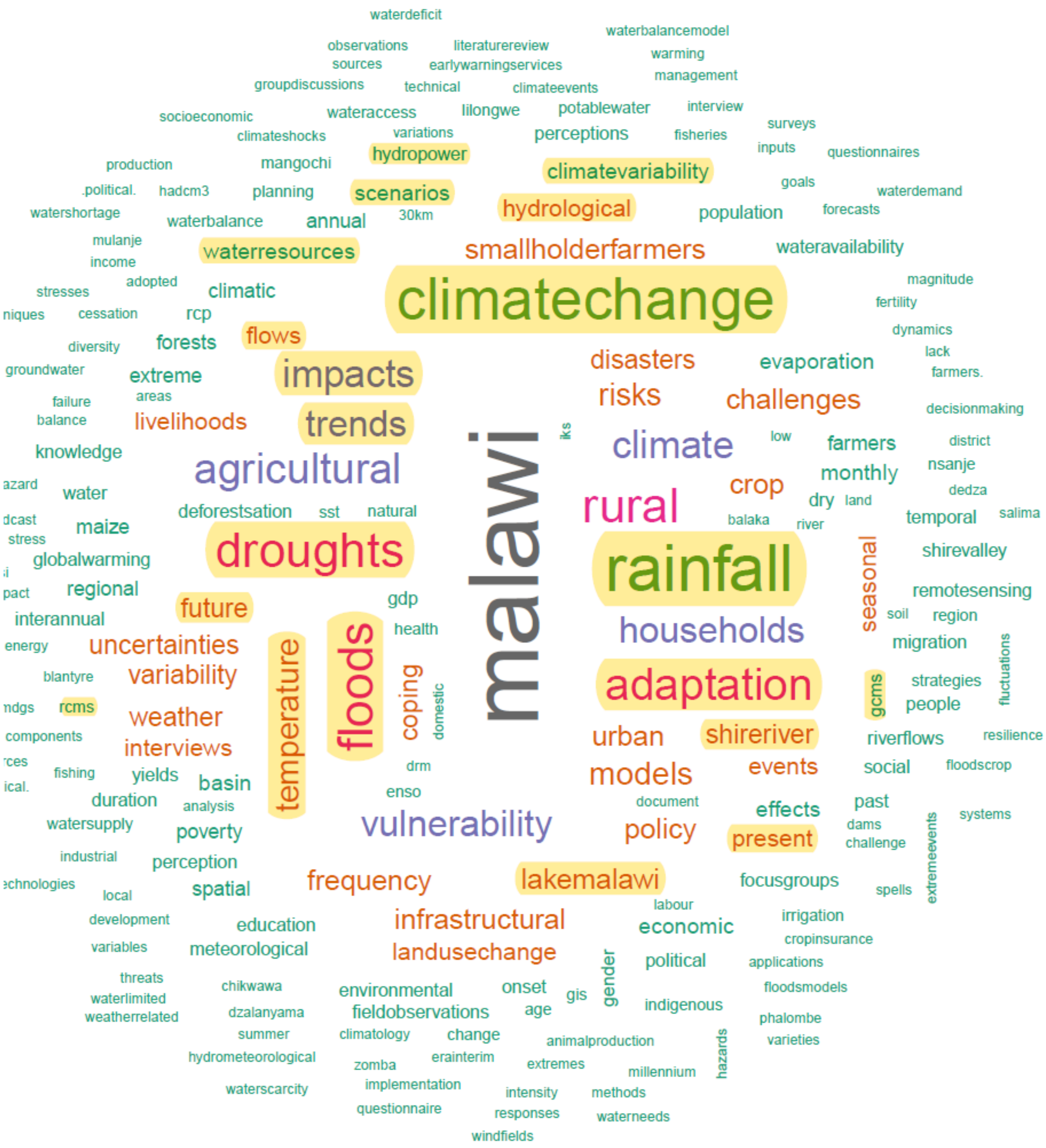


Figure I - 1 *Frequency of terms found in the objectives of climate -related studies conducted in Malawi from 1980 to 2020. The shaded terms are those that this study is having a particular interest.*

Out of the studies analysed, 57% are climate change connected (e.g. Bezner Kerr et al., 2018; Chidanti-Malunga, 2011; Chingala et al., 2017; Chinowsky et al., 2015; Katengeza et al., 2012; McSweeney et al., 2010; Nkomwa et al., 2014; Suckall et al., 2017; Syroka & Nucifora, 2010; Umesh & Pouyan, 2016; Vizy et al., 2015; Warnatzsch & Reay, 2019), and 39% of these are addressing climate change adaptation (e.g. Babu & Chapasuka, 1997; Bezner Kerr et al., 2018; Brown, 2011; Chidanti-Malunga, 2011; Holden & Fisher, 2015; Katengeza et al., 2012; Nkomwa et al., 2014; Syroka & Nucifora, 2010) that mainly focus on agriculture (31%) (e.g. Bezner Kerr et al., 2018; Chidanti-Malunga, 2011; Coulibaly et al., 2015; Holden & Fisher, 2015; Jayanthi et al., 2013; Katengeza et al., 2012; Syroka & Nucifora, 2010). The agricultural adaptation studies are mainly focussing on maize crop (Holden & Fisher, 2015; Katengeza et al., 2012) as it is the main staple food in Malawi and it shows that the adoption of drought tolerant varieties is high by the recently drought impacted farmers (Holden & Fisher, 2015). The inclusion of indigenous knowledge (Kalanda-Joshua et al., 2011; Nkomwa et al., 2014) is also addressed in some of the climate change studies based on household surveys, interviews and focus group discussions (Coulibaly et al., 2015; Katengeza et al., 2012). As smallholder farmers in developing countries rely much on climate dependant natural resources (Suckall et al., 2017), climate change is severely affecting the production due to the increase in temperature, droughts, floods and rainfall variability (Bezner Kerr et al., 2018). The growing seasons are predicted to be shorter in the future by 25 to 55% by late century over Malawi south of 13.5°S latitude due to earlier cessations of rainfall season (Vizy et al., 2015). Lobell et al. (2011) estimated the maize yield fall of 1% for each growing day spent above 30° Celsius and as much as 1.5% during drought conditions in Africa. Meanwhile, the 1992 drought reduced the yeild that resulted into the decline of about 7.9% of GDP in Malawi (Nhamo et al., 2016). It was also observed that lack of financial resources and infrastructure for adaptation will likely exacerbate the climate change effects in Malawi (Suckall et al., 2017).

Drought related studies addressing climate change are at 42% (e.g. Babu & Chapasuka, 1997; Holden & Fisher, 2015; Jayanthi et al., 2013; Khamis, 2006; Lobell et al., 2011; Nhamo et al., 2016; Pangapanga et al., 2012; Syroka & Nucifora, 2010) and only 8% includes the drought dynamics in their investigations based on Palmer drought severity Index (PDSI) and standardised precipitation index (SPI) for meteorological droughts (Jury, 2014; Munthali et al., 2003). Jury (2014) also established large-scale systems that are associated with droughts in Malawi. Climate change and flood related studies are given similar attention as drought studies (e.g. Drayton et al., 1980; Jury, 2014; Khamis, 2006; Pauw et al., 2011; Umesh & Pouyan, 2016; Zuzani et al., 2019), but unlike drought studies, the 19% of flood studies contains flood dynamics that include analysis of parameters such as rainfall and river flows (e.g. Drayton et al., 1980; Jury, 2014; Zuzani et al., 2019). El nino Southern Oscillation (ENSO) – La nina cool phase and low pressure area over northeastern Africa are associated with floods in Shire river Basin (SRB) (Jury, 2014). A few studies have attempted to combine the drought and flood studies (extremes) in Malawi (Jury, 2014; Zuzani et al., 2019). Zuzani et al (2019) addressed extremes based on annual maxima and annual minima of the daily hydro-meteorological data, where the decreasing trend of both peak and low flows were observed in SRB.

Malawi is predominantly hydropower dependent (Taulo et al., 2015), this will remain as the main electricity source, in the near and medium term (GOM, 2010; Millenium Challenge Corporation, 2015). The impact of climate change on hydropower is anticipated to be either small or positive globally, but the impacts will vary at a regional or country level (Berga, 2016). In Malawi, climate change is expected to alter the hydrology of Lake Malawi and Shire River Basins (Bhave et al., 2020; Umesh & Pouyan, 2016), hence affecting the hydropower generation on Shire River. And yet none of the climate change studies has addressed the quantification of the impacts on hydropower generation on Shire River, despite that 8% of the climate related studies have included hydropower in their objectives. This shows how hydropower studies in relation to climate change are underrepresented in Malawi. Therefore, the thorough study that quantifies the sensitivity of hydropower due to temperature and rainfall changes will provide a guide on the future and the sustainability of hydropower generation in Malawi. Already, the reduction of hydropower generation at Lujeri Micro-Hydropower scheme in Southern Malawi for the period between 1980 and 2011 is associated with the increasing temperature (Kachaje et al., 2016). Therefore, as further temperature increase is anticipated in the future, the impact on hydropower generation is expected to be high, which may be exacerbated by the decrease in rainfall. Previously, reduced hydropower production is projected in the future on Zambezi River until 2080 (Harrison & Whittington, 2002; Yamba et al., 2011) in the region. Therefore, the study investigates the impacts of observed and projected climate change on water resources, droughts and hydropower productivity in Malawi including the Greater Lake Malawi Basin (Lake Malawi and Shire River Basins).

2. Physical geography of the Greater Lake Malawi Basin (GLMB)

2.1 Study area

The Greater Lake Malawi Basin (GLMB) is referred to in this study as the combination of Lake Malawi Basin (LMB) and Shire River Basin (SRB). The basin is about 149 000 km² including the lake which covers almost 20% of the total surface area. It is located in Malawi but extends into Tanzania and Mozambique, Fig. I-2. The basin is characterised by highlands, plateaus, rift valley escarpments and rift valley plains (Kumambala, 2010). The lowest altitudes are located in Lower Shire Valley where the altitude is below 60 m.a.s.l. making it susceptible to floods. Whence, the land rises from the Shire valley into the southern highlands and also towards Southern Lake Malawi valley, where Lake Malawi lies at about 457 m.a.s.l.. The highest point in SRB as well as Malawi is the Mulanje Mountain located within the Southern highlands which its highest peak Sapitwa is at 3,002 m.a.s.l. (Point 1 1 on Fig. 1-2). Mulanje Mountain is the origin of several rivers including Ruo which is one of the main tributaries of Shire River. At north-west SRB, there is a Kirk Range Plateau that runs along Malawi and Mozambique border to Dedza Mountain in south-west LMB (2 on Fig. 1-2). Dedza Mountain lies at 2198 m.a.s.l.. at its highest ultimate point. From Lake Malawi valley in LMB, the land rises again and some highest points in this basin are Viphya plateau (3 on Fig. 1-2), Nyika Plateau (4 on Fig. 1-2) and Southern Tanzania Highlands (5 on Fig. 1-2) which reach 2605, 1800 and 2961 m.a.s.l. respectively. Nyika plateau is the source of rivers such as North Rukuru, North Rumphi, Chilinda and Runyina. While Kasitu, Luweya and Limphasa Rivers originate from Vipya Plateau. Fig. 1-2[1]. The Southern Tanzania Highlands are a series of mountains such as Rungwe, Mtorwe and Kipengere that lie in the Northern part of LMB (Watson, 1995). The Songwe and Ruhuhu Rivers are Lake Malawi inflows that originate from these highlands.

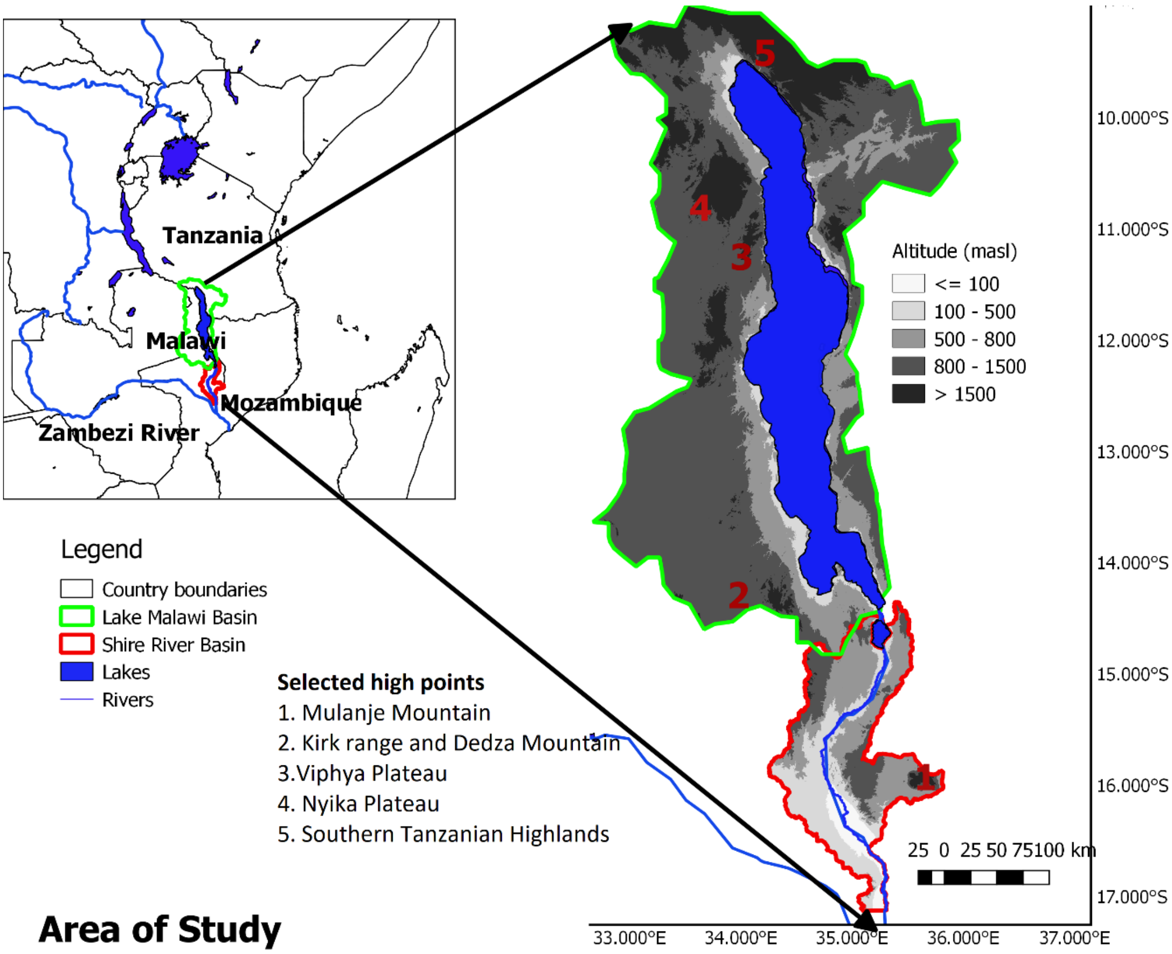


Figure I - 2 *The Lake Malawi and Shire River Basins in South-east Africa. The topography and river network in the basins are shown.*

[1]Source: https://en.wikipedia.org/wiki

2.2 Population of Malawi

The total population of Malawi was almost 18 million in 2018 and increasing at 2.9% per year. 93.8% of Malawi's population is in the GLMB where 55.9% is in LMB and 37.9% lies in SRB (National Statistical Office, 2018). The population has increased by 35% from 2008 to 2018, and at this growth rate, the population is expected to double by 2042 (National Statistical Office, 2018). The average population density has increased to 186 persons per square kilometre from 138 persons per square kilometre. The highest density is in Southern Region (244 persons per square kilometre) and lowest is in Northern Region (84 persons per square kilometre) (National Statistical Office, 2018). The increase in population is adding pressure on arable land (Mutunga et al., 2012) and other natural resources (Kelly et al., 2019). Hence it is not surprising to note that the Northern Region has a larger proportion of natural forests than the Southern and Central Regions (Kumambala, 2010).

2.3 Climate of Malawi

Climate of Malawi is tropical where mean annual rainfall ranges from about 800 over western Malawi and most parts of Southern areas to more than 1800mm over Northern LMB, along some lakeshore areas and around Mulanje Mountain in Southern Malawi, Fig I-3a. The rainfall season is predominantly from October to April over many places but stretches into May over Northern LMB. The pattern of rainfall has an east-west gradient where higher values are on the eastern areas. The mean air temperature in LMB has also the east-west gradient, highest temperatures are along the lakeshore areas. While cooler conditions are experienced over Northern LMB and some central and northern areas. But looking at the SRB, the temperatures are generally high with the highest values over lower Shire Valley. The mean annual temperature ranges from 18 to 26 °C Fig I-3b.

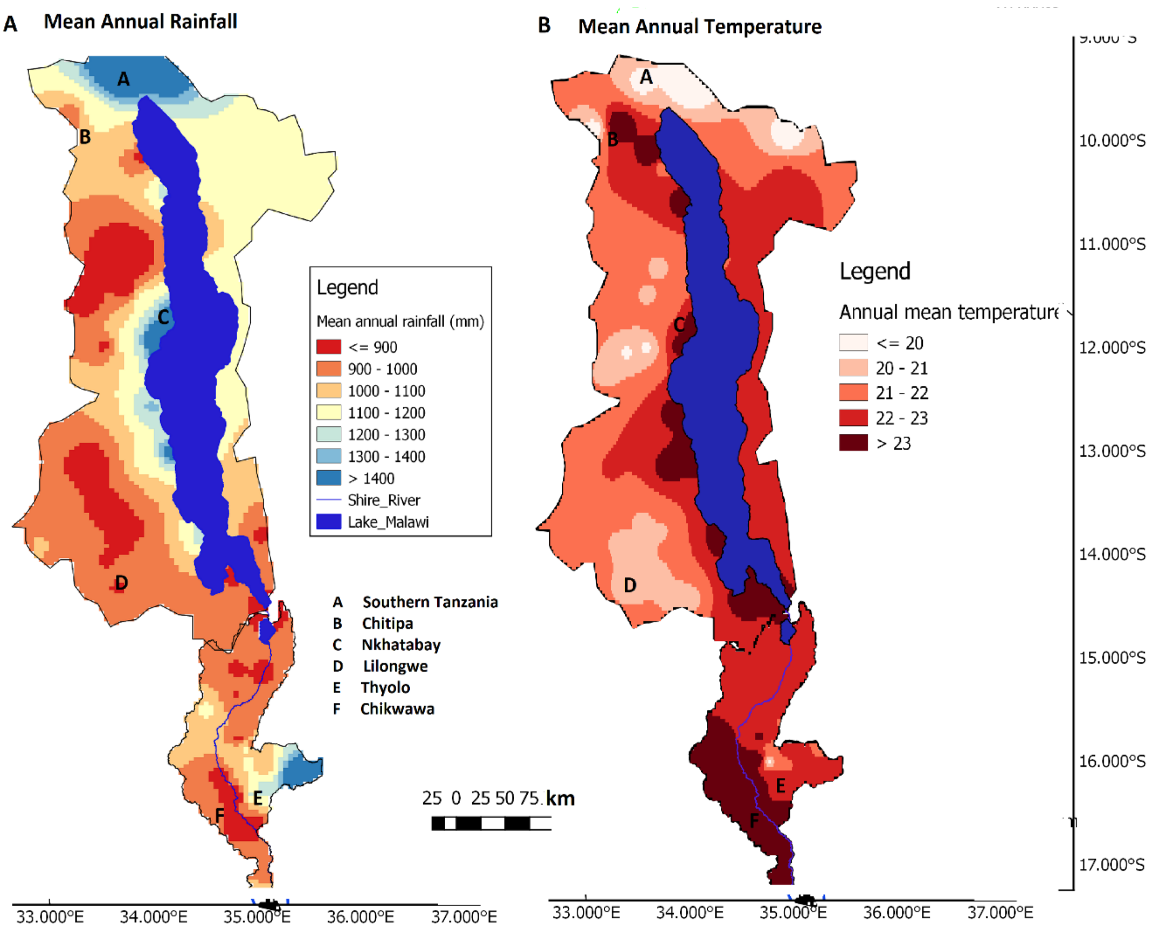


Figure I - 3 *The mean annual rainfall in mm (A) and mean annual temperature in °C (B) in the Lake Malawi and Shire River Basins. Labelled locations on the maps represent A Southern Tanzania, B Northern Areas-Chitipa, C Lakeshore Areas-Nkhatabay, D Central Plains-Lilongwe, E Southern Highlands-Thyolo and F Shire Valley-Chikwawa. Data source: Department of Climate Change and Meteorological Services in Malawi*

The northern LMB has longer rainfall season as it stretches into May and the highest amounts are experienced in April where rainfall gets up to 480mm on average during this month. The area gets about 200 mm of rainfall on average during the rest of the rainfall months of December, January, February, March and May Fig I-4A. The mean air temperature is highest in October and November up to about 24 °C while the coolest month is July with the average of about 16 °C. Due to the east-west rainfall orientation that exists in LMB, the rainfall is also high in March and April in Nkhatabay District along the lakeshore (Fig I-4C), where the mean average is over 300 mm. While the rest of the rainfall season months of December, January and February can get up to 200 mm on average. The temperature is highest in summer, especially in October, November and December where the mean temperatures being above 25 °C and up to 27 °C in November. The coolest month is July with the mean temperature of about 20 °C.

While the eastern side of LMB has also substantial amounts of rainfall during winter months (June, July and August), the western domain is generally dry during these months (Fig I-4B and D). But the rainfall amounts are highest in February (Fig I-4B) and January (Fig I-4D). The highest rainfall amount in Chitipa District (Fig I-4B) is in February of about 240mm on average, but December and January have also substantial rainfall amounts of about 200 and 220 mm respectively. Temperature-wise, the hottest month is also November with mean temperature up to 24 °C and the coolest is July with about 16 °C. The highest rainfall in Lilongwe District (Fig I-4D) in January is about 250mm on average and 200 and 180 mm in February and December respectively. Highest mean temperatures are also recorded in November of about 24 °C and July lowest temperature is about 16 °C.

In SRB, the highest rainfall months are in January in both Thyolo (Fig I-4E), and Chikwawa Districts (Fig I-4F). At Thyolo the mean January rainfall is 270 mm while in Chikwawa is 210 mm. The other rainfall months of December and February have values around 200mm for Thyolo and 150 mm for Chikwawa District. Thyolo District is cooler than Chikwawa, where the highest mean temperature is 22 °C in November and June is the coolest month with 16 °C. Located in Lower Shire Valley, Chikwawa is very hot, and the highest mean temperature of 28 °C is recorded in November and coolest is July with 21 °C.

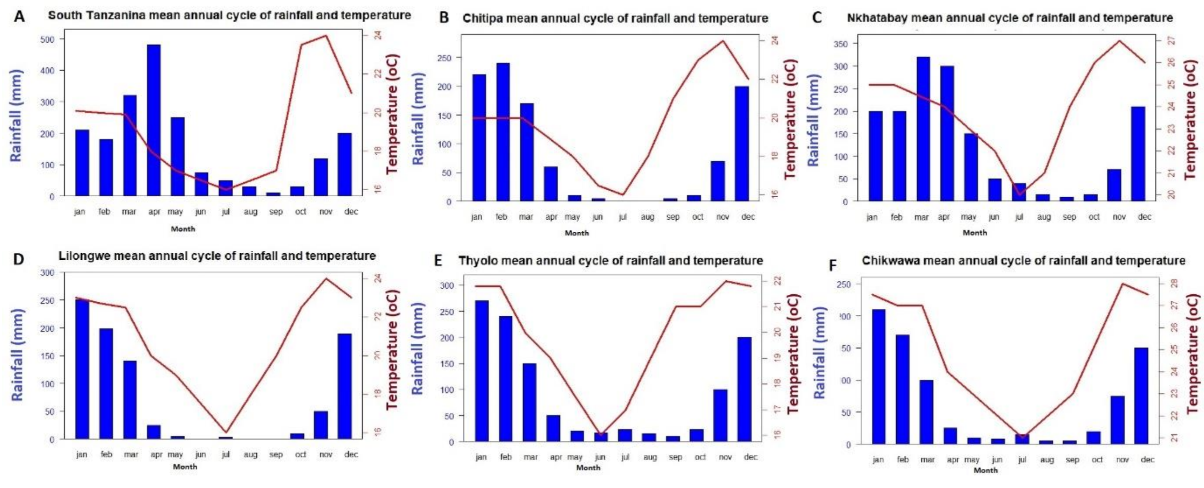


Figure I - 4 The monthly rainfall and temperature at various points in the Greater Lake Malawi Basin as shown in Fig. I-3. A Southern Tanzania, B Northern Areas-Chitipa, C Lakeshore Areas-Nkhatabay, D Central Plains-Lilongwe, E Southern Highlands-Thyolo and F Shire Valley-Chikwawa. Data source: Department of Climate Change and Meteorological Services in Malawi

2.4 Water Resources in Malawi

Malawi has a network of lakes, rivers and streams which cover about 21% of the total land area (MAIWD, 2012a). After Lake Malawi, one of the southern-most lakes in the East African Great Rift Valley, the other important lakes are Lake Chilwa, Lake Malombe, Lake Chiuta and Lake

Kazuni. Lake Malombe and Lake Kazuni are both located within the GLMB. Shire River is the biggest river in Malawi which is also the only Lake Malawi outlet (Fig I-5).

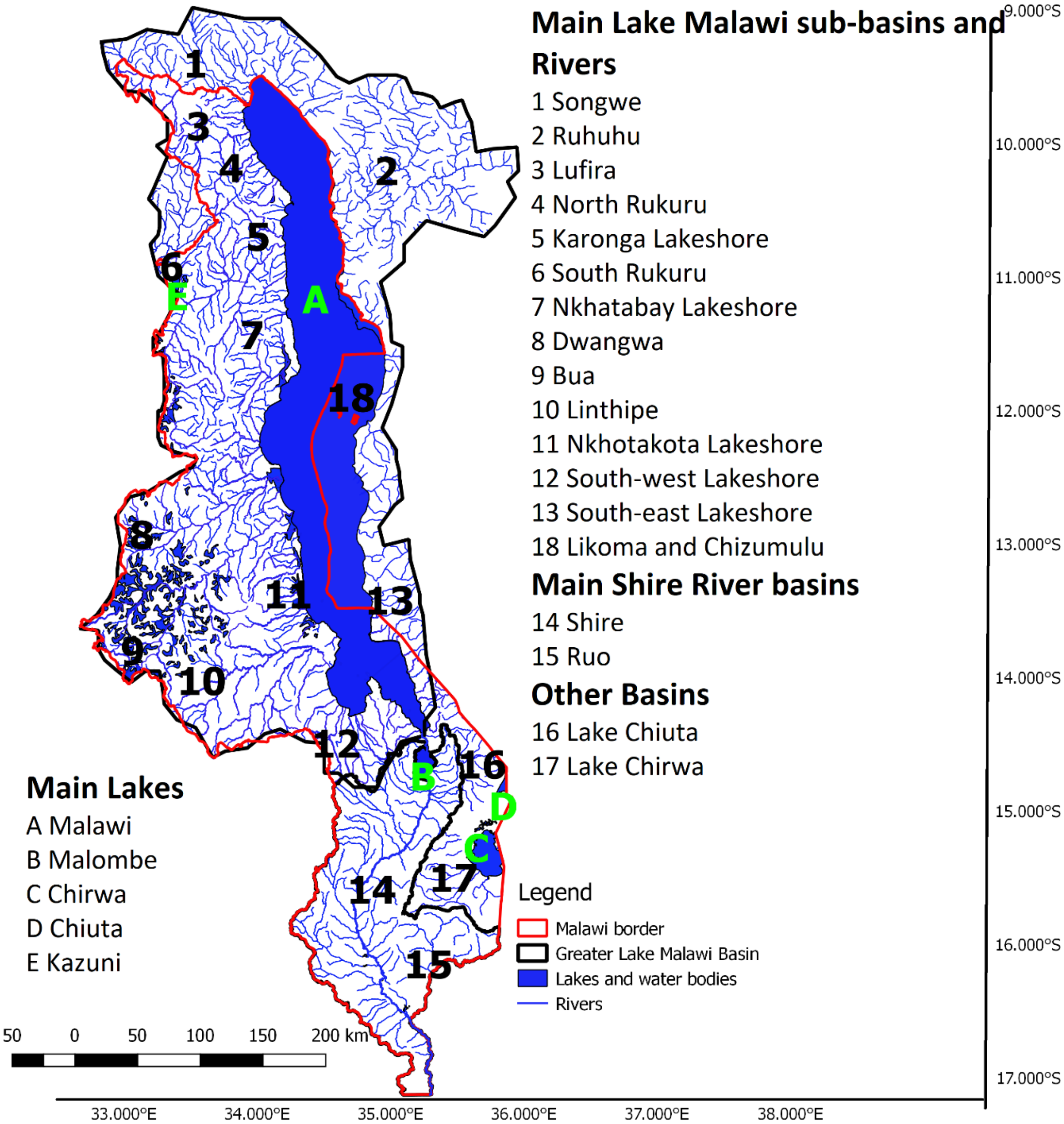


Figure I - 5 *The main water bodies and rivers in the Greater Lake Malawi Basin (GLMB). Also included in the figure are Lake Chilwa and Chiuta Basins.*

2.4.1 Lake Malawi

Lake Malawi is one of the southernmost lakes in the Great East African Rift Valley (Fig I-5 (**1**)) that is rich in almost 1000 fish varieties (Duponchelle & Ribbink, 2000). It is the third and nineth largest lake in Africa and the world respectively, but second deepest in Africa[2]. The Lake Malawi is about 560 km long and the maximum width is about 75 km with an average depth of 292 m. The lake has the surface area of 29 600 km^2 and has several tributaries that run from the escarpments and plateaux such as Ruhuhu (Fig I-5(**2**)) and Songwe Rivers (Fig I-5(**1**)) from Southern Tanzania Highlands, Lufira (Fig I-5(**3**)), North Rukuru (Fig I-5(**4**)), South Rukuru (Fig I-5(**6**)), Nkhatabay Lakeshore rivers including Luweya (Fig I-5(**7**)), Dwangwa (Fig I-5(**8**)), Bua (Fig I-5(**9**)), Linthipe (Fig I-5(**10**)), Southwest Rivers including Bwanje (Fig I-5(**12**)).

Lake Malawi level varies quite a lot both intra- and inter-seasonally. The lake level follows the rainfall patten as such the highest levels are during April and May while the lowest are in November and December Fig I-6B. The lowest lake level was in 1916 where the level reached 469.9 m.a.s.l.. and the highest ever recorded level was in 1980 with the level height of 477.2 m.a.s.l... (Fig I-6A).

The lake reports indicate that the outflow from the lake ceased completely during early 1900s. There are various speculations on the reasons that may have caused this interruption, including tectonic movements that lowered the lake basin thereby lowering the lake level, or the accumulation of sand bars from rivers at the head of Shire River that blocked the outflow, or the reduced rainfall (Drayton, 1984; Shela, 2000). However, there is the general decrease in lake level in 2010 decade (2010-2018) (Fig. I-6B), that has been associated with the reduction in hydropower production to more than half on the Shire River (ESCOM, n.d.a). The records show that the level decrease in 2010 period was similar to the reduction experienced in 1990 decade (1990-1999), Fig. I-6B, where the monthly mean level was about 474.1 m.a.s.l., bearing the range from 473 to 475.8 m.a.s.l.. The highest lake level records were observed in 1970 (1970-1979) and 1980 decades (1980-1989), where the mean monthly level was 475.7 m.a.s.l., ranging from 474.4 to 477.2 m.a.s.l.. Therefore, further understanding of the potential future lake level dynamics is essential for the management and the planning of the water resources in Malawi.

[2] https://en.wikipedia.org/wiki/Lake_Malawi

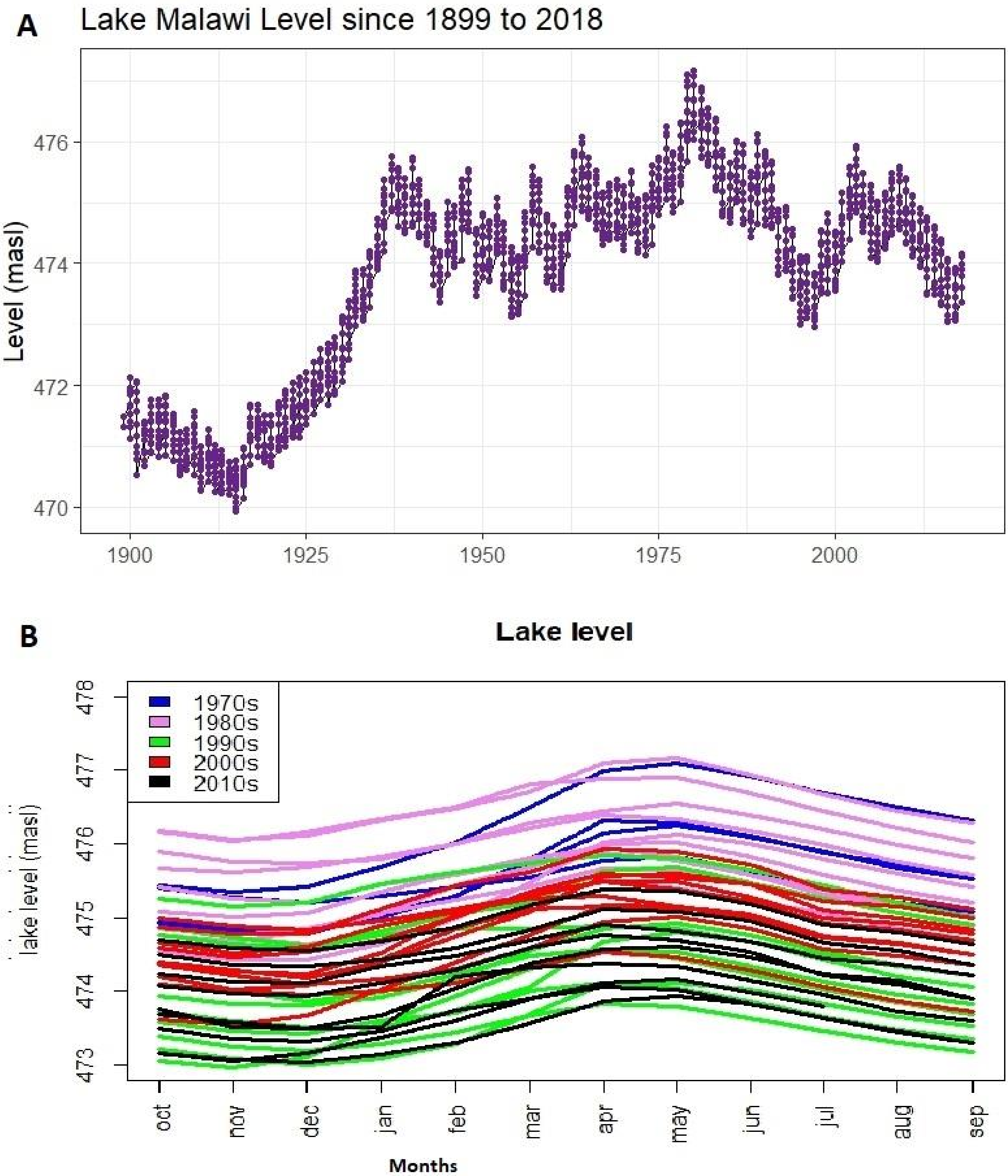


Figure I - 6 *Monthly Lake Malawi timeseries (A) and seasonal Lake Malawi level from 1970 to 2019 (B). Data Source: Department of Water Resources, Malawi.*

As observed from the previous studies, the Lake Malawi level is controlled by river inflows, precipitation over the lake, lake evaporation and outflow into the Shire River. The annual rainfall on the lake ranges from 30.1 to 33.9% of the annual lake water budget while annual evaporation is higher than rainfall between 39.4 and 42.1%. The lake inflow is in the range between 16.3 and 21.3% while the outflow from the lake is between 8.4 and 9.9% (Drayton, 1984; Kidd, 1983; Kumambala, 2010; Neuland, 1984). As most of the studies that looked at the water balance of the lake were conducted in 1980s, the comparison of these studies with

Kumambala (2010) has shown the decrease in rainfall and inflow while evaporation has increased. The knowledge of future evaporation vis-à-vis rainfall is important for the water balance of the lake.

2.4.2 The Shire River

The Lake Malawi outlet, Shire River, is 401km long[3] from Lake Malawi to Zambezi River. The river has many tributaries but the five major ones are Rivirivi, Lisungwi, Wamkulumadzi, Mwanza and Ruo Rivers. The supply of the water from minor tributaries is usually perennial and 80% of their contribution is during the rainy season between November and April (Moyo et al., 2013). The biggest Shire River tributary is Ruo that originates from Mulanje Mountain and flows along Mozambique-Malawi boarder before joining the Shire River at Chiromo. Ruo River has several tributaries including Lichenya, Likabula, Mloza, Mombezi and Thuchila that constitutes the Ruo catchment area of 4760km², and about 27% of the catchment lies in Mozambique (GOM, 2011).

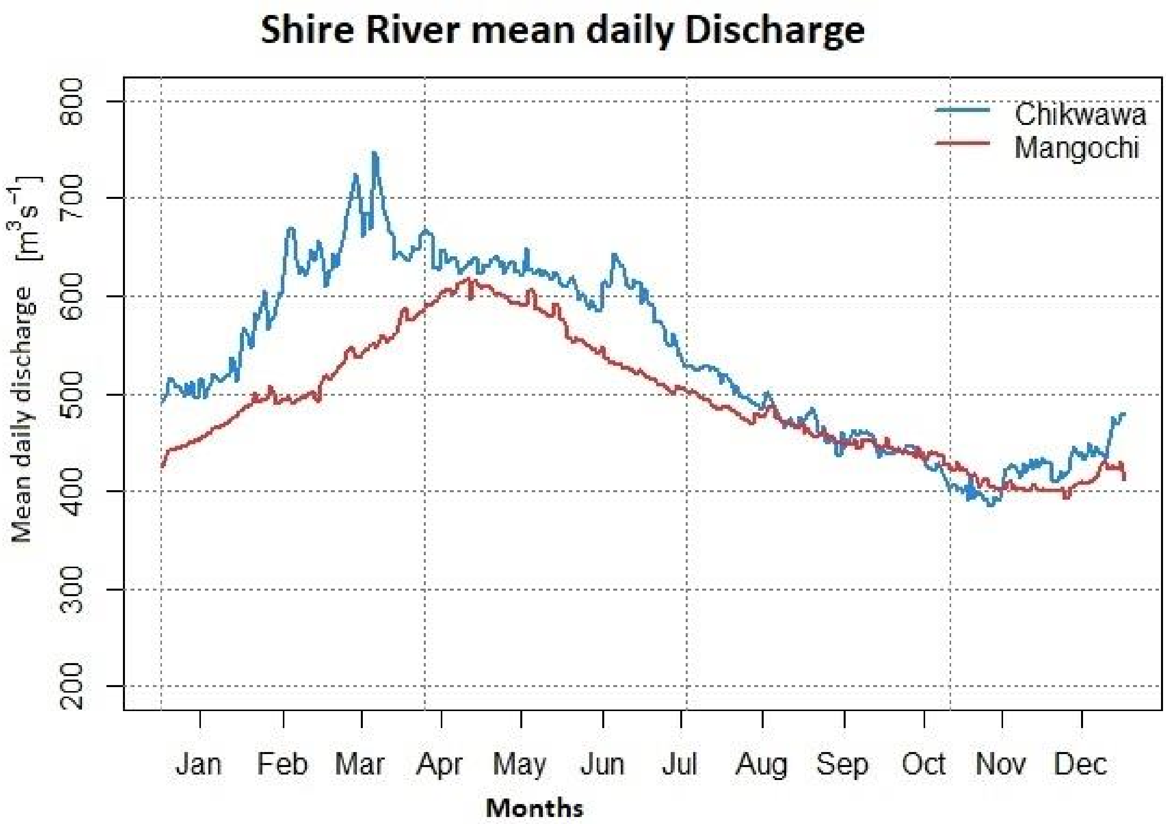


Figure I - 7 *Annual hydrograph of Shire River at Mangochi and Chikwawa.*

[3] https://en.wikipedia.org/wiki/Shire_River

The Shire River flow is highly variable (Fig 1-7) and the highest flows were in 1979 and 1980 which match with highest lake level in Fig 1-6a. The flow also exhibits the intra-annual variability where the highest flows are within February to June and lowest in October and November, Fig I-7.

The Shire River basin covers 16% (3.1 million hectares) of Malawi`s land (Mvuma, 2014) and 37.9% of country´s population is found in this area (National Statistical Office, 2018). Apart from generating hydro-power, the Shire River also supplies water for irrigation. The combined area under irrigation in both Lake Malawi and Shire River Basins was between 15 000 to 18 000 ha around 2003 (Mulwafu et al., 2003), but increased to about 43 000 ha in 2011 (MAIWD 2012b) which is about 3.5% of the agricultural land (MAIWD 2012b). The increase in irrigated land is associated with the increase in crop production from 4 million to about 1 billion kg per year (Nhamo et al., 2016). The main Southern Region cities and towns also draw water from the Shire River for domestic and industrial use and there is a steady increase in new water connections every year (Tiwale et al., 2018) as the population in the cities and towns is growing (Magombo & Kosamu, 2016; Tiwale et al., 2018). The riparian communities also depend on the same river for portable water. With increasing demand of water by different stakeholders, which was at 34% for domestic, 17% industrial and 49% agricultural use in 2003 (Mulwafu et al., 2003), it provides a quest to understand the availability of water in the future to satisfy the growing demand including power generation.

2.4.3 Other water bodies in Malawi

The other important water bodies in Malawi are Lake Chilwa, Malombe, Chiuta and Kazuni. Lake Malombe is about 20 km from Lake Malawi on Upper Shire River (Fig I-5 (**2**)). It is part of the Shire River Basin as water from Lake Malawi flows into Lake Malombe and then flows out again and continues as Shire River. The lake is about 6 m deep, 30 km long and 17 km wide with a surface area of about 450 km² (Dulanya et al., 2012). The main economic activity around the lake is fishing and approximately 65,000 people rely on the lake from the 65 fishing sites (Makwinja et al., 2021).

Lake Chilwa also lies in Southern Region (Fig I-5 (**3**)) and is 1.5 to 2.5 m deep, with a maximum depth of 5 m at the south-eastern part of the lake (Howard-Williams & Walker, 1974). The lake is surrounded by wetlands and marshes which are a home of more than 150 bird species (Wilson & Zeger, 1998). The surface area of the lake is about 700 km² (Howard-Williams & Walker, 1974) but including the wetlands the area is about 1750 km² (Van Zegeren, K Munyenyembe, 1998). The open water can cover 1500 km² in years with average rainfall (Njaya et al., 2011). The lake has a total catchment area of about 7000 km² (Howard-Williams & Walker, 1974). The Lake Chilwa which shares its catchment with Mozambique has a number of islands including Chisi (Kalanda-Sabola et al., 2008). The lake has several inlets and the main are Domasi, Likangala, Phalombe and Sombani Rivers in Malawi and Mnembo River from Mozambique (Howard-Williams & Walker, 1974) but no outlet. The Lake Chilwa is highly affected by siltation that promotes flooding. At the same time, the lake level fluctuates by 2 to 3 m which sometimes lead to a partial or complete drying of the lake. During the 20th century the dryness had occurred at least nine times (Njaya et al., 2011). The main economic activities around the lake are fishing and agriculture that includes rice cultivation (Njaya et al., 2011). Lake Chilwa's fishing alone contributes to about USD 21 million of Malawi economy (Chiwaula et al., 2012).

Lake Chiuta also lies in Southern Region, and shares boarders with Mozambique. Located north of Lake Chilwa, (Fig I-5 (**4**)), it is evidenced that Lake Chiuta and Chilwa were once connected during the late Pleistocene (Dissi & Njaya, 1995), hence what separates the two lakes is a

20 m sand bar (Njaya et al., 2000). The lake has a mean depth of 5 m and a total surface area of about 200 km² (FAO, 1994). It has several tributaries including Lifune, Chitundu and Mpili Rivers and the outlet is the Lugenda River which is a tributary to Ruvuma River in Mozambique (Njaya et al., 2000). There are a lot of fishing activities on the lake at about 23 sites including the lake islands of Big Chiuta, Small Chiuta, Nthambalale, Nanyowe, Likanye and Phiri la Nsatsi (Njaya et al., 2000).

2.4.4 Water access

The total renewable water resources in Malawi are estimated at 1 728 km³ per year and the water withdrawn from these resources is only at 7.9% (World Bank, 2015). Agriculture uses 79% of the withdrawn water and the rest is for domestic and industrial use (Nhamo et al., 2016). The population accessing potable water for domestic use is at 85% and the sources of water include piped supply, well (manual pumped, boreholes or protected wells), public standpipes and rainwater (Chidammodzi & Muhandiki, 2017; National Statistical Office, 2018). 61.7% of the population uses boreholes, 8.1% community standpipe and 10.3% piped water (National Statistical Office, 2018).

2.5 Land cover in Malawi

Chavula et al. (2011) classified land cover into four types in Malawi, water, cropland, savanna/shrub/woodland (SSW) and forest land. The predominant land cover was cropland in 2005 in LMB with 33.7%, forest cover 24.3%, water 22.1% and SSW 19.9%. Cropland increased by 18% from 1989 to 2002 in upper SRB due to population growth (Palamuleni et al., 2011) and much of the land was claimed from SSW (Chavula et al., 2011; Palamuleni et al., 2011). As the population increase is affecting the SSW due to agricultural expansion, it was also noted that energy and construction material demands have also contributed towards the declining of forests and SSW (Palamuleni et al., 2011). The forest cover in LMB declined from 64% in 1967 to 51% in 1990s (Calder et al., 1995). And comparing with 2019 land cover status from Copernicus Global Land Service (Buchhorn et al., 2020), it shows a big departure from the findings of Chavula et al.(2011). The forest cover was estimated at 34% (closed and open forest) while cropland was at 26%, water 20%, shrubs and herbaceous vegetation 18% and build-up area 2% in Lake Malawi and Shire River Basins (Fig. I-8). The differences could mainly be due to different classification methods used. But it is clearly noted that most of the forest cover had remained in designated areas such as Forest reserves, National Parks and Game reserves (Kelly et al., 2019). The rate of deforestation was at 3.5% per year from mid-1970s to late 1980s, but declined to 1.6% by 1994 since the forested land had deteriorated (Environmental Affairs Department, 1994). The land use changes are modifying the river flows which include high peak stream flows, reduced base flows, enlarged river channel and increased siltation (Palamuleni et al., 2011).

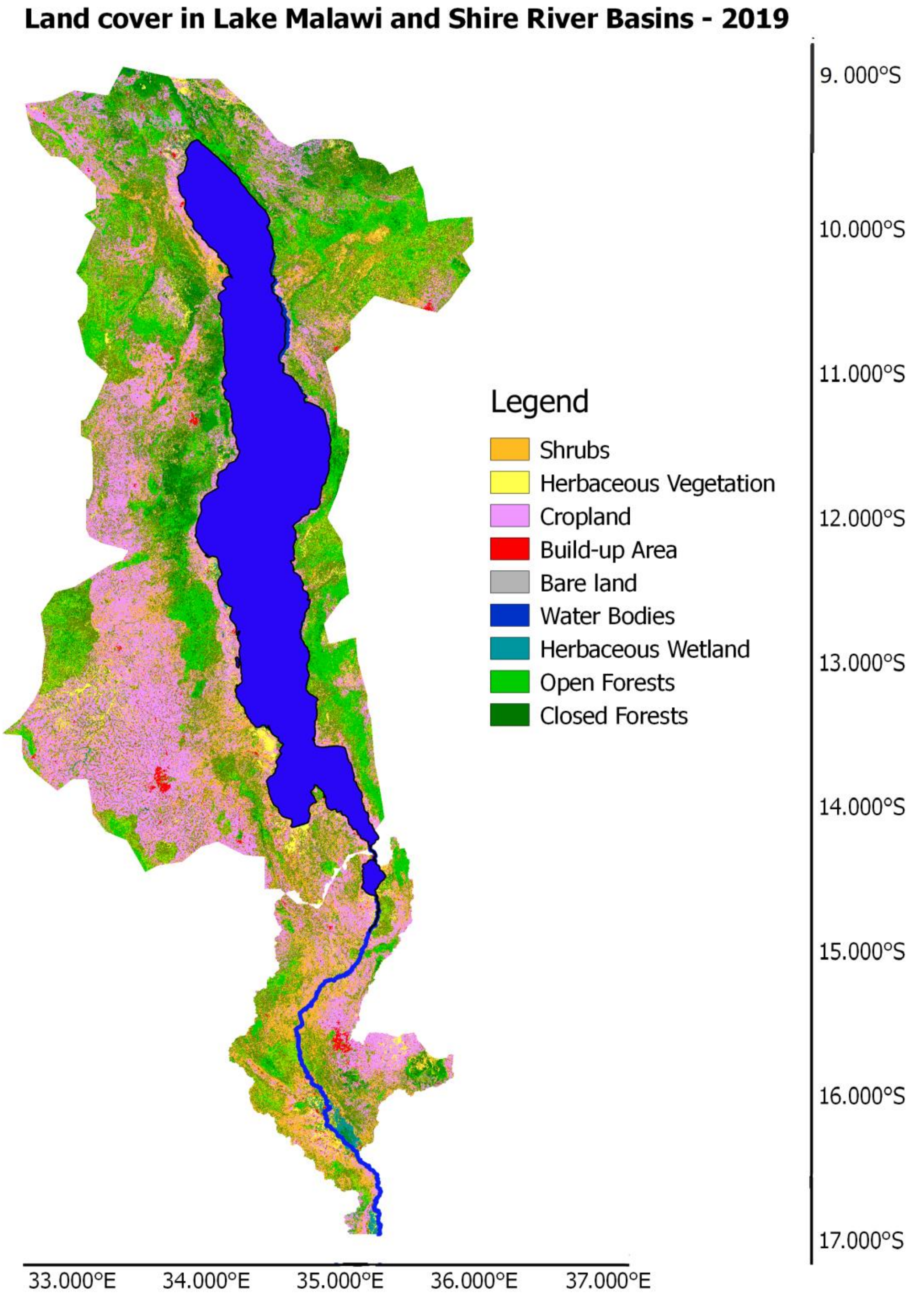


Figure I - 8 *Land cover in Lake Malawi and Shire River Basins in 2019. Source: Copernicus Global Land Service (Buchhorn et al., 2020) https://lcviewer.vito.be/2019.*

2.6 Energy in Malawi

The predominant energy source in Malawi is biomass which takes about 88.5%, followed by petroleum fuel 6.4, electricity 2.8 and coal 2.4% (Kambewa & Chiwaula, 2010). Woodlands are a primary source of energy in a form of firewood (55.9%) and charcoal (44.1%) (Chavula et al., 2011) that is mainly used for household cooking. Therefore, the population increase is exerting pressure on the woodlands as the energy demand increases. By 2015, the population that was accessing electricity at least for lighting was at 10% (Taulo et al., 2015) and increased to 11.4% in 2018 (National Statistical Office, 2018). Otherwise, other lighting sources range from cell batteries 52.9%, solar 6.6% and firewood 4.4% (National Statistical Office, 2018). There is a plan by Malawi Government to increase electricity access to 30% by 2030 and also making it 100% sustainable (Borgstein et al., 2019).

3. The climate change, drought and water resources assessment

3.1 Assessing current climate change

The trend analysis is one of the methods that is used to assess the change signal in timeseries. The purpose of performing trend analysis is to determine whether there is either an increasing or decreasing trend in a series. There are commonly two ways when a trend can occur, and these are: monotonic trend; thus, when the change is gradual over time and step trend; where the shift is abrupt (Meals et al., 2011). The trend analysis can be applied on a site data and does not require calibration. It can even be applied to large waterbodies such as lake levels that are responding to various processes (Meals et al., 2011) such as evaporation, rainfall, inflow and outflow.

Trend analysis is usually applied to observed climate data to assess historical climate change signals. An example of commonly used method is the non-parametric Mann-Kendall (MK) test (Kendall, 1975; Mann, 1945). The MK test which is based on the ranked-transformed time series identifies the presence of the monotonic trend in the timeseries without any assumptions on the underlying statistical distribution. Unlike the parametric methods, the MK method is more robust against outliers, skewed distribution and missing data as such it is also commonly applied in climatological and hydrological studies (Mondal et al., 2012; Ngongondo et al., 2011, 2015). However, though the trend analysis indicates the direction of change, it does not provide the cause of change. And the MK test has also challenges for data with seasonal effects (Meals et al., 2011) therefore, it is recommended that all periodic effects be removed before applying the MK test (Pohlert, 2017). It was also found that parametric tests are more sensitive to detect significant trend than nonparametric tests (Meals et al., 2011).

3.2 Assessing future climate change

The assessment of future climate change depends on the climate models such as the Coupled Model Inter-comparison Project 5 (CMIP5) General Climate Models (GCMs) which are used in this study. This study begun before Coupled Model Inter-comparison Project 6 (CMIP6) General Climate Models (GCMs) were developed. CMIP5 which is the predecessor of the Coupled Model Inter-comparison Project 3 (CMIP3) produces the model dataset that is designed to address climate variability and climate change. The models are used for many climate change studies around the globe and some contribute towards the assessment reports by the Intergovernmental Panel on Climate Change (IPCC, 2018). The models produce the climate projections from mid-nineteenth century to the 21st century and beyond (Taylor et al., 2012) and are performed by Earth System Models of Intermediate Complexity (EMICs) that respond to time-varying concentrations of various atmospheric constituents; the Atmosphere–Ocean Global Climate Models (AOGCMs), that include the representation of the atmosphere, ocean, land and sea ice; and Earth System Models (ESMs), that take a full carbon cycle and include biogeochemical components that account for the flux of carbon between ocean, atmosphere and terrestrial biosphere carbon reservoirs (Taylor et al., 2012). The CMIP5 models are driven by emission scenarios based on mitigation assumptions that assume that some actions will be taken to achieve certain emission targets. The scenarios are based on the range of future population growth, technological development and societal responses. One of the widely used emission scenario is Representative Concentration Pathway 8.5 (RCP8.5) which is the business as usual (high emission) scenario where the radiative forcing increases throughout the twenty-first century before reaching 8.5 W/m^2 at the end of the century (Taylor et al., 2012). The low emission scenario RCP2.6 (peak scenario) is in which the radiative forcing reaches a maximum near the middle of the twenty-first century before decreasing to 2.6W/m^2. The scenario is aimed at keeping the temperature increase below 2° C by reducing 70% of greenhouse gases from the baseline (Vuuren et al., 2011). In between the RCP8.5 and RCP2.6 are RCP4.5 and RCP6, the mid-range scenarios. The RCP4.5 is the moderately controlled scenario that incorporates moderate population growth and economic growth, while the forest area increases as the crops and grassland decline (Wise et al., 2009) to stabilise the radiative forcing at 4.5 W/m^2 in the year 2100. Finally, the RCP6 is the scenario that employs high greenhouse gas emission rate in conjunction with a stabilization setting that includes a range of technologies that reduces the emissions and hence stabilise the radiative forcing at 6.0 W/m^2 by 2100 (Masui et al., 2011). The GCMs have usually a horizontal resolution in range between 250 and 600 km. This resolution and inadequate atmospheric process description (Bronstert et al., 2007) limits the application of GCMs at regional scales on impact models.

To fit the GCMs into impact assessment needs at regional scales, models are sometimes downscaled. There are various methods of downscaling including dynamical approach that incorporate the regional limited area models (LAM) that use GCM outputs as the boundary conditions to estimate regional climate usually at a finer scale. In this case, the outputs are dependent of the GCM that they are derived from (Prudhomme et al., 2002). The COordinated Regional climate Downscaling Experiment (CORDEX) has used 22 GCMs to provide driving conditions for over 35 Regional Climate Models (RCMs) on 14 domains including Africa. The downscaling is applied on 0.44°, 0.22° and 0.11° grid resolution and generates the historical, RCP2.6, RCP4.5 and RCP8.5 scenarios[4].

The other commonly used method is statistical downscaling approach that employs the relationship between the atmospheric variables generated by the GCMs and locally measured climate variables such as rainfall on the assumption that there are certain physical relationships (Prudhomme et al., 2002; Themeßl et al., 2012). The statistical methods include multiple-regression, artificial neural network (ANN) and empirical orthogonal function (EOF) analysis. Compared with dynamical approach, the statistical methods assume that the physical relationships exist regardless of the internal changes, that may not be true with climate change (Prudhomme et al., 2002).

It is however, noted that despite that GCMs are downscaled, the bias usually still exits. Therefore, the downscaled models are sometimes bias corrected. There are various methods of bias correcting model outputs, and these include: delta method, scaling method, empirical quantile mapping, histogram equalisation (Déqué, 2007; Maraun et al., 2010; Piani et al., 2010; Themeßl et al., 2012; Lange, 2019; Casanueva et al., 2020). Different methods provide varying results that is why bias correction methods are found to contribute 35% of the uncertainty in the future projections (Wu et al., 2021).

3.3 The climate change impact assessment on the hydrological systems

Usually, hydrological models use climate variables from GCMs or downscaled outputs (GCM-RCMs) as inputs to obtain the impacts of climate or climate change on water resources, and this is referred to as top-down approach. In addition, some studies have used the scenario-

[4] Retrieved from (https://cordex.org/wp-content/uploads/2020/12/Summary_CORDEX_simulations_Nov_2020.pdf)

neutral method (Prudhomme et al., 2010) that involves the systematic linear scaling of input variables (rainfall and temperature) to the reference period. Thereafter, the possible range of climate impacts are generated to provide the estimate on how the water resources respond to climate change. Furthermore, in this project, the impacts of climate change on hydropower are derived from the possible future changes of Shire River discharge.

The hydrological models are derived from the water cycle that comprise of the water movement between cycle's compartments ice, oceans, land and atmosphere and the water storages in different parts and areas of these compartments. There are many processes that contribute towards the movement and these include; precipitation, evaporation, transpiration, runoff, percolation, interflow and routing. Rainfall that is usually collected at the various points is one of the inputs into the hydrological model. The water from the precipitation is either infiltrated into the soil, or becomes the surface runoff or evaporated back into the atmosphere. Infiltration and runoff are functions of land cover type, soil structure and slope that contribute towards the roughness of the land surface and the storage capacity of the soil. The evaporation and transpiration depend on the temperature, land cover type, while the interflow (which is the flow of water within soil layers) also depends on soil type and terrestrial sloppiness which contribute towards the hydraulic conductivity of the land. Finally, routing which is the movement of water downstream is the collection of all water from interflow, runoff and precipitation into a river channel. The comprehensive hydrological model covers all these components including properties of glaciers and snow in areas where they are applicable. This shows how complex the hydrological model can be, as all these processes have various parameters to consider.
There are many types of hydrological models depending on the processes that are employed as well as the sampling procedures. The simpler model type is the lumped model, that considers the entire river basin as a single unit, as such only one constant set of parameters is used for the whole basin (Devi et al., 2015; Ranit et al., 2014). This is an easy model to compute however, the problem is that it does not take into consideration the physical and dynamical spatial variations (Devi et al., 2015). An example of these models is GR model (Génie Rural Journalier) (Coron et al., 2017). The improved model is the distributed model that divides the catchment into sub-catchments that sometimes are subdivided further into hydrologic response units (HRU) in that way parameters vary in space. In most cases the parameters are distributed using the discretisation schemes on a grid which are at high resolution to capture ground water models (Anderson et al., 2015). Examples of much applied distributed hydrological models are SWAT (Soil and Water Assessment Tool), SHE (Système Hydrologique Europeén), mHM (mesoscale Hydrologic Model**)** or VIC model (Variable Infiltration Capacity model) (Devi et

al., 2015; Marhaento et al., 2017; Refsgaard et al., 2010; Liang et al., 1994). In between these two hydrological model types are semi-distributed models that calculate the hydrological processes at selected few spots in the basin. The process involves grouping areas of similar parameters and examples of these models are HBV model (Hydrologiska Byrans Vattenavdelning model) and TOPMODEL (Topography-based Hydrological Model).. (Beven et al., 2021; Devi et al., 2015). The use of the complex model in the impact-based analysis does not guarantee better results, as there are other factors that contribute towards the effectiveness and skill of the model including data availability. Surely, an extensive and detailed spatial units in the model should match with adequate data points (Santos et al., 2018).

In this study, an mHM model is adapted in Lake Malawi and Shire River Basins. A model developed by Samaniego et al. (2010) at UFZ (Helmholtz Centre for Environmental Research) is scalable and has been applied in various basins of varying sizes (Samaniego et al., 2010; Thober et al., 2019; Eisner et al., 2017; Kumar et al., 2013; Kumar et al., 2013; Rakovec et al., 2016). mHM is a grid based conceptual hydrologic model that is based on numerical approximations applied in common hydrologic models such as HBV (Samaniego et al., 2010).

3.4 The assessment of droughts

Many studies have used the standardised precipitation index (SPI) (Mckee *et al.* 1993) that has been found to better explain the dry (meteorological droughts) and wet (floods) periods than other statistical measures such as percentiles (Bordi et al., 2007). Since the SPI is calculated based on rainfall only, does not take into account the changes in water balance associated with evapotranspiration (temperature) changes. Therefore, the standardised precipitation and evapotranspiration index (SPEI) (Vicente-Serrano et al., 2010) is also applied in some cases to cater the temperature effects on droughts. For hydrological droughts, various indices exist but many such as Palmer hydrological drought index (PHDI) and surface water supply index (SWSI) require a lot of datasets (Nalbantis, 2008). However, the simplest method is streamflow drought index (SDI) that is calculated in a similar way like SPI (Nalbantis, 2008). The challenge with this method is that it may underrepresent in big catchments like Lake Malawi basin, unless if it is applied at multiple sites of the lake's tributaries, though this may also be difficult due to data scarcity. As evaporation is an important element on tropical lakes (Kumambala & Ervine, 2010), the hydrological drought index that captures the water balance of the lake may represent the catchment better. In this study, we introduce the lake level change index (LLCI), that is calculated in similar way as SPI. This makes also easier to compare meteorological droughts with hydrological droughts in a basin since they use similar statistical calculations.

3.5 Sensitivity tests of climate change

According to many climate change studies including Sherwood et al. (2020), the climate sensitivity is generally defined as the quantitative measure of the vulnerability or susceptibility of the earth's climate to human influence. Many consider how the earth will warm up with doubling of atmospheric carbon dioxide (CO_2) concentration compared with pre-industrial period. The warming is found to lie within 1.5° C and 4.5° C per doubling of CO_2 with the assumption that all other factors remain unchanged (Sherwood et al., 2020). The knowledge of climate change due to CO_2 increase supports the climate impact estimates of anthropogenic global warming.

However, in this study the sensitivity tests take a slightly different approach taken from Prudhomme et al. (2010) who introduced scenario-neutral approach. The method involves the systematically perturbed climate (e.g., rainfall and temperature) inputs into impact models such as hydrological models to simulate possible environmental system response to the changes of climate. The temperature and rainfall parameters are scaled within a range of possible change linearly (Vormoor et al., 2017). The target variables assessed from the impact hydrological models could be runoff or lake levels which can later be used to analyse peak flows, floods or drought. The outcomes can be plotted on a two-dimensional domain (e.g., temperature vs rainfall) referred to as response surface where the target variable is presented (Vormoor et al., 2017). Each point on the surface represents the average change of the variable resulting from the combined change of rainfall and temperature. The projected climate models can also be added on the surface to determine the possible future climate impact (Vormoor et al., 2017). The approach has been applied in various fields such as agriculture (Hirschi et al., 2011), ecology (Fronzek et al., 2011) and hydrology (Prudhomme et al., 2010; Vormoor et al., 2017).

3.6 Challenges and limitations

There are always assumptions that are taken into consideration when applying various methods that provide some limitations and challenges in climate change studies. The involvement of multi-model approach in the climate change impact assessments is faced with uncertainties across the whole model chain setup, from the availability and quality of input (initial) data to climate models'- and impact models' systems (Bosshard et al., 2013; Gusev et al., 2017; Joseph et al., 2018; Kay et al., 2009). Even though the uncertainties exist, that does not hinder the decisions made from the impact studies (Knutti & Sedláček, 2013), but however, it is recommended to communicate the uncertainties to support informed decisions.(Bloschl & Montanari, 2010).

The trend analysis and calibration of hydrological models for instance, require long and continuous dataset, which is not always easy to acquire. And various climate change studies, only use rainfall and temperature (Pinto et al., 2016; Russo et al., 2016; Shongwe et al., 2009) in their analysis which assumes that other climate parameters are being embodied by these two which may not be right considering the complex nature of the climate and hydrological system. The scarcity of data sometimes forces the estimation of evaporation (evapotranspiration) to be based on temperature alone (Al-Sudani, 2019) which is also rarely verified due to lack of evaporation measurements (Bautista et al., 2009; Van Der Schrier et al., 2011). In some instances, researchers combine different datasets (Contractor et al., 2020; Di Luzio et al., 2008) which may compromise the quality of the data. In addition, to obtain the best and reliable discharge data for the tributaries in many African countries for the calibration and testing of the models is a challenge as many rivers are not gauged regularly (Brocca et al., 2020; Mwale et al., 2014).

GCMs have also limitations that provide some uncertainty in the projected future climate (IPCC, 2007b). One of the major sources of uncertainty in GCMs is cloud parameterisation scheme as this parameterisation is performed using large-scale model variables and yet cloud processes often occur on smaller spatial scales (Wang & Su, 2013). Therefore, different cloud parameterisation in GCMs results into large differences in the simulated future climate among GCMs (Wang & Su, 2013). The tropical region has also its own uncertainty due to the differences in the convective parameterisation schemes (Wang & Su, 2013). So even though in some studies there are similar sign of the GCMs' rainfall outputs within the ensemble members in the tropics, the spread of the models is usually large (Shongwe et al., 2009; Wang & Su, 2013). Furthermore, capturing the feedback that comes with the changes in climate by models is still a challenge (Bloschl & Montanari, 2010). The other uncertainty with GCMs is downscaling procedures from low to higher resolution. Over the years, several methods and approaches have been developed that are either dynamical or statistical and these different methods provide different outcomes (Prudhomme et al., 2002; De Sales & Xue, 2011; Wilby and Wigley, 1997). The statistical downscaling also demands good quality and high-resolution observation data to establish the empirical relationship with the GCM outputs (Yoon, 2012) which is not usually available. It is also not always correct that the finer the resolution the better the results (Taylor et al., 2012). Though low-resolution scale has lower variability due to some local variations that offset each other when spatially averaged (Taylor et al., 2012). This is why when comparing gridded GCM output with point data some spatial mismatch is expected and in many cases they also fail to pick extreme events (Mtilatila, 2010; Zhu et al. (2004)). All in all, the dynamical downscaling methods are computationally expensive and, in some cases, do not simulate precipitation well (Cubasch et al., 1996) and that creates model biases (Graham et al., 2007; Taylor et al., 2012). There are also some discrepancies when comparing simulated outputs and observations due to failure by the models to capture the timing of the unforced variabilities such as El Niño Southern Oscillation (ENSO) as the initiation of the historical runs are based on an arbitrary point of a quasi-equilibrium control run (Taylor et al., 2012). The uncertainties and discrepancies among the ensemble members call for the use of the ensemble mean (Jin et al., 2007; Van Loon et al., 2012) of the models in some cases. Though the mean provides the consensus representation of the climate, the knowledge of the spread of the members provides the level of the confidence on the consensus (Taylor et al., 2012).

The hydrological models have also their own share of uncertainty (Joseph et al., 2018; Thober et al. 2018)). Apart from the uncertainty that comes with data scarcity, there are also vagueness due to model structure (Seiller et al., 2012) and model parameters (Wagener et al., 2001). And also, different approaches produce differing outcomes that is why it is recommended to include a range of alternatives at each step within the model chain to capture the associated uncertainties (Bosshard et al., 2013; Hagemann et al., 2013). It is however, also observed that the hydrological models and their relevant parameters are stationary and that creates challenges in their application towards the transient climate and hence applying the same parameters to both present and future conditions is the major limitation (Vormoor, 2016). There are studies that have indicated that the use of a single hydrological model underestimates the uncertainty in flood analysis (Dankers et al., 2014).

4. Research questions, objectives and structure of the thesis

The thesis has used various indicators and approaches to study both meteorological and hydrological droughts and their drivers. The trends of drought drivers and drought indicators including the relationship between meteorological and hydrological droughts are established. Using dynamical hydrological models, climate models and statistical approaches, the study has evaluated the future drought changes; examined the sensitivity of the hydrological system of the GLMB towards the changes in key climate elements (temperature and rainfall); estimated the potential impacts of future climate change on droughts and the hydrological system by means of scenario-neutral response surfaces; and finally estimated the future changes of hydropower production and reliability. The study has attempted to respond to the following questions:

(1) What are the changes in the hydro-meteorological drivers for droughts; and do these impact meteorological drought characteristics in the GLMB?

(2) How does temperature (evapotranspiration/evaporation) affect meteorological droughts?

(3) How are meteorological and hydrological droughts related to each other in the study area?

(4) How reliable are (bias-corrected) climate models in simulating meteorological drought characteristics in the Greater Lake Malawi Basin?

(5) As climate is expected to change in the future, what are the expected changes in future drought characteristics like their intensity, duration and number of occurrences as compared to the recent past in this region?

(6) How sensitive are lake levels and discharges to variations in precipitation and temperature in the GLMB?

(7) What are the impacts of future climate change projections on the water budgets of the GLMB, and how do these impacts translate into changes in hydropower productivity and reliability?

There are three studies that have been conducted to address the research questions. The studies are presented in chapters II, III and IV within this thesis. Tab. I.1 is the list of the objectives of the three studies and the approaches that are used to address them.

Table I - 1 *The outline of study objectives addressed by the three studies and the corresponding approaches applied*

Study	Research questions	Objectives	Main approaches
I	(1) – (3)	i. To study the changes and trends in rainfall, temperature, evaporation and lake level variations; and ii. Their implications on drought occurrence, duration, severity, frequency and intensity in the GLMB. iii. To establish the relationship between meteorological and hydrological droughts in the study area.	i. Meteorological droughts are estimated using Standardised Precipitation Index (SPI) and Standardised Precipitation and Evapotranspiration Index (SPEI) ii. The hydrological droughts are estimated using the newly proposed lake level change index (LLCI) iii. Mann-Kendall tests and Sen’s slope are used to detect trends and slopes.

II	(4) and (5)	i. To assess the reliability of climate models in simulating meteorological drought characteristics in the GLMB. ii. To assess the severity of the future droughts in relation to historical events.	i. The Coordinated Regional Climate Downscaling Experiment (CORDEX) models for Africa are used for the future projections. ii. The models are bias corrected using empirical quantile mapping (EQM) method iii. The sensitivity tests of temperature and rainfall are applied to determine their effect on meteorological drought characteristics and models' temporal structures which are presented on response surfaces. Meteorological droughts are also assessed based on SPEI as in study I.
III	(6) and (7)	i. To examine the sensitivity of the GLMB hydrological system towards the climate change. ii. To estimate the potential impacts of the future climate change on the hydrological system. iii. To estimate the future changes of hydropower generation.	i. The climate models in study II are also applied in this study to obtain the possible future changes of lake level, lake outflow and Shire River discharge. ii. The sensitivity tests that were applied in study II are also applied here to summarise the potential range of changes of lake level, Shire River discharge, hydropower production and hydropower reliability on a two-way dimension response surfaces. iii. The hydrological models are Shire River discharge at the hydropower stations is used to estimate hydropower productivity and reliability.

To address the research questions (1) to (3) the Study I in Chapter II of this document assesses the variability and trends of both meteorological and hydrological droughts from 1970 to 2013 in Lake Malawi and Shire River basins using the standardized precipitation index (SPI) for meteorological droughts. To determine the effects of temperature on droughts in the GLMB, standardized precipitation and evapotranspiration index (SPEI) is comparatively used. The newly proposed lake level change index (LLCI) is applied to assess the hydrological droughts. Trends and slopes in droughts and drought drivers are estimated using Mann-Kendall test and Sen's slope, respectively. The studies that combine both meteorological and hydrological droughts and seek the relationship between the two are rare in Malawi, and the hydrological drought analysis in the GLMB rarely uses the lake level of Lake Malawi and yet is the vast water resource in Malawi. The change in lake level signifies the overall result of water balance of LMB.

The research questions (4) and (5) in Study II, Chapter III of this document employs the use of SPEI that is used in Study I to estimate the future drought characteristics which are compared with historical period to determine the changes. The climate models are bias corrected using the empirical quantum mapping (EQM) method. The sensitivity tests of temperature and rainfall are also applied to determine not only their impacts but also the effects of the models' temporal structures on drought characteristics which are presented on the response surfaces for meteorological water balance (MWB), drought intensity (DI), total drought months (DM) and drought events (DE). This is the neutral-scenario approach where daily temperature (additive) and rainfall (multiplicative) are systematically perturbed and the generated values are used to generate SPEI. The CORDEX models downscaled dynamically for Africa based on two scenarios Representative Concentration Pathway 4.5 (RCP4.5) and Representative Concentration Pathway (RCP8.5) for 2021-2050 and 2071-2100 periods are used to determine possible future climate (rainfall and temperature). The models' changes are overlaid on the response surfaces to determine the range of drought characteristics. The spread of the ensemble members indicates the uncertainty of the impacts (Wetterhall et al., 2011).

While in Chapter IV of this document, Study III addresses the research questions (7) and (8). The mesoscale Hydrological Model (mHM) is applied separately on LMB and SRB to simulate the lake inflow and Shire River discharge respectively. The Lake Malawi Model (LMM) that focuses on reservoir routing processes and lake water balance is interlinked in between the two mHMs to generate the dynamics of lake level and lake outflow (Fig. I-9).

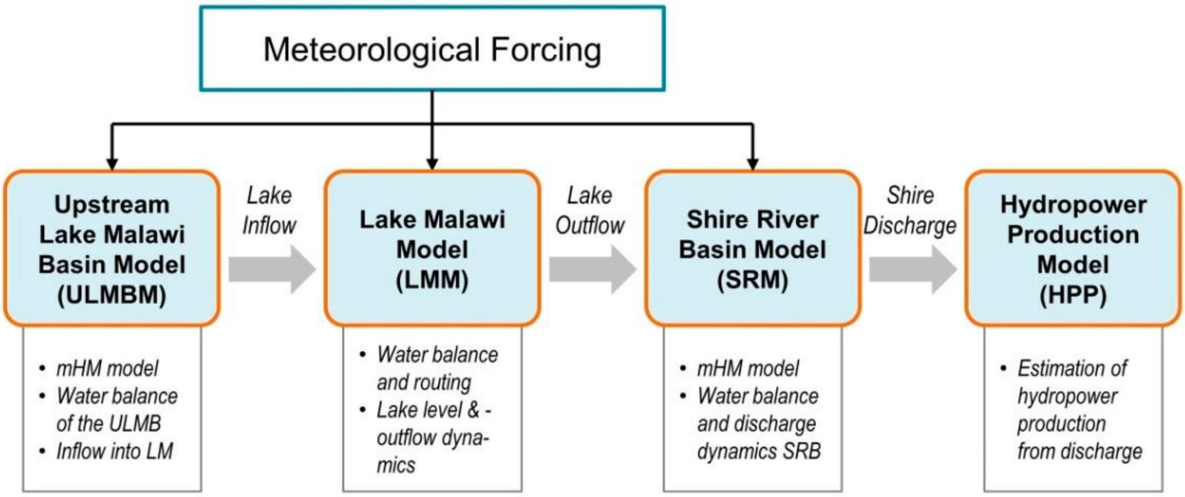


Figure I - 9 *The cascade model arrangement that was used in study III. mHM is modified for Upstream Lake Malawi Basin Model (ULMBM) and Shire River Basin Model (SRM). Lake Malawi Model (LMM) is interlinked in between the ULMBM and SRM. Hydropower Production (HPP) model estimates the power production.*

The climate information is fed into the hydrological models to determine the lake inflow, lake level and Shire River flows from which the hydropower production is derived. To determine the susceptibility of water resources in GLMB, the sensitivity tests using neutral-scenario approach like in Study II are also applied where the range of possible lake levels, Shire River discharge, hydropower production and hydropower reliability are presented on the two-dimensional response surfaces. Then again, the results from the top-down approach of the ensemble climate members of the GCM-RCMs are also overlaid on the matrix to visualise the projected range of future impacts.

Chapter V concludes by summarising the main achievements of the three studies according to the research questions and their contributions to the research world. The chapter also relates the findings with the International Climate Change Protocols and Agreements as well as the Sustainable Development Goals.

5. Publications and Author's Contribution

The three studies presented in this thesis are separately published or accepted for publication in international peer-reviewed journals. The articles have been reproduced as they have been published. However, cross-references to figures, tables, equations and sub-chapters have been adjusted wherever required. The studies are as follows:

Study I: L. Mtilatila, A. Bronstert, G. Bürger, K. Vormoor, 2020, Meteorological and hydrological drought assessment in Lake Malawi and Shire River (1970-2013). *Hydrological Sciences Journal*, Vol. 65, No. 16, 2750-2764, https://doi.org/10.1080/02626667.2020.1837384

Study II: L. Mtilatila, A. Bronstert, K Vormoor, 2022, Temporal Evaluation and Projections of Meteorological Droughts in the Greater Lake Malawi Basin, Southeast Africa. *Front. Water*, 4:1041452. doi: 10.3389/frwa.2022.1041452

Study III: L. Mtilatila, A. Bronstert, P. Shrestha, P. Kadewere, K. Vormoor, 2020, Susceptibility of water resources and hydropower production to climate change in the tropics: The case of Lake Malawi and Shire River Basins, SE Africa. *MDPI-Hydrology*, 7, 54, https://doi.org/10.3390/hydrology7030054

II Meteorological and hydrological drought assessment in Lake Malawi and Shire River Basins (1970-2013)

Abstract

The study assesses the variability and trends of both meteorological and hydrological droughts from 1970-2013 in Lake Malawi and Shire River basins using the standardized precipitation index (SPI) and standardized precipitation and evapotranspiration Index (SPEI) for meteorological droughts and the lake level change index (LLCI) for hydrological droughts. Trends and slopes in droughts and drought drivers are estimated using Mann-Kendall test and Sen's slope, respectively. Results suggest that meteorological droughts are increasing due to a decrease in precipitation which is exacerbated by an increase in temperature (potential evapotranspiration). The hydrological system of Lake Malawi seems to have a >24-month memory towards meteorological conditions since the 36-months SPEI can predict hydrological droughts ten-months in advance. The study has found the critical lake level that would trigger hydrological drought to be 474.1 m.a.s.l.. The increase in drought is a concern as will have serious impacts on water resources and hydropower supply in Malawi.

Mtilatila, Lucy *et al.* (2020) 'Meteorological and hydrological drought assessment in Lake Malawi and Shire River basins (1970 – 2013)', *Hydrological Sciences Journal*. Taylor & Francis, 65(16), pp. 2750–2764. doi: 10.1080/02626667.2020.1837384.

1. Introduction

Droughts are natural hazards that may affect many regions in the world, not exclusively limited to (semi-) arid areas only. They generally arise due to shortage of water availability which may result from the interaction of various factors including meteorological, hydrological, or water management conditions. However, a comprehensive definition of droughts is hardly available due to the range of possible causes, complex interactions and feedbacks between them, and different impacts on nature, society and the economy. Due to this variety, WMO (2012) and Spinoni et al. (2014) distinguish four different drought categories ranging from meteorological and hydrological droughts to agricultural and socio-economic droughts. Meteorological drought refers to lack of rainfall compared to long-term means while hydrological drought refers to water availability deficits leading to shortages in consumable water resources. Agricultural drought is defined as soil water deficits for crops, and socio-economic drought refers to consequences of water shortages that restrict access to water or to goods and services that rely on the availability of water. Various statistical measures are available that describe the duration, frequency, and severity of droughts based on different thresholds and predictors (Mishra & Singh, 2010).

The Southern African region is frequently affected by water shortages. Rouault and Richard, (2005) studied droughts from 10 degrees south (which covers parts of Malawi) and identified eight severe drought years from 1901 to 1999. Based on the Standardised Precipitation Index (SPI), they found the worst droughts in terms of extent area covered at the 6-month-scale in (1916, 1924, 1933, 1949, 1970, 1983, 1992 and 1995) and at the 2-year scale (1906, 1933, 1983, 1984, 1992, 1993, 1995 and 1996). They further found an increase in areal drought extension in Southern Africa from the 1970s onwards, and the particularly intensive and extended droughts between 1970 and 1998 were linked to the southern oscillation index (SOI) (Richard et al., 2001). Similarly, Rouault and Richard, (2005) found an increase in the frequency of droughts in Southern Africa from 1980.

Water resources in Malawi highly depend on the hydrology of Lake Malawi and its basin. As the ninth largest lake in the world (in terms of water volume), it is the key water resource and reservoir for hydro-power generation on the Shire River, which originates at the only southern outlet of the lake. The capacity installed and electricity generated at the seven hydropower plants on the Shire River account for 80.2% and 98%, respectively, of the country's total electricity power (Taulo *et al.*, 2015). Because of the utmost importance of Shire River flow for electricity production, lake level fluctuations of Lake Malawi affect lake outflow and thus impacts power generation enormously. For instance, the below normal rainfall seasons of 2014/2015 and 2015/2016 resulted into falling lake water levels and reduced river flows, which decreased power production by more than 50 % (ESCOM, n.d.-b). Between 1915 and 1935, outflow from the lake into the Shire River was even totally interrupted (Shela, 2000), which nowadays would lead to a complete failure in energy supply. As the demand of electricity is increasing, hydropower will maintain its position as the main source of electricity in the short to medium term compared to other energy sources in Malawi. To date, there are plans to invest into more hydropower stations on the Shire River to secure future energy demands (GOM, 2010; Millenium Challenge Corporation, 2015). However, the impacts of climate change related modifications of the hydrological cycle on hydropower productivity in Lake Malawi and Shire River basins have barely been investigated, yet.

In addition to the importance for hydropower production, Lake Malawi and the Shire River supply water to adjoining cities and towns. The lake and river also supply water for irrigation purposes at crop plantations. As such, the recurrence of droughts leads to intensive water rationing in Shire River basin as it was the case in 2015/2016 (World Bank, 2017). Also affected by the occurrence of droughts is the fishery industry which plays a considerable role both on Lake Malawi and Shire River. Lake Malawi has extraordinary fish richness as it contains between 500 and 1000 fish species and 99% of these are cichlids which are endemic in Lake Malawi (Duponchelle & Ribbink, 2000). All these aspects illustrate the economic importance of the lake and the Shire River, and it highlights the importance of a proper basin management for the availability, sustainability and accessibility of water resources.

The literature reveals that below normal rainfall amounts in the past have affected the economy of Malawi in various sectors including hydropower generation, hydrology and agriculture (Fisher et al., 2015; Makoka, 2008; Pauw et al., 2011). Combined droughts and floods effects contribute to at least 1.7% loss of Malawi’s gross domestic product (GDP) each year (Pauw et al., 2011). In this perspective, the recurrence of droughts might increase the vulnerability of many affected households as it contributes to rise in food shortages, -food prices, -farm inputs prices and -household business failures (Makoka, 2008).

Strategies to either reduce the impacts of or enhance resilience to droughts are essential in all sectors including hydropower generation. However, this requires the full understanding of weather events and their effects on economy (Pauw et al., 2011). For Malawi, several drought studies have focused on drought impacts and adaptation based on drought insurance (Syroka & Nucifora, 2010), drought tolerant crops (Fisher et al., 2015; Holden & Fisher, 2015), food security and nutrition (Babu & Chapasuka, 1997), household vulnerability (Makoka, 2008) and ground water management (Calow et al., 1997). In addition to Richard *et al.* (2001) and Rouault and Richard (2005), who have investigated meteorological drought dynamics at much broader spatial scales, Munthali *et al.* (2003) identified six drought events during the 20th century in Malawi and attributed five of them to El-Niño Southern Oscillation (ENSO). A link of the Pacific Ocean dynamics to extreme rainfall in Malawi was also found by Jury and Gwazantini (2002), and Jury (2014) who attributed floods and drought to large scale circulations from both in the Pacific and Indian Oceans. Zuzani *et al.* (2019) found that the Shire River Basin has the potential of experiencing hydrological droughts due to observed decreasing minima of both rainfall and streamflows.

In this study, we consider drought dynamics of Lake Malawi Basin (LMB) and the upper part of the Shire River Basin (SRB) both from a meteorological and hydrological perspective. By using several meteorological and hydrological drought indicators, we intend to study changes in rainfall, temperature and evaporation dynamics as well as lake level variations and their implications on drought occurrence, -duration, -severity, -frequency and -intensity in the LMB and SRB. We also seek to establish the relationship between meteorological and hydrological droughts in these socio-economically important region. The following specific research questions are addressed by this study:

(1) What are the changes in the hydro-meteorological drivers for droughts; do these impact meteorological drought characteristics in Lake Malawi- and Shire River basins?

(2) How does temperature (evaporation) affect meteorological droughts?

(3) How are meteorological and hydrological droughts related to each other in the study area?

2. Study area and data

2.1 Study area

The LMB is located in South-Eastern Africa and shares borders with Malawi, Tanzania, and Mozambique (Fig. II-1). It covers an area of 125,500 km² including the lake surface area of 29,600 km². The LMB lies in the East African rift valley where the lake surface is at around 457 m.a.s.l. and the land rises from the lake to high plateaus. The highest points of the basin reach elevations of more than 2000 m.a.s.l. Much of the land in the basin has experienced massive land cover changes from woodlands to mostly cultivated land (Palamuleni *et al.*, 2011). For instance, the agricultural land has increased by 18 % from 1989 to 2012 in Shire River upper catchment (Palamuleni *et al.*, 2011). The forest cover in LMB has decreased from 64 % in 1967 to 51% in early 1990s (Calder et al., 1995).

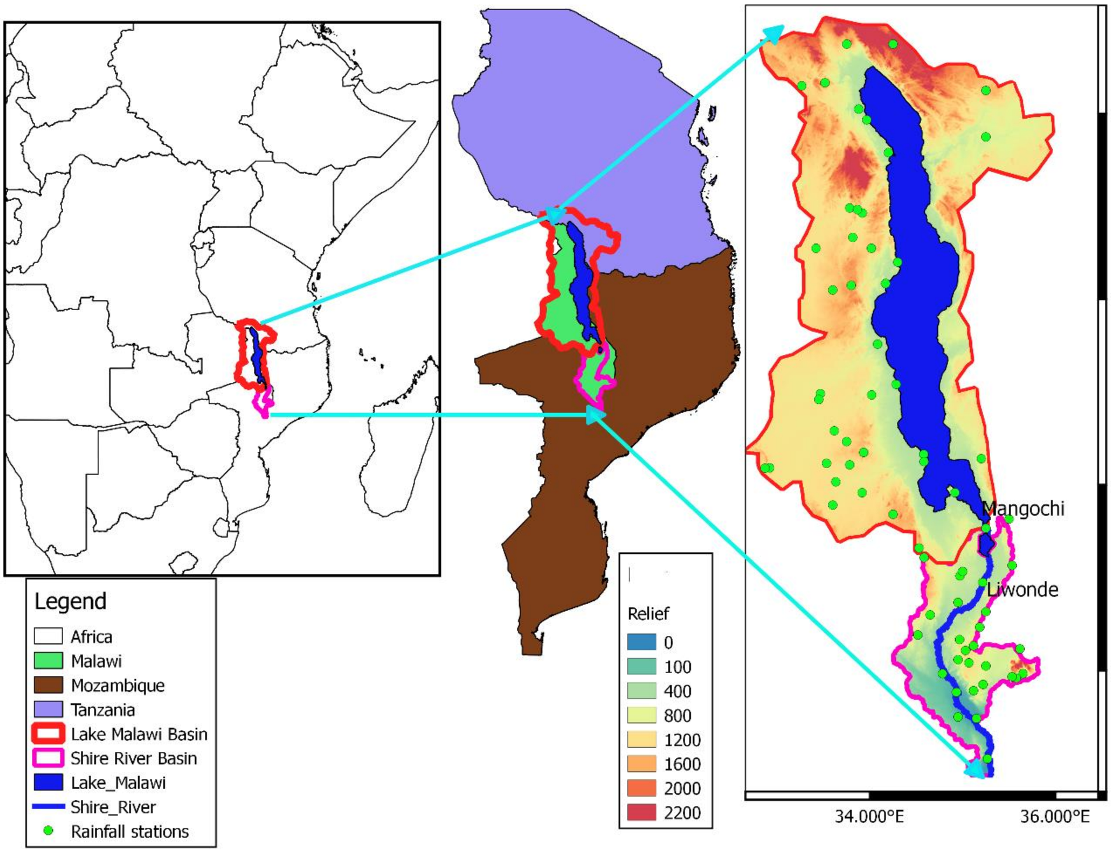


Figure II - 1 *The study area, Lake Malawi and Shire River basins.*

The lake has more than nine major tributaries, and it drains into its only outlet in the south, the Shire River. As such, the lake is the main reservoir for hydropower generation on the Shire River. In size, the Shire River has a catchment area of 23,500 km² and is 401 km long before it drains into the Zambezi River in Mozambique. The middle Shire, where hydro-power generation takes place is 80 km long and is characterized by deep gorges with steep slopes. The hydraulic gradient of 370 m provides a considerable potential for hydropower generation (Shela, 2000).

The climatology of both the LMB and SRB is dominated by tropical climate throughout the year and a pronounced rainy season is between October and April. The largest rainfall amounts fall between December and April (maximum mean value in January is 240 mm, Fig. II-2). It is generally dry from June to September with monthly rainfall below 10 mm on average. Mean annual rainfall ranges from 800 to more than 1800 mm. The LMB shows a west-east gradient with larger rainfall amounts towards the eastern part of the domain, around the lake area, Fig. II-2.

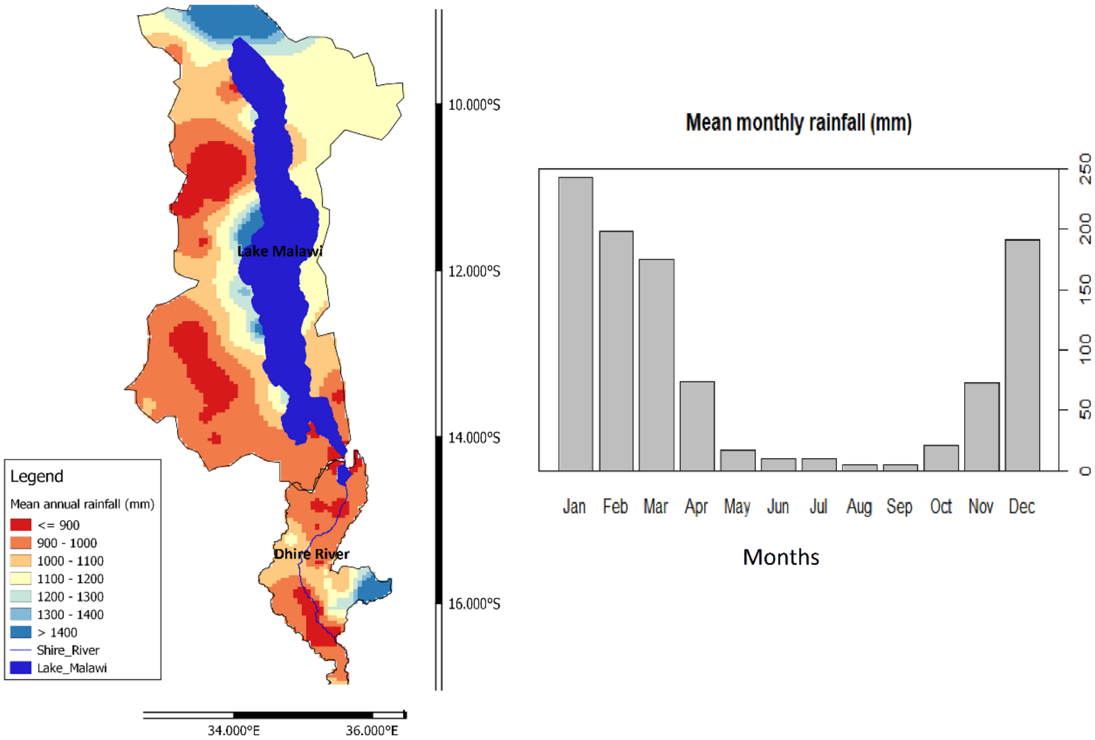
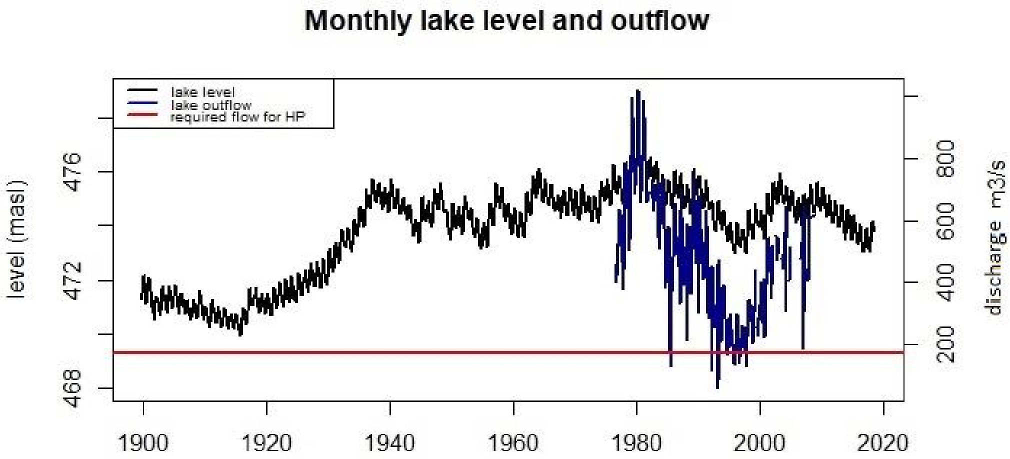


Figure II - 2 *The mean annual rainfall pattern and monthly mean rainfall in Lake Malawi and Shire River basins.*

The annual and seasonal variability of lake levels highly affects discharge in the Shire River (Fig. II-2), which requires a firm river flow of > 170 m^3s^{-1} for sufficient hydropower generation (Shela, 2000). High flows occur from January to May and the lowest flows usually occur in October and November. About 80 km downstream of the outlet at Liwonde (Fig. II-1), a barrage was constructed in 1960s to control water flow for hydro-power generation. The barrage operates only at lake levels between 473.2 and 475.32 m a.s.l. Although the barrage is 80 km downstream from the outlet, literature indicates that backwater still affects the outflow from the lake so that the lake level is 0.2 m to 0.6 m higher due to the control of the barrage (Drayton, 1979; Kidd, 1983; Shela, 2000). Drayton (1984) and Calder et al. (1995) concluded that changes in lake level are highly attributed to rainfall, and land use change effects were less significant. The water balance of LMB is

$$\frac{dS_b}{dt} = P_b - E_b - Q_{out}, \qquad \text{(Equation II-1)}$$

where P_b is basin rainfall, E_b is basin evapotranspiration, Q_{out} is outflow and $\frac{dS_b}{dt}$ is change in storage, which is mainly expressed by changes in lake level which is assumed that the surface area is constant with height. It is assumed that at longer time scales, the water received in the catchment will be transferred to outflow at the lake outlet at Mangochi (Fig. II-1), if it is not lost by evaporation. The water balance of the LMB is mainly driven by rainfall and evaporation since only between 16.3 % to 19.5 % of the water received in the basin from rainfall is transferred to outflow and the rest is lost by evapotranspiration, (Drayton, 1984; Kidd, 1983; Neuland, 1984). Since Eq. II-1 considers the whole lake basin area, changes in lake inflow through the lake tributaries are assumed to be inherently included and reflected as part of changes in lake level.



Parameter	Minimum	25th percentile	Mean	75th percentile	Maximum
Lake level (from 1970) m.a.s.l.	472.97	474.39	474.93	475.44	477.16
Lake outflow (m^3/s)	57.11	315.28	473.92	610.40	1020.94

Figure II - 3 *The lake level and -outflow. Statistical parameters are from 1970 to 2013 for lake level and from 1976 to 2009 for outflow.Red line is the flow required for maximum hydropower generation.*

2.2 Data

The climate data utilised in this study is obtained from the Department of Climate Change and Meteorological Services in Malawi. Daily rainfall data from 65 locations in the LMB and SRB (Fig. II-1 (far-right)) is used covering the period 1970-2013. Since the LMB covers parts of Tanzania and Mozambique, rainfall data in this region is complimented with gridded 0.5° resolution Global Precipitation Climatology Centre (GPCC) at four grid points and it is retrieved from https://climatedataguide.ucar.edu/climate-data/gpcc-global-precipitation-climatology-centre (Schneider et al., 2018). GPCC rainfall data has been found to reasonably represent rainfall characteristics in this region (Mtilatila, 2010). Since GPCC is estimated from station data, its performance increases with number of stations per grid. For instance, the Pearson correlation between GPCC and station rainfall data in Malawi ranged between 0.82 in one station per grid cell to 0.94 with seven stations (Mtilatila, 2010). The temperature data used in this study is from the Climatic Research Unit (CRU), University of East Anglia, and can be obtained from http://www.cru.uea.ac.uk/data. Monthly lake level and daily lake outflow datasets are provided by the Department of Water Resources in Malawi and available from 1899 to 2015 and 1976 to 2009, respectively.

3. Methods

3.1 Meteorological drought estimation (SPI and SPEI)

Several drought indices have been developed in recent years, and all of them aim to quantify drought characteristics in a certain way (Mishra & Singh, 2010). One of the most commonly used drought indices to quantify meteorological droughts is the standardized precipitation index (SPI) which is also applied in this study. The SPI is developed by Mckee *et al.* (1993) and it is used to quantify precipitation excess and -deficits, respectively, over a certain period (usually several months). The estimation of the SPI is based on long-term observation records, which are transformed to a normal distribution after they have been fitted to a probability density function. In turn, the mean and median of the long-term record is zero. The SPI of monthly rainfall can then be interpreted as the number of standard deviations by which a certain monthly rainfall deviates from the long-term mean. Mathematically, the SPI is defined as the difference between monthly precipitation on a given time scale x_i and the mean value $\bar{x}$ of the entire observation period, divided by the standard deviation, σ:

$$\mathrm{SPI} = \frac{x_i - \bar{x}}{\sigma} \quad \text{(Equation II-2)}$$

Long term precipitation of at least 30 years is recommended for the estimation of the SPI (WMO, 2012), and in this analysis, the SPI refers to the rainfall record period from 1970 to 2013. The SPI can quantify the precipitation anomalies for various time scales. For the sake of water resources, and also the vastness of Lake Malawi basin, 12 consecutive months or more are preferred in this study.

However, precipitation-based drought indices like SPI neglect the importance of (increasing) temperature effects on drought conditions since they assume other variables than precipitation to be less variable and stationary in time. Considering heat-stress amplified drought situations, e.g. in Europe during summer 2003, 2018 (Rebetez et al., 2006; Vogel et al., 2019), the importance of temperature and evapotranspiration for drought conditions is evident, and increasing temperature may potentially exacerbate drought situations. To account for this issue, we also estimated the standardized precipitation and evapotranspiration index (SPEI). The SPEI is computed similarly to the SPI, with the difference that x_i and $\bar{x}$ in Eq. 2 do not represent precipitation but the meteorological water balance (MWB), i.e. the difference between precipitation and potential evapotranspiration (PET) (Vicente-Serrano *et al.*,2010). Here, we used the Thornthwaite (1948) equation to model monthly PET as this method requires only sunshine hours and temperature as data input:

$$\mathrm{PET} = 16.\frac{S}{12}.\frac{d}{30}.\left(\frac{10.t}{I}\right)^{\propto},$$ (Equation II-3)

where *S* is sunshine hours, *d* is total days of the month, and *t* is average temperature. *I* is the annual heat index which is calculated as a summation of monthly heat indices *i* (Vicente-Serrano *et al.*,2010):

$$i = \left(\frac{t}{5}\right)^{1.514}$$ (Equation II-4)

The comparison of the SPEI with the SPI then allows for the insights of the relative role of temperature (PET, respectively) on drought situations in the study area.

3.2 Hydrological drought estimation based on lake level change index

Since this study also aims to investigate (trends in) hydrological droughts and their relationships to meteorological droughts, we need to apply an estimation of hydrological droughts which is comparable to the meteorological drought indices. As illustrated in chapter 2.1, changes in lake level highly depend on rainfall characteristics, and streamflow within the Shire River highly depends on the outflow from the Lake Malawi which is dominantly controlled by the lake level. Therefore, we applied a similar analysis as Shukla and Wood (2008), who compared a standardized runoff index (SRI – computed similarly to the SPI but with runoff instead of precipitation) with the SPI in a river basin in Northern California. Instead of runoff, we focused on lake level variations by introducing the lake level change index (LLCI) which incorporates hydrologic processes that describe the response lag of precipitation on lake level. This provides a further understanding of the impact of meteorological droughts on lake level, which may designate hydrological droughts within the LMB and potentially in the SRB due to the close relation between lake level and outflow from the lake. Therefore, corresponding to the SPI, LLCI is calculated as follows:

$$\mathrm{LLCI} = \frac{\mathrm{l_i} - \bar{l}}{\sigma}, \qquad \text{(Equation II-5)}$$

where l_i represents monthly lake level over a given time scale (here 12 months), $\bar{l}$ is the lake level mean over the period 1970-2013, and σ is the standard deviation of normalized lake level. Analog to the interpretation of the SPI and SPEI, the LLCI for a certain month represents the number of standard deviations from the long-term median lake level.

3.3 Definition of drought characteristics

Positive SPI, SPEI and LLCI values indicate greater than median (wet, higher), and negatives values indicate less than median (dry, lower) conditions and lake level, respectively. Referring to Mckee *et al.* (1993) and WMO (2012), the interpretation follows criteria where a meteorological drought starts when the SPI (SPEI, LLCI) value is equal or below -1 and ends when the SPI (SPEI, LLCI) turns positive (Tab. II-1). The start- and end-point of a meteorological- or hydrological drought provide its duration (DD) in terms of number of months. The lowest SPI (SPEI, LLCI) value obtained during the certain drought duration (DD) is the intensity of the drought (DI). The absolute accumulated SPI (SPEI, LLCI) values over drought duration (DD) indicate the drought severity (DS) (Dayal *et al.*, 2017).

Table II - 1 *Modified standardised precipitation index (SPI) classification. Information source: World Meteorological Organization (2012). (Standardised precipitation and evapotranspiration index (SPEI) and lake level change index (LLCI)).*

SPI (SPEI, LLCI) value	Explanation	Drought intensity
> 2.0	Extremely wet	No drought
1.5 to 1.99	Very wet	No drought
1.0 to 1.49	Moderately wet	No drought
-0.99 to 0.99	Near normal	No drought
-1.0 to -1.49	Moderately dry	Moderate drought
-1.5 to -1.99	Severely dry	Severe drought
< -2	Extremely dry	Extreme drought

In this study, moderately dry -1 ≤ SPI (SPEI, LLCI) ≤ -1.49 is defined as moderate drought, severely dry -1.5 ≤ SPI (SPEI, LLCI) ≤ -1.99 is a severe drought and extremely dry SPI (SPEI, LLCI) ≤ -2 is an extreme drought (Tab. II-1). Drought frequency (DF) is the number of drought events at a particular location from 1970 to 2013. The percentage of total drought months from 1970 to 2013 is also presented to provide further information in cases where less frequent droughts take place for a longer period of time. The spatial extent of a certain meteorological drought event is estimated by the number of stations that show corresponding SPI (SPEI) <-1 during the particular event. Obviously, the drought characteristics described above are not independent from each other. They only serve to characterize detected drought events and to identify potential differences in spatial patterns.

3.4 Trend analysis

The non-parametric Mann-Kendall (MK) test (Kendall, 1975; Mann, 1945) is used to obtain trends in lake level, rainfall, temperature and the drought characteristics described in chapter 3.3. The MK test is based on ranked-transformed time series so that it can only identify the presence of monotonic trends in a particular time series but it cannot quantify its absolute magnitude. The main advantage of the MK test is that it is non-parametric and, thus, does not require any assumption regarding the underlying statistical distribution of the time series. This makes the MK test highly robust towards skewed distributions which are often characteristic of environmental data.

The MK test examines the null hypothesis that the data come from a population with independent realizations and identical distribution, i.e., that the time series is independent from time with no trends. The alternative hypothesis is that the random variable of a distribution follows a monotonic trend over time. The MK S-statistic is calculated as:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \mathrm{sign}(\mathrm{x_j} - \mathrm{x_k}), \qquad \text{(Equation II-6)}$$

where

$$\mathrm{sign} = \begin{cases} +1, & \mathrm{x} > 0 \\ 0, & \mathrm{x} = 0 \\ -1, & \mathrm{x} < 0 \end{cases}$$

Thus, for j > k, S sums up the number of times that observation x_j exceeds x_k relative to that x_k exceeds x_j. The direction of a trend is indicated by the sign of S. Detected trends are tested for their significance based on two-sided p-values at the 10%, 5%, and 1% significance levels ($p \leq 0.1$; $p \leq 0.05$; $p \leq 0.01$). To account for seasonal changes in the data series, we apply the MK test on monthly values. That is, trends are firstly detected for each month separately, and secondly, the trends in individual monthly trends are estimated over the considered time series.

We also estimate regional trends, S_R, for the larger basin area (meteorological trends and trends in drought statistics). For this, the MK scores are generated for each site in a first step, before they are corrected based on the systematic variance-covariance matrix σ_{ij} according to Libiseller and Grimvall (2002)

$$S_R = \frac{\sum_{i=1}^{d} S_i}{\sqrt{\sum_{j=1}^{d}\sum_{i=1}^{d}\sigma_{ij}}}, \qquad \text{(Equation II-7)}$$

where S is the vector of Mann-Kendall scores for each site $1 \leq I \leq d$ (Helsel & Frans, 2006; Pohlert, 2017).

The magnitude of (significant) trends is estimated by the robust linear Sen`s slope estimator (Helsel & Hirsch, 2002) which is estimated from the median of slopes between all pairs of data points in the particular time series. In turn, the MK test and Sen`s slope estimator provide complementary information regarding the existence and magnitudes of the significant trends.

4. Results

4.1 Hydro-meteorological trends

In this section, regional and individual trends of rainfall, temperature (as a proxy for evapotranspiration) and lake level are presented. For rainfall, the regional trend analysis reveals that rainfall at the basin scale (both LMB and SRB) is decreasing, although this decrease is statistically not significant (Tab. II-2). Looking at the rainfall trends at individual stations in both the LMB and SRB (Fig. II-4, left), about 88.4 % of the stations show negative trends, and 47.8 % are statistically significant ($p < 0.05$). Only four stations, each in the LMB and SRB, show positive but insignificant trends in rainfall.

Table II - 2 *Mann-Kendall (MK) test (tau) and Sen's slope results for precipitation, temperature and lake level at the regional scale. Only Sen's slopes of significant MK test trends are presented.*

Parameter	Overall		Lake Malawi Basin only	
	Trend, tau	Sen's slope	Trend, tau	Sen's slope
Precipitation	-1.3461		-1.1262	
Temperature	2.796***	0.02***	2.795***	0.02***
Lake level			-10.278***	-0.0248***

*** significant at $p < 0.01$

Temperature trends are consistently positive and statistically significant both at the larger basin scale and for the individual stations (Tab. II-2, Fig. II-4, right). The regional trend analysis reveals that temperature has increased by 0.02 °C per year (0.8 °C over 40 years). This regional trend is statistically significant at $p < 0.01$. Trends for individual stations are statistically significant at least at $p < 0.05$.

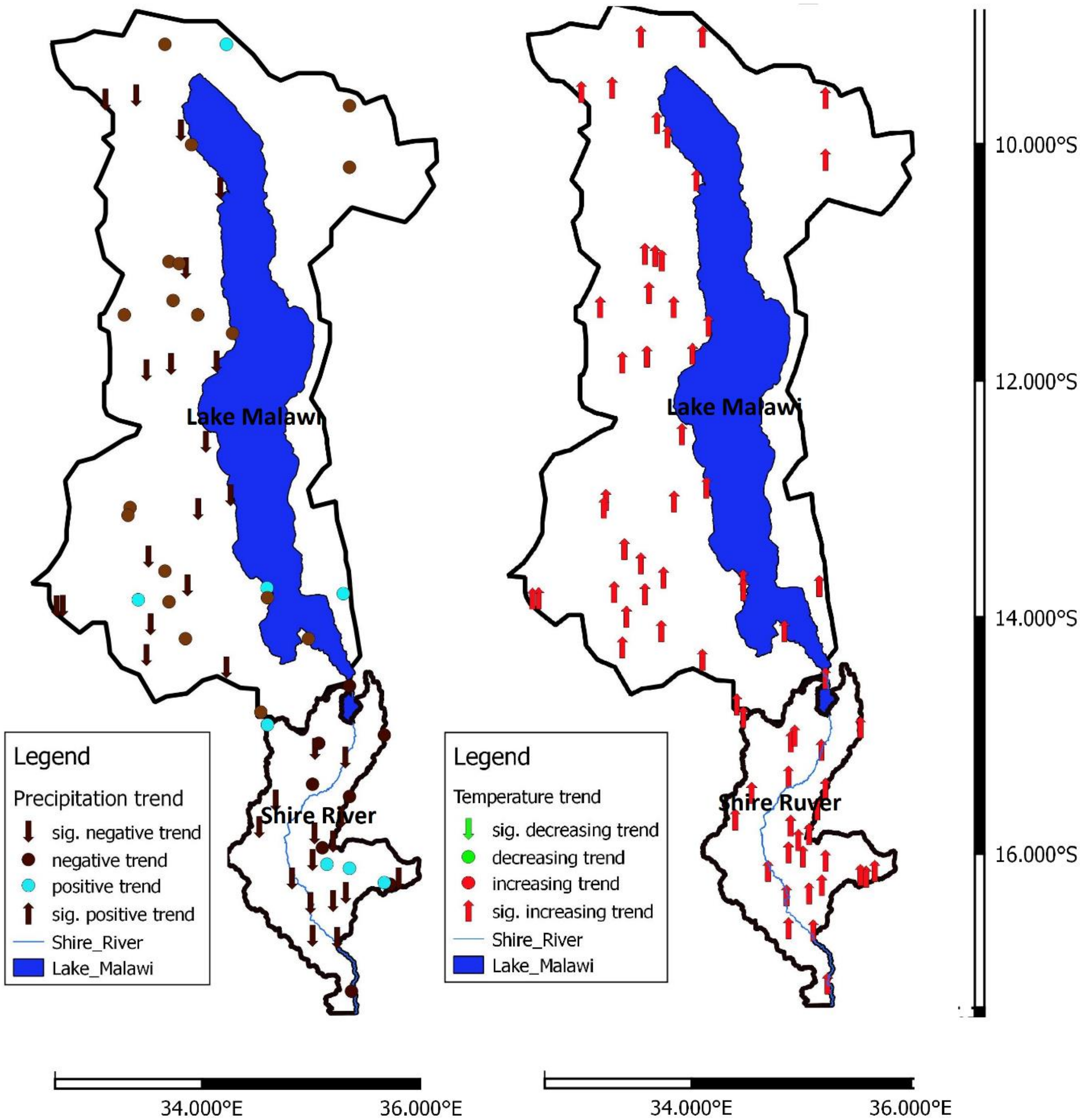


Figure II - 4 *The Mann-Kendall (MK) test results from 1970 to 2013 in Lake Malawi and Shire River Basins for rainfall (left) and temperature (right). The significance of the trends is based on $p < 0.05$.*

For the same period (1970-2013), the water level of Lake Malawi has decreased by 0.025 m per year (~1.0 m over 40 years) (Tab. II-2). This negative trend matches with the decrease in rainfall and the increase in temperature (evaporation). Although the lake level decline started in around early 1980's, the most considerable decrease in the early 1990's led to the minimum lake level of 472.97 m.a.s.l. in 1997 for this period. This low lake level resulted in almost no outflow from Lake Malawi to the Shire River (Bootsma & Jorgensen, 2006).

4.2 Drought detection

This section presents the result of the meteorological drought analyses based on the SPI and SPEI (4.2.1) and the hydrological drought analysis based on the LLCI (4.2.2).

4.2.1 Meteorological drought

The meteorological droughts at the basin scale are estimated using the SPI12 and SPEI12 drought indices (calculated based on consecutive 12 months). At the basin scale, eight drought events are detected for each drought index (Fig. II-5; Tab. II-3). Due to the similarity of both drought indices, the detected drought events show large temporal commonalities as expected. However, one drought event (1973-1974) is only captured by the SPI and not by the SPEI, whereas another event (1998-1999) is only captured by the SPEI and not by the SPI. The vast majority of drought events last for more than one year, and the most severe and intense droughts occurred in 1990s (Fig. II-5). The most extensive coherent meteorological drought in the basins identified by SPEI was from 1992 to 1996 and covered 62.5% of the stations. For the SPI, the most extensive coherent drought was from 1990 to 1993 and covered 61.2% of the stations (Tab. II-3). On average, the percentage of stations covered by droughts is higher for the estimates based on the SPEI (50.3%) as compared to the estimates based on SPI (40.7%).

Table II - 3 *Meteorological drought events in Lake Malawi and Shire River Basins between 1970 and 2013 as detected by standardised precipitation and evapotranspiration index and standardised precipitation index at 12-month scale (SPEI12 and SPI12).*

SPEI-12				SPI-12			
Event	**Period**	**Intensity**	**Spatial extent (%)**	**Event**	**Period**	**Intensity**	**Spatial extent (%)**
				1	1973-1974	-1.1	25.1
1	1983-1984	-1.51	48.7	**2**	1983-1984	-131	25.3
2	1987-1988	-1.45	49.8	**3**	1987-1988	-1.32	38.7
3	1990-1991	-1.32	41	**4**	1990-1993	-2.65	61.2
4	1992-1996	-2.16	62.5	**5**	1994-1996	-2.31	53.1
5	1998-1999	-1.02	42.4				
6	2004	-1.70	47.6	**6**	2004	-1.52	41.7
7	2005-2006	-1.92	73.1	**7**	2005-2006	-1.92	51.8
8	2009-2013	-1.32	37.5	**8**	2009	-1.02	28.5

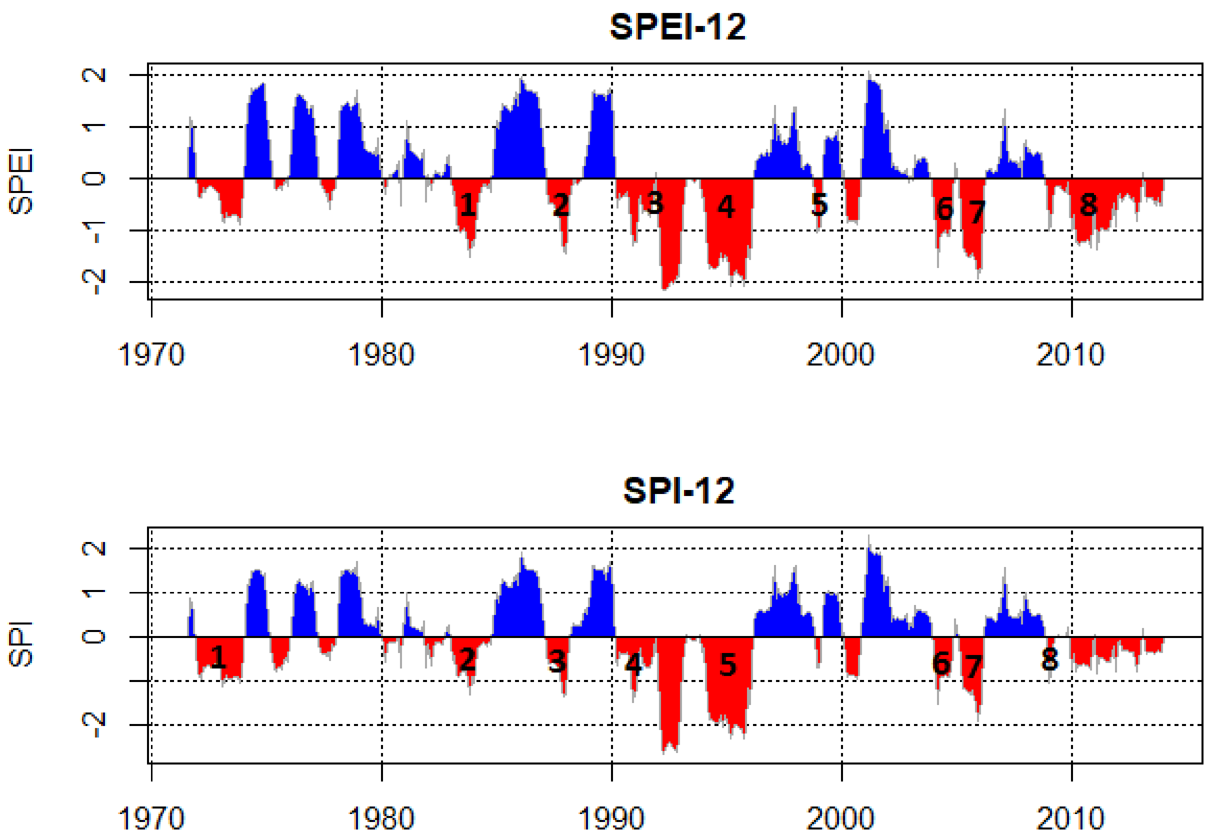


Figure II - 5 *The SPEI12 and SPI12 series for Lake Malawi and Shire River basins from 1970 to 2013. Numbers represent drought events.*

Tab. II-4 compares the mean SPI12 and SPEI12 at the larger basin scale in terms of mean drought severity, -intensity, -duration, -frequency and the percentage of months with occurring droughts over the period 1970-2013 (cf. 3.3). Except for drought intensity, the estimates based on the SPEI are slightly larger than the estimates based on the SPI which indicates more severe drought situations based on SPEI. However, as indicated by the t-test (Tab. II-4), the differences between the estimates based on the SPEI and SPI are rarely significant due to the similarity between both indices.

Table II - 4 *Comparison of mean spatial standardised precipitation index and -standardised precipitation and evapotranspiration index at 12-month scale (SPI12 and SPEI12) in terms of the mean drought severity, intensity, duration and frequency and the percentage of total drought months, using t-test.*

	Severity	Intensity	Duration (months)	Frequency	Total drought months (%)
SPEI (mean)	19.4	-1.6	18.4	9.4	30
SPI (mean)	18.4	-1.7	17.2	8.9	27.7
Difference (%)	4.7	-6***	6.2	5.4	7.3***

*** significant at $p < 0.01$

Droughts established by SPEI show longer drought duration (by 6.2 %), and consequently, a larger percentage of months with occurring droughts (difference by 7.3 %). Still, drought intensity based on SPEI is 6 % weaker as compared to SPI. As a result, mean drought severity at basin scale (which is a function of both drought intensity and drought duration) shows the smallest differences between SPEI and SPI (4.7 %). This illustrates how closely related the chosen drought characteristics are.

Fig. II-6 presents maps which illustrate the spatial variability of mean drought characteristics over the period 1970-2013 within the LMB and SRB for the SPEI12 and SPI12. Again, the spatial patterns for each drought parameter are fairly similar for both meteorological drought indices. Still, there are some smaller spatial differences, particularly regarding drought severity. The SPEI indicates a slightly larger drought severity at 41 (59%) of the stations compared to the SPI. The SRB shows a higher drought severity than the LMB. Regarding drought intensity, only very few stations (7 for SPEI, 6 for SPI) show droughts of moderate intensity on average. Some stations (2 for SPEI, 5 for SPI) show “extreme droughts”, while the majority of stations show “severe droughts”. On average, droughts last longer in SRB (based on both indices), although the station with the longest drought duration (> 48 months) is located in the northern part of the LMB. Most stations show mean drought durations of 12-18 months while the estimates based on SPEI tend to be slightly larger as compared to SPI. In turn, the percentage of months with drought occurrence situations is also slightly larger for SPEI than for SPI (Fig. II-6, right). Here, the largest values are found for the western part of the LMB. The largest frequency of meteorological drought events is found at the south-western part of LMB, and the estimates based on SPEI tend to be larger than those based on SPI. The maps also illustrate that the presented drought characteristics are not independent from each other. It is obvious, for instance, that long drought event areas do naturally have less frequent drought occurrences and vice versa (over a 43-year period).

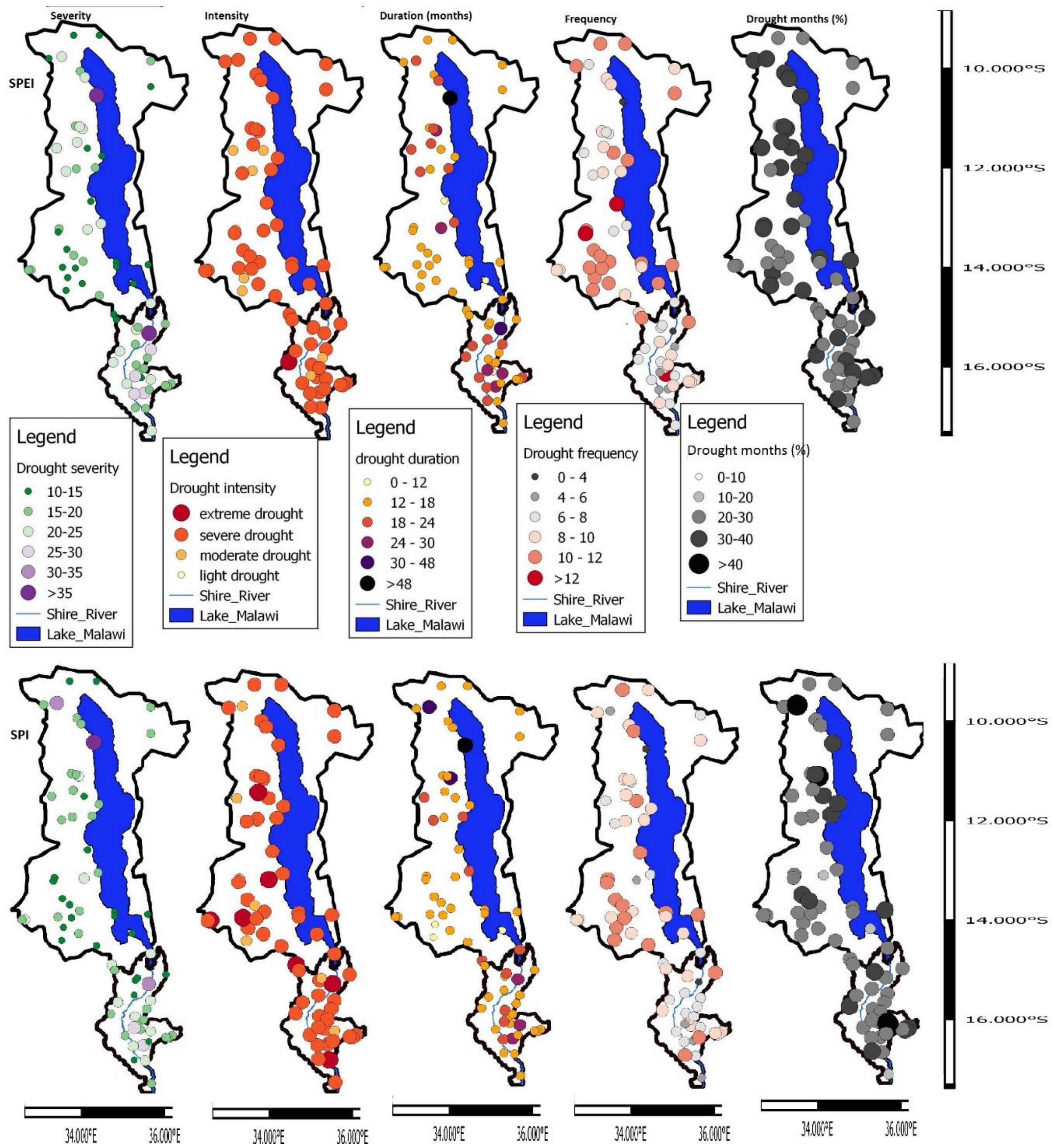


Figure II - 6 The mean drought characteristics generated from SPEI and SPI in Lake Malawi basin (LMB) and Shire River basin (SRB) for the period 1970-2013. The parameters from left to right are severity, intensity, duration, frequency and percentage of total drought months.

4.2.2 Hydrological droughts in Lake Malawi Basin and their link to meteorological droughts

Hydrological droughts are determined by the proposed LLCI12 (based on 12 consecutive months). The temporal occurrence of hydrological droughts in the LMB is illustrated in Fig. II-7(A). Only one hydrological drought is identified for the period 1970-2013. This drought, though, lasts for 101 consecutive months from June 1994 to October 2002. The intensity of this hydrological drought is -2.2 ("extreme drought") and its severity is 132.9. During this drought period the lake level dropped on average by 0.9 m, while during its most intensive time in 1997, lake level dropped by 1.9 m to the lowest level during 1970-2013.

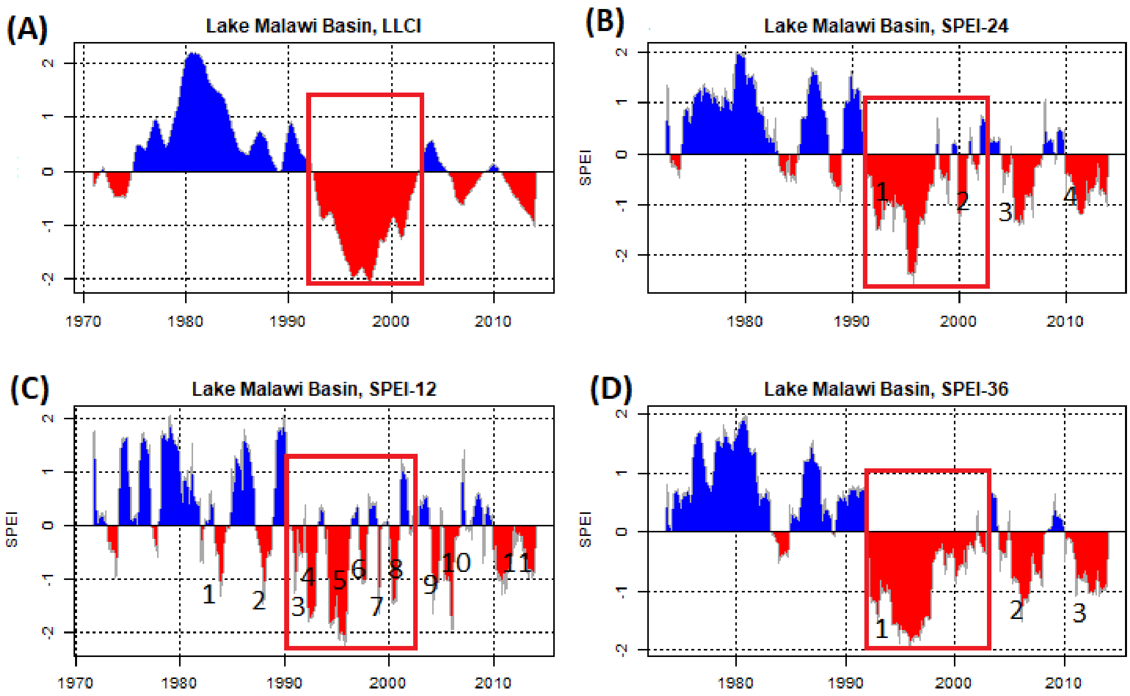


Figure II - 7 *The hydrological and meteorological droughts in Lake Malawi basin from 1970 to 2013. Numbers represent drought events. (A) LLCI based on 12 consecutive months. Meteorological droughts (C) based on 12 consecutive months (SPEI12), (B) 24 consecutive months (SPEI24) and (D) 36 consecutive months (SPEI36).*

The critical lake levels associated with moderate drought (LLCI < -1), severe drought (LLCI < -1.5) and extreme drought (LLCI < -2) are obtained using Eq.II-5 and are 474.1 (which marks the onset of a hydrological drought when water level falls below this level), 473.7 and 473.3 m a.s.l., respectively. Hence, from 1970 to 2013 the hydrological drought covered 14.9% of the months, while severe and extreme droughts covered 8.5 and 2.5% of the months, respectively.

Since it is assumed that a hydrological drought occurs subsequently to a meteorological drought, Fig. II-7 also displays the temporal occurrences of meteorological droughts in LMB only. The temporal variability of the SPEI12 (Fig. II-7(C)) is much larger as compared to the LLCI12 so that in total 11 meteorological drought events with a much shorter duration are detected in LMB. The difference in the numbers of meteorological drought events as compared to Fig. II-5 is due to the adjusted spatial reference and numbers of stations when estimating the regional average. It also seems that it needs either a meteorological drought of certain intensity or droughts at frequent intervals to trigger a hydrological drought due to the compensation capacity of the lake. The lowest SPEI12 values and the most frequent drought occurrences are found in 1990s which match with the single hydrological drought detected by the LLCI12. The two lowest values for both SPEI12 (-2.0, -2.1) and LLCI12 (-2.1, -2.2) show a temporal offset of more than one year; i.e., the lowest LLCI12 follows the lowest SPEI12 by more than one year.

In this regard, Fig. II-7(B) and (D) also show time series for SPEI24 and SPEI36 (based on 24 and 36 consecutive months, respectively). It becomes apparent that LLCI12 follows SPEI24 and SPEI36 much better than the SPEI12. Considering SPEI24 and SPEI36, the frequency of meteorological droughts is decreasing while the duration is increasing which also leads to an increasing linear relationship with the LLCI12 (Fig. II-8(C)). The meteorological drought based on SPEI36, which matches the best with the hydrological drought, has a duration of 116 months (April 1992 to November 2001) as compared to 101 months for the hydrological drought (June 1994 to October 2002). However, as the pattern becomes more linear, many degrees of freedom from the series are removed, and this leads to inflated estimates of SPEI24 and SPEI36. The correlation between the LLCI12 and the SPEI, however, improves from 0.42 (SPEI12) to 0.64 (SPEI24) and 0.8 (SPEI36) (Fig. II-8). The percentage of months with occurring meteorological droughts (SPEI < -1) does not considerably differ between the different aggregation levels: 17.4 % (SPEI12), 17.7 % (SPEI24), and 17.2 % (SPEI36).

Figure II - 8 *The comparison of hydrological drought (LLCI12) and meteorological droughts (SPEI12, (A); SPEI24, (B); and SPEI36, (C) in Lake Malawi basin only. Also included is the relationship between SPEI36 and LLCI12*$_{t10}$ *(10-month lag), (D). Vertical and horizontal yellow lines mark drought threshold.*

Although the time series of the SPEI36 matches well with the LLCI12, there is still a time lag between both time series, i.e., peaks and lows of the SPEI36 occur earlier as compared to the LLCI12 (Fig. II-9). Shifting the LLCI time series forward in time by 10 months leads to the largest improvement in the correlation between the SPEI36 and LLCI12$_{t10}$ to 0.89 (Fig. II-8(D)). This indicates that SPEI36 can predict LLCI12 at least 10 months in advance. Therefore, LLCI12 and SPEI36 are related by

$$LLCI12_{t10} = 0.919SPEI36 - 0.0016. \quad (8)$$

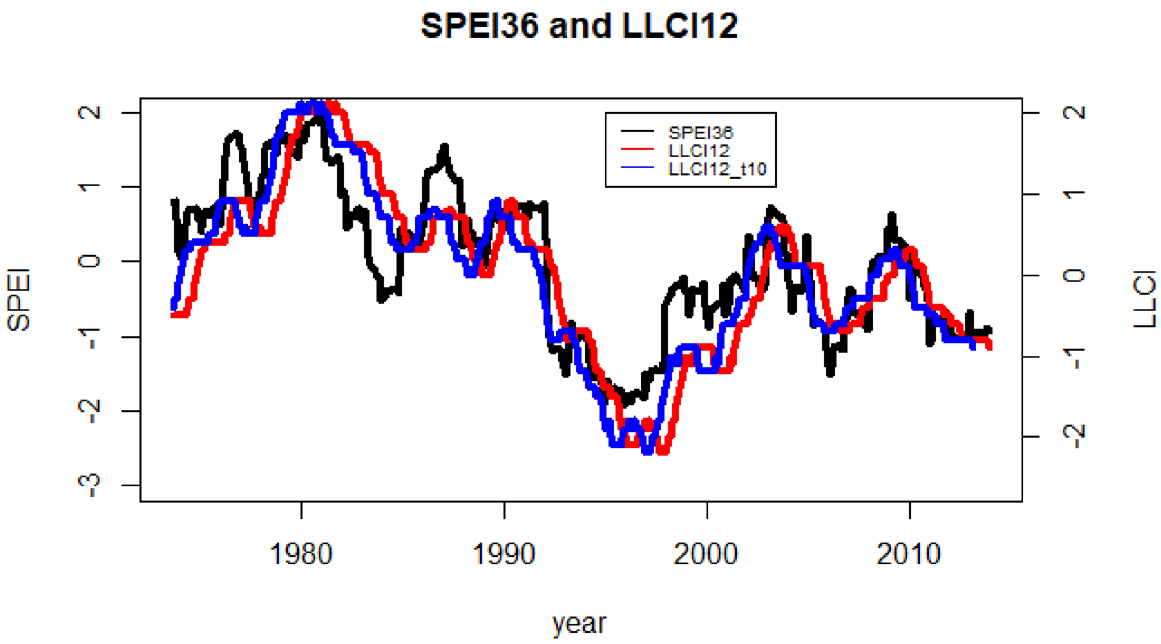


Figure II - 9 *The comparison of SPEI36, LLCI12 and LLCI12$_{t10}$.*

4.3 Trends in meteorological and hydrological droughts

Fig. II-10 illustrates the trends in SPI12 and SPEI12 for the meteorological stations within the LMB and SRB. The SPEI (Fig. II-10 left) is significantly decreasing at 60.9 % of the stations. The largest density of stations with significant decreases in SPEI is found in the northern and western part of the LMB. The SPI is significantly decreasing at only 47.8 % of the stations with a similar spatial pattern. Note, that this is the same percentage of stations with significant negative trends as before for rainfall (cf. 4.1), although the spatial patterns differ to some degree. At nine stations (in contrast to only one station for the SPEI), the SPI shows significant positive trends indicating less severe droughts over time. Most of the stations with positive trends are primarily located in the SRB.

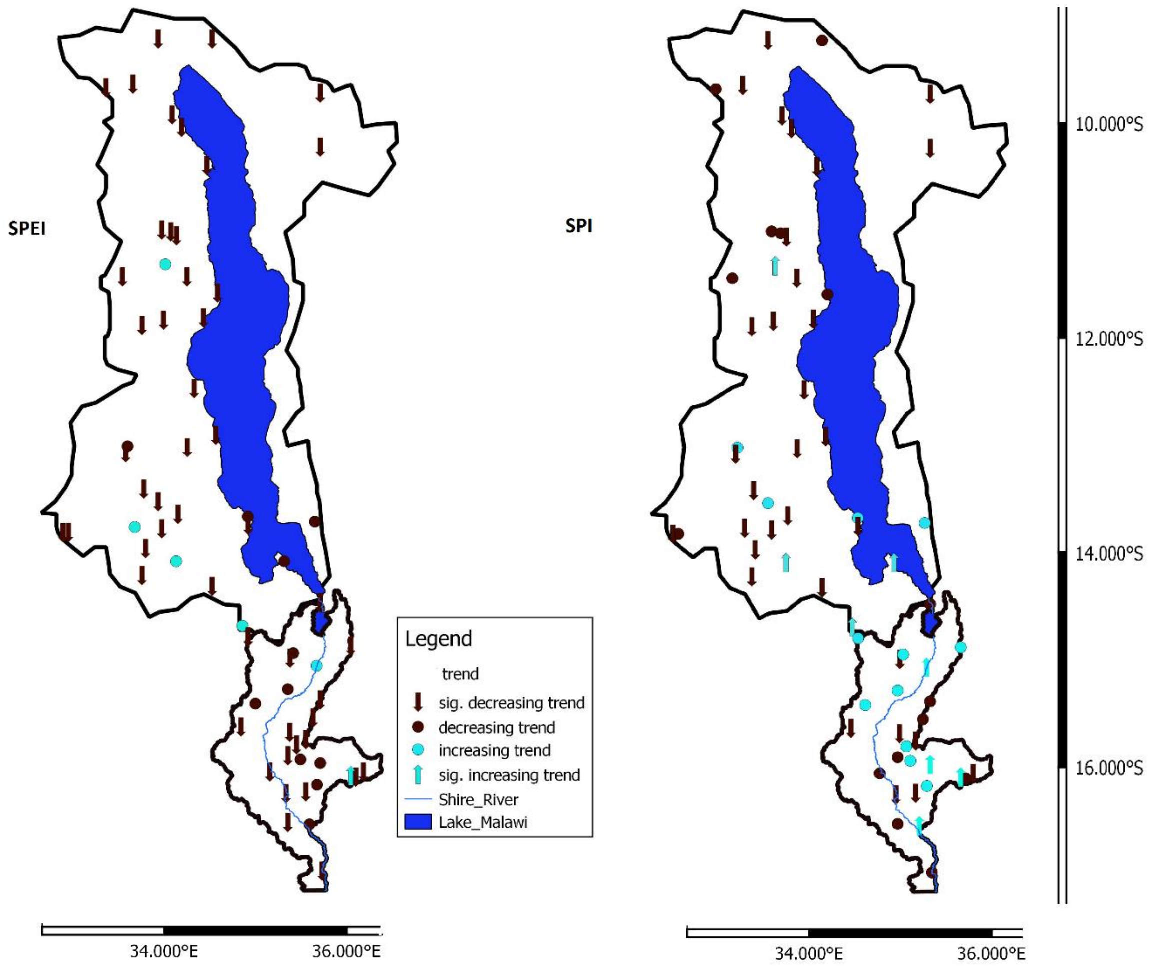


Figure II - 10 *The meteorological drought trends in Lake Malawi and Shire River basins for SPEI and SPI. The significance of the trends is based on $p < 0.05$. The decreasing trend implies increase in drought.*

The results of the regional trend analyses (Tab. II-5) at the annual scale underline the picture of an overall decrease in SPEI12 and SPI12 values (i.e., an increase in drought intensity). The trend magnitude regarding significant increasing meteorological drought indices is larger for the SPEI (tau = -7.91) than for the SPI (tau = -3.86). Note that, in contrast to the regional trend statistics for rainfall, the regional trend in the SPI is significant. This relates to the transformation of the time series and the aggregation over 12 months.

Table II - 5 *Mann-Kendall (tau) and Sen's slope results for meteorological and hydrological drought characteristics. A negative trend for drought intensity signifies an increasing trend of drought. Only Sen's slopes for parameters with significant trends are presented.*

	SPEI		SPI	
Parameter	**Trend, tau**	**Sen's slope**	**Trend, tau**	**Sen's slope**
Overall Meteorological drought				
SPEI/SPI	-7.91***	-0.018***	-3.86***	-0.0075 ***
Drought area proportion	7.06***	0.02***	1.5	
Drought severity	3.81***	0.25***	0.942	
Lake Malawi Basin only Meteorological drought				
SPEI	-9.3218***	-0.021 ***	-5.4815***	-0.011 ***
Hydrological drought				
LLCI-	-9.53***	-0.003 ***		

**** are significant at $p < 0.01$ SPEI: standardised precipitation and evapotranspiration index; SPI: standardised precipitation index; LLCI: lake level change index.*

In addition, while the differences between mean SPEI and SPI in terms of the drought characteristics such as severity, duration and frequency are not significantly different (cf. 4.2), increasing trends in drought severity at the larger basin scale are larger and only significant for SPEI (0.25% per year which is 10% in 40 years) and not for the SPI (Tab. II-5). This is also reflected in the increase of proportion of stations experiencing droughts at the same time in the basin which is significant for only the SPEI (0.02 % per year which is 0.8% in 40 years) (Tab. II-5).

Comparing trends in meteorological- and hydrological droughts is only possible for the LMB. As suggested by Fig. II-10, the regional trend estimates for the LMB underline those meteorological droughts are significantly increasing for both meteorological drought indices (again, slightly larger for the SPEI). Hydrological droughts, as determined by the LLCI, are also slightly but significantly increasing (i.e., decreasing LLCI values). The decrease in the LLCI (-0.003% per year), though, is slightly smaller as compared to the trends in SPEI and SPI (Tab. II-5).

5. Discussion

5.1 On the link between trends in meteorological drivers and meteorological droughts

The detected trends in the hydro-meteorological drivers agree with findings from Ngongondo *et al.*(2011, 2015) who have studied the spatial and temporal variability of rainfall and changes in the components of the water balance in Malawi for the periods 1960-2006 and 1971-2000, respectively. Droughts have become more relevant for the LMB and SRB over the past 43 years, and the most severe and intense drought situation occurred during the 1990s. This agrees with the findings from Rouault and Richard (2005) for the whole Southern Africa, suggesting that the drought situation in Malawi can be seen in a larger geographical context. However, similar findings from Malawi (e.g. Menon, 2007; Denning *et al.*, 2009; Syroka and Nucifora, 2010) also underline the drought dynamics detected in this study, although they were based on different indicators such as low farm production and famines. Such drought indicators do not fully reflect the meteorological drought in the area since there are many other factors that may result into famine or low farm production such as e.g., a dry spell during a critical crop stage, crop varieties used and usage of fertiliser (Holden and Fisher, 2015). Some consensus and deviation appear when comparing our results to (Munthali *et al.* (2003) who also applied the SPI for drought detection in Malawi. There are, however, differences regarding the spatial extent (whole Malawi), the time period (1948-2003), and the time scale (one month instead of 12 months) applied to detect drought events which might explain the deviations.

The comparison between both meteorological drought indices (SPI, SPEI) has shown that both indices detect comparable drought situations in terms of their spatial and temporal distribution for the period 1970 to 2013. This is expectable since both indices are similar to each other, as the SPEI is based on the SPI but considers effects of PET in addition to rainfall variability. The fact that (a) the detected droughts based on the SPEI tend to be more severe and longer lasting than those based on the SPI, (b) the percentage of stations affected by droughts is higher for SPEI than for the SPI, and (c) the significantly decreasing trends in monthly and annual SPEI values are larger than the decreasing trends in SPI values, highlights the particular role of PET on the water- and energy budget in the study region. Given that Ngongondo et al. (2015) found PET to increase in Malawi for a similar time period, it appears that meteorological droughts in the LMB and SRB are sensitive to an increase in evapotranspiration. For the evolution of droughts, this is particularly relevant since over 70% of the water received in Lake Malawi is lost through evaporation, (Drayton, 1984; Kidd, 1983; Neuland, 1984). Still, rainfall (or rather the absence of rainfall) is the main driver for droughts, although the detected negative trends in rainfall were often insignificant both in this and former studies (e.g., Ngongondo et al., 2015).

5.2 On the link between meteorological- and hydrological droughts

The newly proposed LLCI is able to identify hydrological droughts in LMB based on lake level variations, which reflect variations of the hydrological processes within the basin. Only one hydrological drought is detected for the period 1970-2013, but this single hydrological drought lasted for 101 months and led to low lake levels with considerably reduced outflow to the Shire River and hence reduction in hydro-power production in the SRB. This highlights the sensitivity of hydro-power production in the SRB towards the water- and energy-budget of the LMB. Regarding the link between meteorological- and hydrological droughts, it is hardly possible to give general statements on the meteorological trigger mechanisms for the onset of hydrological droughts since only one, long-lasting hydrological drought event has been identified for the study period. For this event, it requires frequent meteorological droughts of certain intensity (SPEI < -1) to trigger the onset of the hydrological drought. However, we could show that the response of the lake to meteorological drought situations is delayed by more than 24 months and we assume that this is due to the attenuation effect of the Lake Malawi given its large size and volume.

The purely data driven relationship established between the SPEI36 and the LLCI has highlighted that the SPEI36 proves to be a well-suited predictor for hydrological droughts ten months in advance. This may provide essential information for preparedness and water management in the basin. The adaptation of a process-based hydrological model to the LMB would be desirable to account for and to better understand the hydrological (response) processes of the lake and within the basin area. This would also allow to validate the established relationship between the SPEI36 and LLCI12.

5.3 Implications of future climate scenarios (on hydro-power production)

Projections on future climate scenarios for Malawi (based on CMIP5 global circulation models driven by the RCP8.5 emission scenario) consistently indicate further temperature increases by +2.5 to +5.5 °C until 2100. The projections, however, highly disagree regarding the direction of changes in precipitation. 12 models suggest an increase in precipitation by +4 % to +28 %; 18 models suggest that precipitation will likely decrease by -3 % to -17 % mm until 2100 (Climate and Development Knowledge Network, 2017).

In turn, three possible modes of future climate change implications on the evolution of meteorological drought situations can be imagined. (1) Increasing temperature in combination with decreasing precipitation will most likely promote future drought situations. (2) Small changes in precipitation (including small increases) in combination with increasing temperatures will possibly lead to more/more severe droughts due to the sensitive role of evapotranspiration on drought generation in the LMB and SRB. (3) Despite increasing temperature, moderate to strong increases in precipitation will lead to less/less severe droughts due to an increase in net-positive water balances in the basins. It is important to point out that these scenarios represent average climate (change) conditions. Since severe meteorological droughts are random events, single extreme drought events (possibly even more extreme that the ones detected in 1990s) can occur for all three modes outlined above. Detailed scenario- and model-based analyses including downscaling of the climate projections would be needed to give more quantitative rather than these qualitative approximations.

The likely increase in future meteorological droughts will also have consequences for hydrological droughts and water management. The presumably increasing role of (lake) evaporation, may strongly impact the water balance of Lake Malawi and its catchment so that water loss through lake evaporation will increase. Assuming only small changes in precipitation input, the outflow from the Lake Malawi to the upper Shire River will further be reduced, and hydropower productivity will considerably be decreased. Given the importance of hydropower production on the Shire River for the energy supply in Malawi, this may have serious consequences for the energy security of the country. Detailed analyses regarding hydrological climate change impacts on streamflow and hydropower potential in the SRB are urgently needed to provide a basis for adaption strategies to ensure a secure energy supply in the future.

6. Conclusion

In this study we have used two meteorological drought indices (SPI and SPEI) to detect meteorological drought dynamics in the Lake Malawi basin and upper Shire River basin which is of key importance for the hydro-power generation and energy supply in Malawi. We have also analysed trends in the meteorological drivers for droughts (changes in precipitation and temperature as a proxy for evaporation) to investigate the importance of these drivers for drought evolution in both basins. We further proposed the lake level change index (LLCI), which is based on lake level variations on Lake Malawi to investigate hydrological droughts in this area. One particular goal of this study has then been to explore the relationship between meteorological- and hydrological droughts. Refacing the three overarching research questions for this study, we can draw the following main conclusions:

(1) *Significant increasing trends in temperature and (often insignificant) decreasing trends in precipitation agree with mostly significant increasing trends in drought conditions!* The most severe drought situations have occurred in the 1990s which agree with previous studies both for Malawi and for larger geographical extents. Only some drought

characteristics show some minor spatial patterns (comparatively longer duration in the south and higher frequencies in the west), otherwise the detected trends in the hydro-meteorological drivers and drought indices are relatively homogenous in spatial perspective.

(2) *The sensitive role of potential evapotranspiration for water resources in general and for drought situations in particular has been outlined for the Lake Malawi area!* Still, rainfall deficits remain the main driver for the evolution of droughts. However, as temperature has significantly increased over the last decades and future projections highly agree on further regional warming, the role of evapotranspiration might even amplify future drought conditions in the greater Lake Malawi area. This will have serious impacts on water resources and hydro-power productivity, and as such this should be focus of future research activities.

(3) *There is no obvious direct link between meteorological droughts and hydrological droughts at 12-month scale as they are defined within this study!* Meteorological droughts are more frequent and shorter as compared to hydrological droughts. In turn, not every meteorological drought triggers a hydrological drought, but the most severe meteorological droughts occur concurrently with the hydrological drought during its largest intensity. The absence of a direct link between meteorological and hydrological droughts is presumably due to the compensation capacity of Lake Malawi. The study, though, has revealed that hydrological droughts at the 12-month scale (LLCI12) can be linked to meteorological droughts at the 36-month scale (SPEI36), and that the SPEI36 is able to reasonably predict the LLCI12 approximately ten months in advance.

III Temporal Evaluation and Projections of Meteorological Droughts in the Greater Lake Malawi Basin, Southeast Africa

Abstract:

The study examined the potential future changes of drought characteristics in the Greater Lake Malawi Basin in Southeast Africa. This region strongly depends on water resources to generate electricity and food. Future projections (considering both moderate and high emission scenarios) of temperature and precipitation from an ensemble of 16 bias-corrected climate model combinations were blended with a scenario-neutral response surface approach to analyse changes in: (i) the meteorological conditions, (ii) the meteorological water balance, and (iii) selected drought characteristics such as drought intensity, drought months, and drought events, which were derived from the Standardized Precipitation and Evapotranspiration Index. Changes were analysed for a near-term (2021-2050) and far-term period (2071-2100) with reference to 1976-2005. The effect of bias-correction (i.e., empirical quantile mapping) on the ability of the climate model ensemble to reproduce observed drought characteristics as compared to raw climate projections was also investigated. Results suggest that the bias-correction improves the climate models in terms of reproducing temperature and precipitation statistics but not drought characteristics. Still, despite the differences in the internal structures and uncertainties that exist among the climate models, they all agree on an increase of meteorological droughts in the future in terms of higher drought intensity and longer events. Drought intensity is projected to increase between +25% and +50% during 2021-2050 and between +131% and +388% during 2071-2100. This translates into +3 to +5, and +7 to +8 more drought months per year during both periods, respectively. With longer lasting drought events, the number of drought events decreases. Projected droughts based on the high emission scenario are 1.7 times more severe than droughts based on the moderate scenario. That means that droughts in this region will likely become more severe in the coming decades. Despite the inherent high uncertainties of climate projections, the results provide a basis in planning and (water-) managing activities for climate change adaptation measures in Malawi. This is of particular relevance for water management issues referring hydro power generation and food production, both for rain-fed and irrigated agriculture.

L. Mtilatila, A. Bronstert, K Vormoor, Temporal Evaluation and Projections of Meteorological Droughts in the Greater Lake Malawi Basin, Southeast Africa. Accepted for publication in the Frontiers in Water on 01 November 2022.

1. Introduction

Droughts are a major hydrological hazard in many regions of the planet affecting several sectors of societies, such as food production, municipal water supply and hydropower generation. Due to increasing demand for food, water resources and energy, droughts have received ever increasing attention in the last decades and innovative methods of drought assessment and analysis (e.g., Stahl and Demuth, 1999; de Araujo et al., 2016; Vogel et al., 2021) and prediction and modelling (e.g., Krol et al., 2006; Pilz et al., 2019; Adnan et al., 2021) have been presented. Though less documented in science literature, droughts are also common in southern Africa and their frequencies and severities are increasing (Masih et al., 2014). This situation has not spared Malawi, which relies heavily on natural water resources of the Lake Malawi and Shire River Basins. Lake Malawi has many water inlets but only one outlet, the Shire River in the South where about 98% of the country's hydropower production takes place (Taulo et al., 2015). Runoff into the Shire River largely relies on outflow from Lake Malawi, which is mainly a function of lake level. However, the lake level has decreased by ~1.0 m over the period 1970-2013 (Mtilatila et al., 2020a). This has created low flows on Shire River and affected the production of electricity (ESCOM, n.d.). The occurrence of drought events also affects agricultural production. Coulibaly (2015) estimated that 53.3% of crop failure in Malawi is due to climatic factors including droughts, floods and high temperatures, and yet agriculture contributes almost 28% to 30% of Malawi's Gross Domestic Product (GDP) (GOM, 2019). Therefore, the combined direct effects of floods and droughts affect Malawi's economy by reducing the annual GDP by 1.7% (Pauw et al., 2011).

According to records from the Department of Disaster Management Affairs in Malawi, there have been ten drought events since 1975 on record eight of which were major. The most severe droughts occurred in 1992 and 2015 and affected almost 7 million and 6.7 million people, respectively. These events may be referred to as agricultural droughts since the effects are linked to agricultural production, and their extent/magnitude is based on the size of the food insecure population. However, according to Spinoni *et al.* (2014), agricultural drought is defined as soil moisture deficit that leads to crop failure. Mtilatila et al. (2020a) studied meteorological droughts in Lake Malawi and Upper Shire River basins based on the standardised precipitation and evapotranspiration index (SPEI) and the standardised precipitation index (SPI). They came up with eight meteorological drought events between 1970 and 2013. The majority of these events lasted for more than a year and the most severe event occurred from 1992 to 1996 (Mtilatila et al., 2020a). Regionally, these events were linked to droughts that were experienced in most of the South African countries, which have generally shown an increase in the frequency of drought events from the 1980s onwards (Rouault & Richard, 2005). The meteorological droughts often trigger hydrological droughts in the Lake Malawi Basin with a delay of more than 24 months due to the attenuation effect of the lake (Mtilatila et al., 2020). A hydrological drought in this regard is considered for lake levels below 474.1 m.a.s.l. developed in reference to the 1970 to 2013 period. Therefore, during 1970-2013 only one hydrological drought was identified. This, however, lasted for 101 months from June 1994 to October 2002. During this drought event, the lake level dropped by 0.9 m on average (Mtilatila et al., 2020a).

There is a link between observed climate change and drought occurrences in Malawi: statistically significant increasing trends in temperature (0.8°C over 40 years) and mostly insignificant decreasing trends in precipitation conditions (Mtilatila et al., 2020a) agree with increasing trends in drought conditions (Mtilatila et al., 2020; Ngongondo et al., 2011, 2015). The temperature increase is enhancing potential evapotranspiration (PET) (Ngongondo et al., 2015). Therefore, droughts identified based on the SPEI tend to be even more severe, last longer and cover a larger geographical extent than droughts identified by SPI (Mtilatila et al., 2020a). Compared to 1976-2013, climate projections indicate future temperature increases of 0.98-2.1°C and 1.8 to 5°C between 2021-2050 and 2071-2100, respectively, based on the Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios (Mtilatila *et al.*, 2020b). This provides an indicator of increasing severity of future droughts, which may even be enhanced if the temperature increases are combined with decreases in rainfall. In this regard, however, future precipitation is subject to a greater uncertainty, in terms of both the extent and direction of changes (Kusangaya et al., 2014). But still, the potential impacts of future climate changes (temperature and rainfall changes) on drought conditions in Malawi have not been quantified.

Usually, the impacts of climate change on environmental systems are investigated against the background of scenario-based climate projections. General Circulation Models (GCMs) are used to estimate future changes in climate component systems and ocean circulation by means of emission scenarios for greenhouse gases and aerosol concentrations (Déqué, 2007). However, these models are at low spatial resolutions which often do not fit well with the impact scale, and the uncertainty that originates from the GCMs is high (e.g. (e.g. Warnatzsch & Reay, 2018; Wu *et al.*, 2021). To address this problem, Regional Climate Models (RCMs) are applied to dynamically downscale the GCMs to higher spatial resolutions. Nevertheless, when using GCMs as boundary conditions, errors from the GCMs are often transferred to the domain of the RCMs such that they may require further correction (Déqué, 2007; Themeßl et al., 2012). For example, Warnatzsch & Reay (2018) found that GCM-RCMs underestimated precipitation in all the seasons and the correlation between the observations and models did not exceed +/-0.57 for monthly rainfall in Malawi. Though the models captured the rainfall trend, they were underestimating the slope and the inter-annual fluctuations compared to the observed dataset. Many models failed at matching observed drought episodes identified based on the SPI. Thus, statistical approaches are often applied to relate the results of GCM-RCMs to the statistical characteristics of meteorological observation data at the local or regional scale (e.g. Wilby and Wigley, 1997; Hundecha *et al.*, 2016). Based on an ensemble of bias-corrected GCM-RCM combinations, potential impacts of climate change on drought characteristics (here based on the SPEI) can be estimated (e.g. Johnson and Sharma, 2015; Aryal and Zhu, 2017).

However, sensitivity of droughts towards rainfall and temperature changes requires a different approach. So alternatively, to the 'top-down' approach described above, scenario-neutral 'bottom-up' approaches can be applied to assess the impacts of climate change on specific target variables (e.g. Prudhomme *et al.*, 2010; Fronzek, Carter and Luoto, 2011; Hirschi *et al.*, 2011). Such approaches assess the sensitivity of a target variable (here the SPEI) to systematic changes in climate variables (here, temperature and precipitation). That is, observed climate data are systematically perturbed and the response (i.e., impact on the SPEI) of a certain combination of systematically perturbed temperature and precipitation time series is plotted as one pixel on a two-dimensional domain: the so-called 'response surface'. However, at least in this simple version, such bottom-up approach neglects likely changes in the temporal sequencing of climate data (e.g., annual, seasonal, day-to-day variability), which may, however highly influence the occurrence and severity of hydrological extremes like droughts.

Therefore, the aim of this study is to examine the development of future drought characteristics in the Greater Lake Malawi Basin (GLMB) under climate change. The study, combines bias-corrected GCM-RCM simulations and projections with a scenario-neutral response surface approach as described in Vormoor et al. (2017) to analyse future meteorological droughts. With reference to 1976-2005, we seek to establish how well the 16 GCM-RCM combinations are able to simulate drought incidents and their characteristics including the number of detected events, their duration, and their intensity as compared to observation data. We also analyse the benefits of applying the bias-correction (i.e., empirical quantile mapping) for the representation of drought characteristics by the GCM-RCM ensemble over this period. In addition, the sensitivity of drought characteristics towards the changes in temperature and precipitation is conducted based on scenario-neutral response surfaces which also incorporates changes in the temporal structure of temperature and precipitation time series as they are projected by the GCM-RCM ensemble. The following specific research questions are addressed by this study:

(1) How reliable are (bias-corrected) climate models in simulating meteorological drought characteristics in the GLMB?

(2) As climate is expected to change in the future, what are the expected changes in future drought characteristics like their intensity, duration and number of occurrences as compared to the recent past in this region?

2. Study Area and Data

2.1 Study area

The study is looking at the combined Lake Malawi and Shire Basins which is referred to as the Greater Lake Malawi Basin (GLMB). Malawi is a land-locked country located in south-eastern Africa (Fig. III-1). It shares borders with Mozambique to the South, Southwest and Southeast, Zambia to the northwest and Tanzania to the North and Northeast. The climate of Malawi is predominantly warm and wet from October to April, with mean temperatures varying roughly between 26 and 28°C and monthly rainfall of above 200mm. It is generally cooler and drier in winter (May - September), with monthly rainfall below 20mm and mean temperatures between 21 and 25°C.

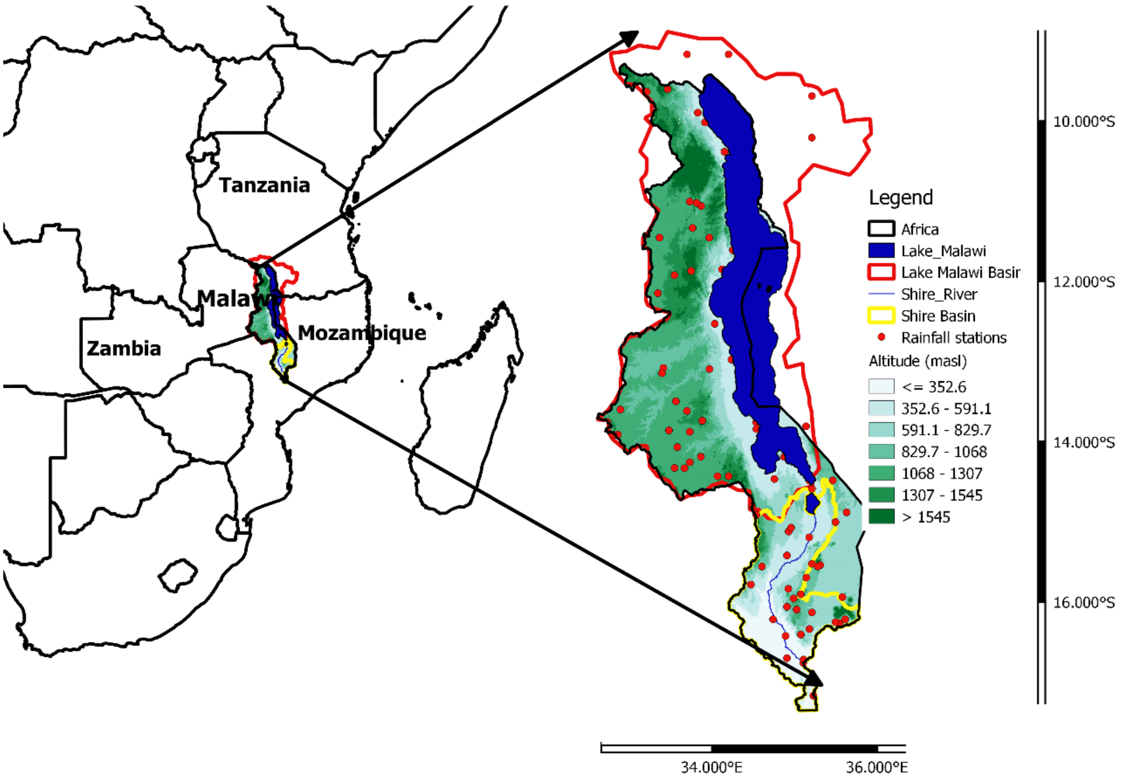


Figure III - 1 *The study area, the Greater Lake Malawi Basin (Lake Malawi and Shire River Basins) in southeast Africa*

In terms of size, Malawi covers 118,484 km², and in 2018, 20.4% of the area was covered by water bodies, 48% by agricultural land, 18.9% by forest and the remaining 12.6% by built-up area, barren land and other wooden areas (Source: https://knoema.com/atlas/Malawi/topics/Land-Use/Area/Surface-area).The population (currently almost 18 million people) is increasing at the rate of 2.9% per year (National Statistical Office, 2018) which adds pressure on the natural resources by increasing land under development and agriculture, hence increasing deforestation (Palamuleni et al., 2011). For example, in the Upper Shire River Basin, agricultural land increased by 18% from 1989 to 2002 (Palamuleni et al., 2011), while forest cover in the Lake Malawi Basin decreased from 64% in 1967 to 51% in 1990s (Calder et al., 1995). In 2018, the population was almost four times that of 1966 (National Statistical Office, 2018) and 86% of Malawi's population was employed in the agriculture sector in 2013 (Nyekanyeka, 2013).

2.2 Data

We used the observed gridded daily rainfall dataset that was used by Mtilatila *et al.* (2020b). The gridded data were generated from station data obtained from the Department of Climate

Change and Meteorological Services (DCCMS) in Malawi, which was complemented by a 0.5° gridded rainfall product provided by the Global Precipitation Climatology Centre (GPCC) (Schneider et al., 2018) to cover Tanzanian and Mozambiquan areas for rainfall. Daily temperature data were obtained from the Climatic Research Unit (CRU) at the University of East Anglia (Osborn & Jones, 2014). The Inverse Distance Weighting (IDW) method by Shepard (1968) was used to grid data into 0.5° to match the resolution of the GCMs. In this study, the gridded observations-based products are used as a reference and for bias-correcting 16 GCM-RCMs combinations provided by the Coordinated Regional Climate Downscaling Experiment (CORDEX) Africa (accessed at https://cordex.org/data$-$access/esgf/). The GCM-RCMs have a spatial resolution of 0.44° and provide daily simulations and projections, respectively, for the periods 1976-2005, 2021-2050, and 2071-2100. In this study, the RCP 4.5 and 8.5 scenarios are considered for the future climate projections to account for the high uncertainty of models in capturing rainfall in the study area (Warnatzsch & Reay, 2018). Tab.III-1 shows the GCM-RCM combinations considered in this study.

Table III - 1 *GCM-RCM combinations from CORDEX Africa used in the study. The ensemble consists of nine GCMs and five RCMs from five centres: Swedish Meteorological and Hydrological Institute (SMHI), Sweden, Max Planck Institute (MPI), Germany, The Royal Netherlands Meteorological Institute (KNMI), Netherlands, The Danish Meteorological Institute (DMI), Denmark, and Climate Limited- Area Modelling Community (CLM).*

No.	Global Climate Model (GCM)	Regional Climate Model (RCM)	Centre
1	CNRM-CM5	CCLM-4-8-17	CLM
2	EC-EARTH	CCLM-4-8-17	CLM
3	MPI-ESM-LR	CCLM-4-8-17	CLM
4	EC-EARTH	HIRHAM5	DMI
5	EC-EARTH	RACMO22T	KNMI
6	EC-EARTH	REMO2009	MPI
7	MPI-ESM-LR	REMO2009	MPI
8	CNRM-CM5	RCA4	SMHI
9	CanESM2	RCA4	SMHI
10	CSIRO-Mk3.6.0	RCA4	SMHI
11	EC-EARTH	RCA4	SMHI
12	IPSL-CM5A	RCA4	SMHI
13	MPI-ESM-LR	RCA4	SMHI
14	MIROC5	RCA4	SMHI
15	Nor-ESM1-M	RCA4	SMHI
16	GFDL-ESM2M	RCA4	SMHI

3. Methods

3.1. Drought analysis

Droughts in the GLMB are estimated based on the SPEI, which is a commonly used index to describe meteorological droughts (Vicente-Serrano et al., 2010). The estimation of the SPEI is based on the meteorological water balance (MWB), i.e., the difference between precipitation and PET. Evapotranspiration can be estimated as reference, potential or actual. The reference evapotranspiration assumes the well-watered grass surface, while the PET is based on the open water surface. In this study PET is adopted as is indicated by Vicente-Serrano et al. (2010). PET is estimated using the Thonthwaite equation (Thornthwaite, 1948), which requires only temperature as measured input, and as such is an advantage in areas where data are scarce. The distribution function of the water balance determined from the precipitation and temperature is transformed into a standard normal distribution. The SPEI then quantifies the water excess and deficits over a certain time period, as the SPEI represents the number of standard deviations by which a certain water balance estimate deviates from the long-term mean:

$$\boldsymbol{SPEI = \frac{x_i - \overline{x}}{\sigma}} \qquad \text{(Equation III-1)}$$

where x_i is the MWB estimate over a given time scale, here 12 months as recommended by Mtilatila et al. (2020a), and $\bar{x}$ and σ are the mean and standard deviation of the MWB, respectively (Vicente-Serrano et al., 2010). For the definition of drought characteristics, we adopted the Mckee (1993) classification based on SPEI instead of SPI. Droughts are defined in four categories: mild droughts ($0 \geq \text{SPEI} > -1.0$), moderate droughts ($-1.0 \geq \text{SPEI} > -1.5$), severe droughts ($-1.5 \geq \text{SPEI} > -2.0$), and extreme droughts ($\text{SPEI} \leq -2.0$). However, since the WMO (2012) characterises mild droughts as near-normal, we neglected this category during the onset of the drought. Consequently, a drought event starts when the SPEI ≤ -1 and ends when the SPEI turns positive, and this period is referred to as drought duration in months. The total drought months (DM) and drought events (DE) are the total number of months during which the drought occurred and the total number of times drought events occurred during a 30-year period, respectively. Finally, drought intensity (DI) is the minimum SPEI value during drought duration (Dayal et al., 2017).

3.2 Empirical Quantile Mapping (EQM)

Future drought characteristics can be analysed based on temperature and precipitation projections from dynamic climate models like GCMs (e.g. Haile *et al.*, 2020) or RCMs (Tomaszkiewicz, 2021). Due to limited descriptions of the atmospheric process and rather coarse spatial resolutions the output of such models need some further statistical downscaling and/or bias correction (e.g. Bronstert *et al.*, 2007). In this study, we applied empirical quantile mapping (EQM) to adjust biased RCM outputs to observations. This method has become popular (e.g. Piani *et al.*, 2010; Themeßl, Gobiet and Heinrich, 2012; Johnson and Sharma, 2015; Osuch *et al.*, 2017; Shrestha *et al.*, 2020; Enayati, Bozorg-haddad and Bazrafshan, 2021), as it seeks for a transfer function to adjust the quantiles of the GCM-RCMs (x_m) to those of the observed data (x_o; here, gridded observations for temperature and precipitation). The method can be expressed as

$$\boldsymbol{x_o = F_o^{-1}(F_m(x_m))} \qquad \text{(Equation III-2)}$$

where F_m is the empirical cumulative distribution function (eCDF) of x_m and F_o^{-1} is the inverse eCDF corresponding to x_o (Piani et al., 2010), The transfer function identified for the current climate conditions is then applied to also adjust the future projections by the GCM-RCMs, assuming that the function is stationary and the shortcomings of the GCM-RCMs are the same for the future period. The bias correction is applied to the daily values at the individual grid points for each climate model. EQM has proved to bias-correct daily rainfall better than parametric and theoretical distribution based methods (Enayati et al., 2021). We then evaluate the performance of the raw and bias-corrected GCM-RCM combinations in terms of their ability to represent drought characteristics during the reference period (1976-2005).

3.3 Climate change impacts on drought characteristics

The potential future impacts of climate change on drought characteristics at the basin scale have been investigated by means of response surfaces. In a two-dimensional domain, response surfaces display the changes in long-term mean drought characteristics when the climatological input data (precipitation and temperature) are systematically perturbed linearly as:

$$\boldsymbol{T(i) \rightarrow T_o(i) + X_t} \qquad \text{(Equation III-3)}$$

$$\boldsymbol{P(i) \rightarrow P_o(i) X_p} \qquad \text{(Equation II-4)}$$

Observed climate data ($T_o(i)$ and $P_o(i)$) for the reference period 1976-2005 is linearly and uniformly scaled at daily time steps, i, within a user-defined range of possible future changes given by the perturbation factors X_t and X_p for temperature (additive) and rainfall (multiplicative), respectively. Temperature is scaled in +0.5°C increments up to +5°C as compared to temperatures of the reference period, leading to eleven (11) different perturbations. Precipitation is scaled in ±5% increments within the range from -35% to +10% as compared to precipitation during the reference period, resulting in ten (10) model realizations. The perturbed time series of temperature and rainfall are applied in Eq. 1 to obtain the SPEI for each of all possible combinations of perturbed input data series (11 x 10 = 110 realizations). Based on these SPEI series, changes in MWB and drought characteristics (DE, DI, DM) are derived. For a specific combination of perturbed time series, the mean change as compared to the reference period is plotted as one realization (i.e., one pixel) within the 11 x 10 domain of the response surface. The climate signals from the bias-corrected GCM-RCMs are then overlaid over the response surfaces to provide an illustration of their specific future projections including their uncertainties (i.e. range of the projections) (Vormoor *et al.*, 2017; Mtilatila *et al.*, 2020b).

However, the linear scaling of observed temperatures and rainfall neglects possible modifications of the temporal structures (e.g. sequences of dry/wet spells) due to climate change, as it is the case with the delta method of statistical downscaling (Sunyer et al., 2012). To overcome this issue, we also perturbed future projections of the 16 GCM-RCMs after having removed their mean climate change signal. That is, temperature and rainfall of the bias-corrected RCP8.5 scenario for the period 2071-2100 is first levelled to the observed data (i.e., removing the mean projected change signal – in magnitude) and then systematically perturbed as shown in Eqs. 3-4 (see Vormoor et al., 2017 for details). This way, we preserve changes in the temporal structure as projected by the climate models.

Again, the MWB and drought characteristics are estimated from the individual SPEI series resulting from the perturbed time series. In total, we generated 17 response surfaces (16 GCM-RCMs and one observed dataset) based on 1,870 perturbed times series (1_{obs} + $16_{GCM\text{-}RCM}$ x $11_{Xt\ x}\ 10_{Xp}$). If the changes in temporal structures of temperature and rainfall have no influence on droughts, then the response surfaces generated by perturbed GCM-RCM data and observed data are expected to be alike. In this study, we illustrate two response surfaces for each target variable: one shows the mean of the 17 individual response surfaces, and the second one summarises the differences between the 17 response surfaces as given by the coefficient of variation (CV) for DE and DM, or the standard deviation (SD) for DI and MWB. The larger the CV or SD, the larger is the influence of the temporal structure on the water balance or a specific drought parameter.

4. Results

The results section is subdivided into two parts. The verification of temperature, rainfall, MWB and meteorological drought characteristics as represented by the 16 GCM-RCM combinations using the historical period of 1976-2005 is presented in Section 4.1. This is followed by changes in the future MWB and drought characteristics in Section 4.2.

4.1 Performance of GCM-RCMs

4.1.1 Precipitation and temperature

The Taylor diagrams (Taylor, 2001) comprising Pearson correlations (r), standard deviation and centered root mean square errors (RMSE) are used to verify the 16 GCM-RCMs against observations for rainfall and temperature. To determine the potential improvement contributed by EQM, both raw and bias-corrected daily rainfall and temperature are presented in Fig. III-2(A) and (B). Since the generation of drought characteristics is done at monthly scales, the verification of monthly rainfall and temperature is also included (Fig. III- 2(C) and (D)). Not only does the Taylor diagram provide the opportunity to compare models with observations, but the models can also be compared with one another.

The ensemble members of the raw dataset have a bias that ranges from -25 to +21% for daily rainfall, hence the need to conduct bias correction. For daily rainfall (Fig. III-2 (A)), the standard deviation of the observed daily rainfall is 3.3 mm, while all the uncorrected raw models except one show larger standard deviations. The deviation of the raw dataset ranges from 3.1 to 5.0 mm. After the bias correction, the dispersion of values in the dataset is reduced as the standard deviation range shifts to between 2.9 and 3.5 mm. The improvement introduced by EQM is also observed with the Person correlation coefficient between the observed and GCM-RCM ensemble members. The correlation improves from between 0.39-0.7 (raw ensemble members) to 0.53-0.71 (EQM ensemble members). Similarly, the root mean square error (RMSE) improves from between 2.6 - 4.8 mm and 2.6 - 3.1 mm per day. Considering the ensemble mean, the RMSE improves from 2.1mm to 1.8 mm, and the correlation coefficient improves from 0.79 to 0.85. At the monthly time scale (Fig. III-2(C)), the skill of the EQM ensemble improves considerably, as the correlation is in the range of 0.66 - 0.87 (0.86 for the ensemble mean) and 0.79 - 0.88 (0.91 for the ensemble mean) for uncorrected and bias-corrected ensemble members, respectively.

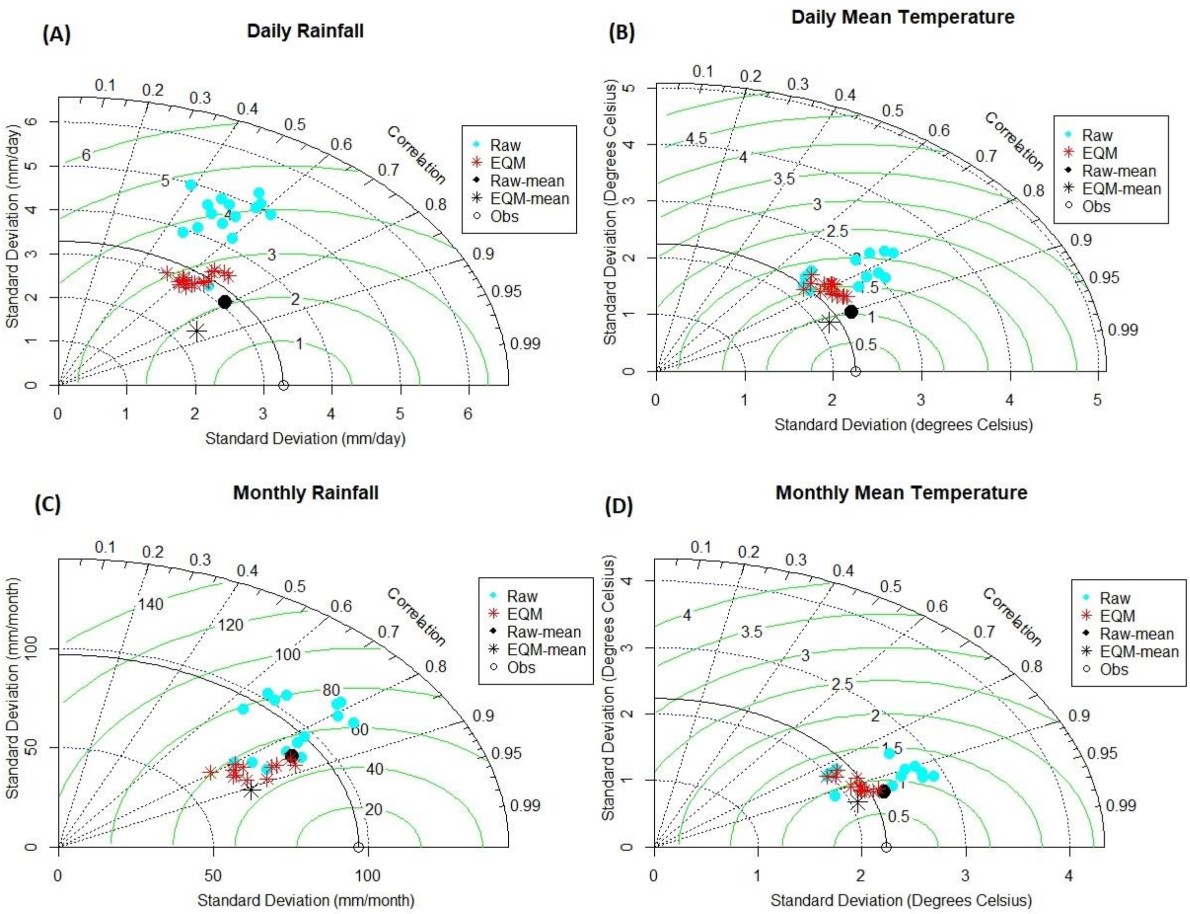


Figure III - 2 *Taylor diagrams of (A) daily rainfall, (B) daily mean temperature, (C) monthly rainfall, and (D) monthly mean temperature. Cyan is for the uncorrected (raw) model outputs, while red is the bias-corrected model outputs. Black shows ensemble means, where • is for uncorrected outputs while* is for the bias-corrected dataset. O represents the observed (reference) dataset. The Pearson correlation which is shown by the azimuth from 0 to 90° is significant at the 0.05 significance level. The centred root mean square error (RMSE) is proportional to the distance from the reference point on the x-axis (green lines) and is in mm/day or mm/month or degrees Celsius for daily rainfall, monthly rainfall and temperature respectively. The standard deviation is proportional to the radial distance from the reference point.*

The bias of daily mean temperature is less than rainfall, as it ranges from -6 to +11% for the raw ensemble members. The correlations are similar for both datasets which range from 0.7 to 0.84 (raw data) and from 0.72 to 0.85 (EQM data) (Fig. III-2(B)). Again, the ensemble mean correlation between the observations and the models are also similar, at 0.91. The standard deviations for both raw and corrected model outputs are near the reference point. However, the RMSE for the ensemble mean slightly improves from 1.1°C (raw) to 0.9°C (EQM). Looking at the raw ensemble members, their standard deviations are greater than those of the observations, while the bias-corrected values are mostly around the observed standard deviation of 2.2°C. At the monthly time scale (Fig. III-2(D)), the standard deviations of temperature for the ensemble members also remain around 2.2°C, while the uncorrected members range from 1.9 to 2.9°C. The correlation coefficients and RMSE show similar patterns as at the daily time scale.

In summary, EQM improves the skill of the GCM-RCM ensemble by reducing the spread and magnitude of ensemble members. Most models represent the temperature of the region better than rainfall. Aggregating individual ensemble members into ensemble means as well as aggregating from daily to monthly time scales improves the statistical measures significantly.

4.1.2 Meteorological water balance (MWB), standardised precipitation and evapotranspiration index (SPEI) and drought characteristics

To illustrate the effectiveness of EQM, the deviations in the MWB as estimated from the raw and bias-corrected climate simulations and compared to observed data for the reference period are also assessed (Fig. III-3 (A)). In addition, the deviations of the SPEI, DE, DI and DM are also evaluated (Fig. III-3 (B), (C), (D) and (E).

Meteorological water balance (MWB)

The observed MWB mean is +5.5mm, and in Fig. III-3(A), the benefit of EQM becomes the clearest, as it corrects the water balance bias from the inter-quartile range (IQR) of between -13.4 and +2.4mm, (ensemble mean: -3.9mm) to between +4.8 and +6.8mm (IQR) (ensemble mean: +5.6). The bias correction has managed to correct all the models from negative to positive MWB and closer to observed MWB values.

Standardised precipitation and evapotranspiration Index (SPEI)

Fig.III-3(B) shows the deviation of the SPEI for moderate drought events (SPEI ≤-1). For the raw dataset, the bias ranges from -14.6% to +1.3% (IQR), and after bias correction the deviation is reduced and counts from -7.9% to -2.1% (IQR). The deviation of the ensemble mean improves from -9.4% for the raw dataset to -4.4% for the bias-corrected dataset (Fig.III-3(B)).

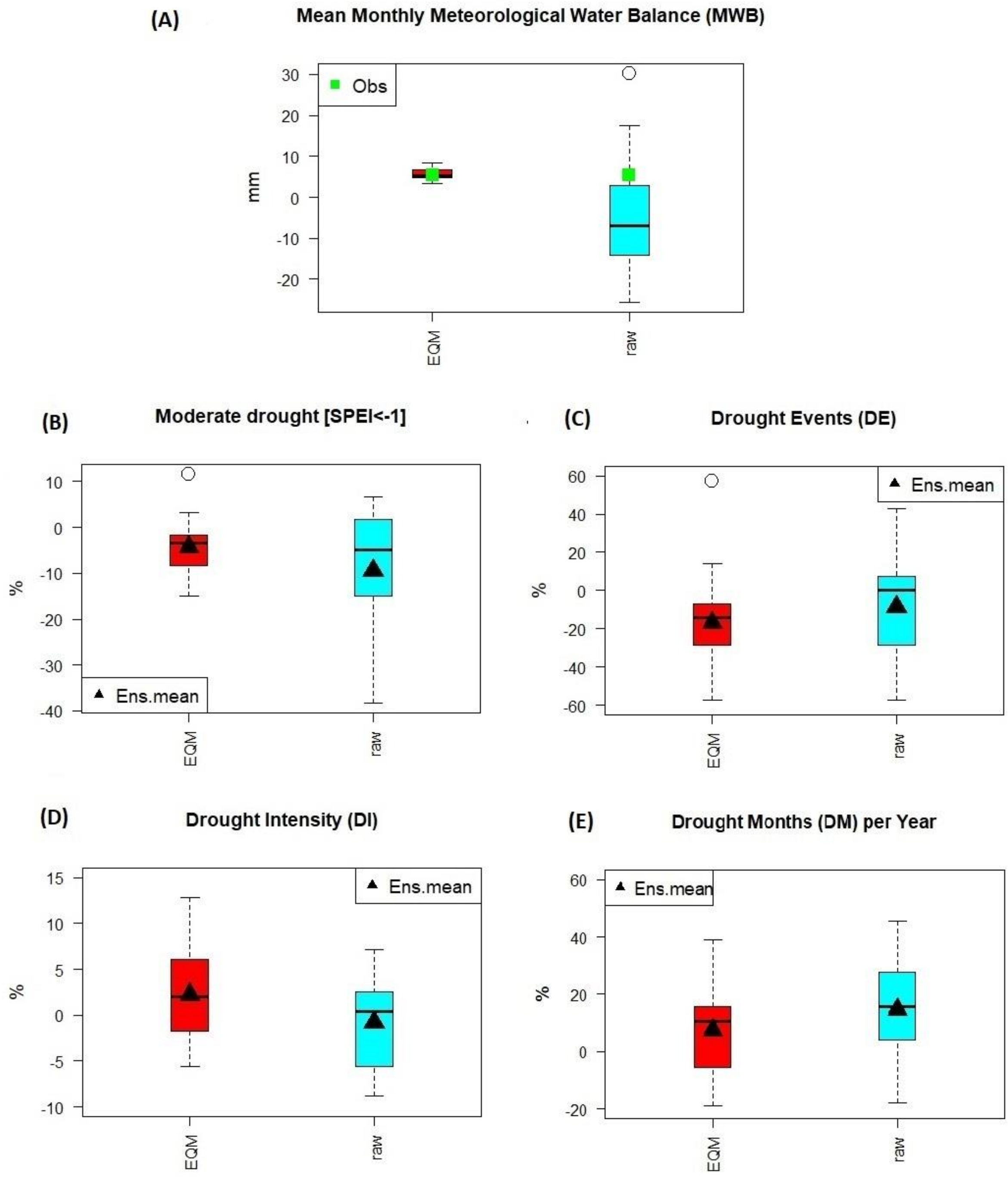


Figure III - 3 *Bias assessment of (A) meteorological water balance (rainfall minus potential evapotranspiration), (B) standardised precipitation and evapotranspiration index (SPEI) for moderate drought (SPEI<-1), (C) drought events (DE), (D) drought intensity (DI) and (e) drought months (DM) per year in the Greater Lake Malawi Basin.*

Drought characteristics

The deviation in the drought characteristics DE, DI, and DM are shown in Fig.III-3(C)-(E). The smallest deviation for both the raw and bias-corrected datasets is found for DI, Fig.III-3(D) (mean raw: -0.8% vs. mean EQM: +2.2%). The size of the ensemble distribution is similar but the EQM ensemble shows slightly larger values. For DM (Fig.III-3(E)), the range in the deviation of the raw and EQM ensembles is also similar, though based on the IQR, the EQM range has smaller deviations than raw values (EQM: -3.3% to +15.6% (IQR) versus raw: +6.4% to +26.7% (IQR)). However, the mean deviation of the EQM ensemble (+7%) is considerably smaller than the raw ensemble (+14%). Less influence of EQM bias correction is noted for the estimation of DE as the deviation of the raw dataset ranges from -28.6 to +3.6% (IQR) while the deviations of the EQM ensemble range from -28.6% to -10.7% (IQR) (Fig.III-3(C)).

To sum up, analogous to the improvement in rainfall, EQM considerably improves the estimation of the MWB from the GCM-RCM ensemble for the reference period. However, the effect of EQM on the estimated drought characteristics is comparably small and does not necessarily lead to an improved representation of drought characteristics for the reference period.

4.2 Projected Drought Characteristics

4.2.1 Standardised Precipitation and Evapotranspiration Index (SPEI)

Fig. III-4 presents the SPEI time series of the 16 GCM-RCMs and their ensemble means for the period 1976-2005 (historical period), 2021-2050 (near-term period), and 2071-2100 (far-term period) using the bias-corrected datasets. The SPEI during the historical period shows high uncertainty and variations among the individual models. As a result, the ensemble mean of the models rarely goes beyond -1 and +1, and it is clearly noticed that the ensemble members are poorly representing the observed SPEI (RED graph) during the historical period. Over time, though, the SPEI decreases which indicates an increase in DI from the historical period to the near- and far-term periods in Malawi. The wet episodes noted during the historical period become fewer and fewer in the future, as dry conditions become more prominent. The increase in drought during 2021-2050 is similar for both RCP4.5 and RCP8.5, but the mean intensity of RCP8.5 is 21% more than that of RCP4.5. During 2071-2100, the SPEI based on RCP4.5 stabilizes, while the SPEI based on RCP8.5 constantly keeps on decreasing. It is also noted with many ensemble members that they have one continuous drought episode during the entire period of 2071-2100. The model uncertainty (spread of models) is large, which starts during the historical period and increases over time. The SPEI based on RCP8.5 shows greater uncertainty than based on RCP4.5, and the mean intensity of the SPEI based on RCP8.5 is 171% larger than that based on RCP4.5 during this period.

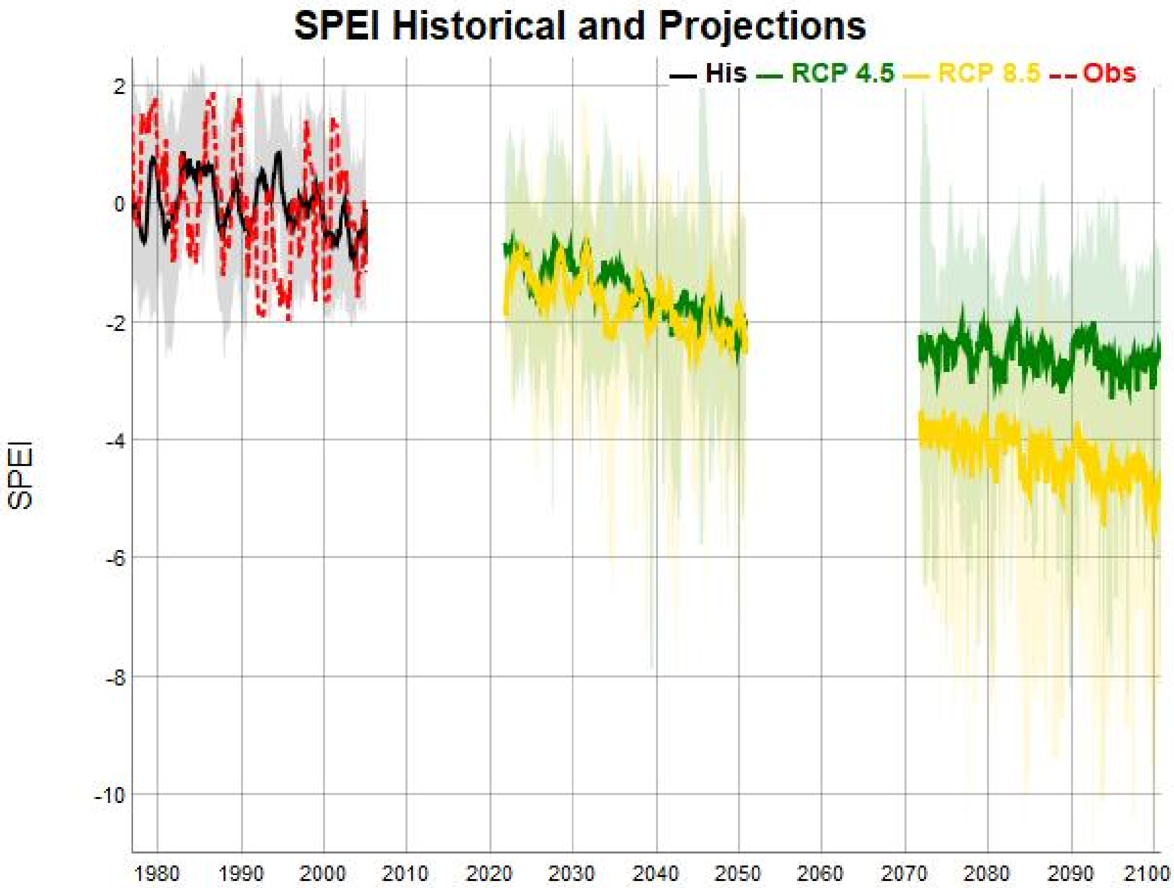


Figure III - 4 *The standardised precipitation and evapotranspiration index (SPEI) series for observations, the 16 bias-corrected GCM-RCM combinations and associated ensemble means for (i) the historical period 1976 to 2005, grey for ensemble members, black for ensemble mean and red for observations. (ii) 2021-2050 and 2071-2100 future periods. Green is for the RCP4.5 and yellow for RCP8.5.*

4.2.2 Projected Changes in Drought Characteristics

The previous sections have illustrated the limited ability of the GCM-RCM ensemble (both raw and bias-corrected) to represent the observed meteorological water balance and drought characteristics for the reference period. This also limits the credibility of the GCM-RCM ensemble in projecting potential future changes. Therefore, we opted for the response surface approach as described in Section 3.3 to illustrate the sensitivity of droughts to systematic changes in temperature and precipitation (Fig.III-5). The future projections of temperature and precipitation of the GCM-RCMs are overlaid on the response surfaces to illustrate the ensemble uncertainty. The summary of the GCM-RCMs is also represented in Tab. III-2.

Meteorological water balance, MWB

The mean MWB is sensitive to both temperature and rainfall changes (Fig.III-5(A)) as the estimates decrease with both increasing temperature and decreasing precipitation. The MWB at the reference point, R (ΔP=0%; ΔT=0°C) is ~+4.1 mm, indicating that the rainfall amount is greater than evapotranspiration (water surplus). However, for the most extreme combination of scaling (ΔP=-35%; ΔT=+5°C), the MWB is negative (~-92.3 mm) implying that evapotranspiration clearly exceeds rainfall. It is also found that already an increase of just 1°C in temperature (ΔP=0%; ΔT=1°C) changes the water balance to -3.9 mm implying that evapotranspiration becomes higher than rainfall in the area. Similarly, the change in rainfall of +/- 5% (ΔP=+/- 5%; ΔT=0°C) changes the MWB to +8.8 mm/-0.5 mm.

Considering the GCM-RCM ensembles, most of the models suggest future MWB between -3.9 and -13.2 mm / +0.8 and -17.9 mm during 2021-2050 for RCP4.5/RCP8.5. These estimates reflect a decrease in MWB between -195 and -422% / -80% and -537% respectively. During 2071-2100 and for RCP4.5, the water balance is in the range of -8.6 mm to -28.8 mm, which reflects a decrease of -320% to -802%. For RCP8.5 on the other hand the water balance is from -25.8 mm to -59.5 mm, reflecting a decrease of -729% to -1551%. The ensemble mean changes for the different periods and RCPs are -3.9 mm (-195%) and -18.4 mm (-549%) (RCP4.5 2021-2050 and 2071-2100), and -8.6 mm (-310%) and -50.2 mm (-1324%) (RCP8.5 2021-2050 and 2071-2100) as seen in Tab.III-2. Otherwise, the mean MWB change per year ranges from -0.1 mm, -0.3 mm, and -0.6 mm to -1.7 mm for RCP4.5 2021-2050, RCP8.5 2021-2050, RCP45 2071-2100 and RCP8.5 2071-2100 respectively. The standard deviation among the models (Fig.III-5(B)) seems to be affected only by temperature scaling which indicates the relative importance of the temporal structure of the input data series on the estimation of PET. However, the overall standard deviation is below 8% which shows a high model agreement, indicating a small influence of the different model temporal structures on mean water balance.

Table III - 2 *Summary of GCM-RCM results. Ensemble mean changes and ranges in DI, DE, MWB, and DM per year compared to the reference period (Ref).*

Period		2021-2050				2071-2100			
Scenarios	**Reference**	**RCP4.5**		**RCP8.5**		**RCP4.5**		**RCP8.5**	
		Ensemble mean	**range**	**Ensemble mean**	**range**	**Ensemble mean**	**range**	**Ensemble mean**	**range**
Mean DI	-1.6	-2	-2.8, -2	-2.4	-3.6, -1.8	-3.7	-5.5, -2.4	-7.8	-9.0 -4.9
Mean DE	6	7	4, 7	6	3, 7	3	2, 6	1	1, 2
Mean MWB (mm)	+4.1	-3.9	-13.2, -3.9	-8.6	-17.9, +0.8	-18.4	-28.8, -8.6	-50.2	-59.5, -25.8
Mean MWB/year (mm)	-0.1	-0.1	-0.4, -0.1	-0.3	-0.6, 0	-0.6	-1.0, -0.3	-1.7	-2.0, -0.9
Mean DM/year (months)	4	7	7, 10	9	5, 11	11	9, 11	12	11, 12
DM change/year (months)	0	+3	+3, +6	+5	+1, +7	+7	+5, +7	+8	+7, +8

Drought events, DE

The number of DE ranges from 1 to 7 for the 30-year period under study (Fig.III-5(C)). The reference point, R, shows 6 events during the reference period. With increasing temperature, the number of DE first starts to increase (up to ΔT=+0.5°C) before gradually decreasing until a single big drought event over a 30-year period is reached (from ΔT=+3.5°C). Combining temperature increase with a decrease in rainfall, which also reduces DE, the situation of only one long lasting drought event occurring over 30-year period is reached earlier. Considering the GCM-RCM ensembles, DE ranges from 4 to 7 events for RCP4.5 during 2021-2050 and from 3 to 7 events for RCP8.5. During 2071-2100, the events are between 2 and 6 for RCP4.5 and between 1 and 2 for RCP8.5. The ensemble average suggests 7 events, and 6 events during 2021-2050 for RCP4.5 and RCP8.5, respectively, and 3 events and 1 event during 2071-2100 for RCP4.5 and RCP8.5, respectively (Fig.III-5(C) and Tab.III-2). The climate models agree well in areas where DE is reduced to one event only (Fig.III-5(D)). The effect of the temporal structure of the GCM-RCM ensemble is greatest within the transition zone from DE=2 to DE=1. Thus, it seems that the models differ in terms of the timing to attain a lower number of DE, Fig.III-5(D).

Drought intensity, DI

Like the water balance, the mean DI is also sensitive to both temperature and rainfall changes (Fig.III-5(E)) i.e., DI increases with increasing temperature and decreasing rainfall. The areas in the response surface with only one DE show the highest DI. The DI for the reference point, R is ~-1.6 (SPEI value), which refers to the severe drought category ($-1.5 \leq DI > -2$). However, with the slight increase in temperature or decrease in rainfall, the mean DI reaches the extreme drought category ($DI \leq -2$). For temperature scaling by $\Delta T > +4°C$, the influence of precipitation scaling on DI decreases. That is, even with increasing precipitation, droughts reach comparatively high intensities due to high PET. It is found that 1°C increase in temperature increases the DI by 28% while the increase/decrease in rainfall by +/- 5% changes the DI changes by -8% and +11% respectively.

For the period 2021-2050, the GCM-RCM ensemble shows a range in DI from -2 to -2.8 (RCP4.5), and -1.8 to -3.6 (RCP8.5). For 2071-2100, the DI ranges from -2.4 to -5.5 (RCP4.5) and -4.9 to -9 (RCP8.5) as shown inTab.III-2. On average (ensemble means), this accounts for an increase in DI of +25%, +50%, +131%, and +388% for RCP4.5 2021-2050, RCP8.5 2021-2050, RCP45 2071-2100 and RCP8.5 2071-2100, respectively. The agreement of the models varies with both temperature and rainfall, there is a higher model agreement at lower temperature changes when precipitation is close to the reference point and the standard deviation is less than 10%. Otherwise, the standard deviation is between 10 and 25% for the rest of the areas implying the influence of the temporal structures on mean DI (Fig.III-5(F)), This influence is larger in areas with only one drought event occurring over the 30-year period (Fig.III-5(D)), indicating that although the 17 different response surfaces agree on a single drought event during these areas they differ considerably in intensity.

Drought months, DM

The pattern of DM per year over the 30-year period is similar to that of DE. Particularly for the combinations of temperature and precipitation scaling leading to only one long-lasting DE over 30 years (Fig.III-5(C)), where there are 12 drought months per year (Fig.III-5(G)). The whole-year drought event is reached when precipitation is scaled by $\Delta P \leq -25\%$ (with no changes in temperature), or when temperature is scaled by $\Delta T=+3°C$ (no changes in precipitation). However, with the increasing temperature of the global limit (United Nations, 2015) of either $\Delta T=+1.5°C$ or $\Delta T=+2°C$, the 12-month drought per year is reached if it is associated with a rainfall decrease of $\Delta P= -15\%$ or $\Delta P= -10\%$ respectively. The GCM-RCM ensemble means suggest DM per year ranging from 7 to 10 months for RCP4.5 and 5 to 11 months for RCP8.5 during the 2021-2050 period. On the other hand, during 2071-2100 the DM range from 9 to 11 months for RCP4.5 and 11 to 12 for RCP8.5 (Tab.III-2). On average, the increase in DM by +3, +5, +7 and +8 more months than the reference period per year for RCP4.5 2021-2050, RCP8.5 2021-2050, RCP4.5 2071-2100 and RCP8.5 2071-2100 respectively as shown in Tab.III-2. The CV is almost zero where the maximum DM is reached indicating a negligible relevance of differences in the temporal structure of the climate input data. Still, in the area where the majority of the GCM-RCM ensemble members cluster especially for the 2021-2050 period, the CV is comparatively large (~30%) (Fig.III-5(H)).

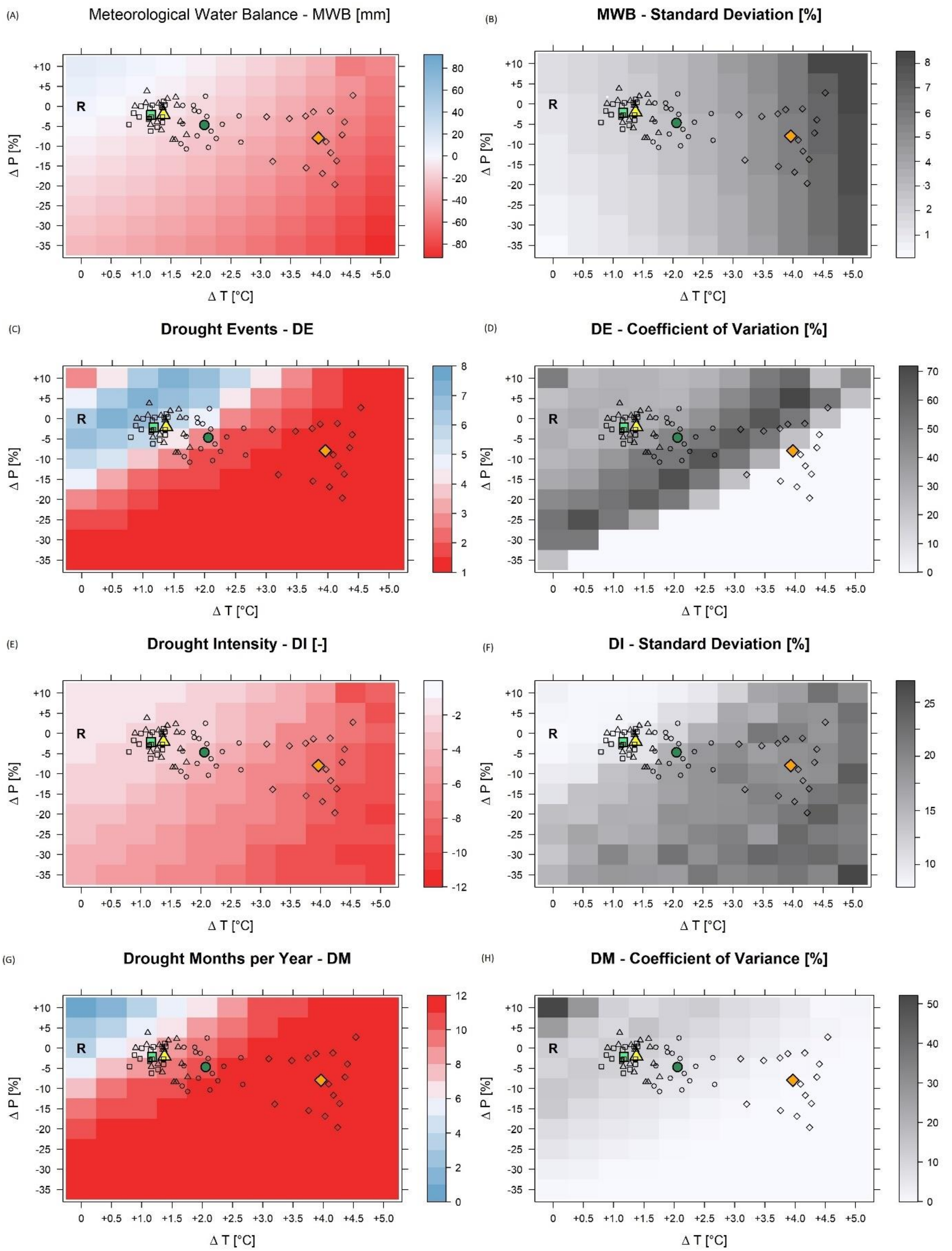


Figure III - 5 *Response surfaces for mean meteorological water balance-MWB [first row-(A,B)], mean drought events-DE [second row-(C,D)], mean drought intensity-DI [third row-(E,F)] and drought months-DM per year [fourth row-(G,H)] at the aggregated scale of GLMB. The response surfaces are produced using systematically perturbed precipitation (y-axis) and temperature (x-axis) data as inputs. The points added on the surfaces reflect climate change signals as projected by 16 GCM–RCM* *combinations. The different symbols refer to different periods and scenarios (rectangle/circle: RCP4.5 2021–2050/2071–2100; triangles/diamonds: RCP8.5 2021–2050/2071–2100) for the bias-corrected datasets. Thick colored symbols are the mean of the climate model ensemble for the bias-corrected datasets for the respective periods and scenarios: light-green/dark-green for RCP4.5 2021–2050/2071–2100; yellow/orange for RCP8.5 2021–2050/2071–2100. Response surfaces in the left column show the mean of 17 individual response surfaces (16 generated based on levelled GCM–RCMs plus 1 based on scaling observed time series). Panels to the right show the standard deviations and coefficient of variation, respectively, of the 17 individual response surfaces. "R" marks the mean of each drought parameter for the reference period, i.e., no scaling.*

5. Discussion

5.1 Reliability of Climate Models

Although the GCM-RCMs simulation results are not the perfect reproduction of the observations, they are found to represent the climate conditions in the region reasonably well. This is particularly the case for temperature at monthly timescales, which has a lower bias between raw GCM-RCM temperature simulations and observations than for precipitation (Enayati et al., 2021). Still, the bias-corrected dataset outperforms the raw dataset and also reduces the uncertainty range. It is also noted that the ensemble mean of both raw and bias-corrected temperature and rainfall performs better than individual models which agrees with Warnatzsch & Reay (2018) who systematically evaluated CORDEX Africa climate simulations for Malawi. This also is in line with the assumption that different climate models are random samples from the distribution of possible models centred around the mean (Jun et al., 2008)

The rainfall simulation performance of the climate models is lower than for temperature, and its error signals are transferred to the estimates of the MWB. With reference to drought characteristics, the deviation of the estimations by the bias-corrected and raw datasets as compared to estimations based on observed climate data are in most cases similar or even worse. That is, the benefit of EQM for adjusting the temperature and precipitation simulations does not translate into an improved estimation of drought characteristics. This is a result of the fact that EQM bias correction preserves the temporal patterns of the climate variables as they are simulated by the GCM-RCMs. Drought characteristics like DE and DM, however, are influenced by the temporal structures of climate model simulations. Imperfect simulation of the temporal structure of precipitation in particular, can lead to incorrect drought estimates, although EQM has improved the mean and variance of simulated temperature and precipitation. This limits the credibility of the GCM-RCM ensemble for future projections on drought characteristics in the region. The limitation of EQM for the adjustment of future projections is that it assumes the transfer function to be stationary in time. This is particularly critical for the highest quantiles making this method less suitable for rare occurrences, i.e., intense precipitation and floods (Paz & Willems, 2022).

Due to the limited representation of the climate model ensemble in the region, we have applied the response surface approach for this task since it allows for an illustrative overview of many possible changes including an illustration of the uncertain projections of the GCM-RCMs given by the overlaid spread of the ensemble member distributions. Like in many climate impact studies, we focus on the differences (future period minus reference period) obtained by the same model instead of the absolute values. In this way, the bias errors from the reference period may be offset (Maraun et al., 2010). In this study, we have only used a single bias correction method, and yet according to Wu *et al.* (2021), about 35% of uncertainty in the future projections is contributed by bias-correction methods. Therefore, it will be interesting to find out whether other bias-correction methods can reproduce results similar to those of the EQM method.

5.2 The potential impacts of climate change on droughts in the GLMB

Despite the internal structural differences and uncertainties that exist among the models, they all agree on the increase of meteorological drought intensity in the future. This is well in line with other studies finding similar results in the (South-)East African region (e.g., Dai, 2013; Nguvava et al., 2019; Haile et al., 2020a). Future drought events between 2071-2100 are projected to be almost four times more intense and by 8 months longer–lasting (ensemble mean RCP8.5) as compared to the reference period. Consequently, the number of events will decrease with higher temperatures and lower precipitation. With the increase in temperature (and therefore a probable increase in evapotranspiration) and decrease in rainfall, the MWB will decrease roughly by -0.1mm to -0.3mm/year during 2021-2050 (Tab.III-2). On the other hand, during 2071-2100 the decrease in the MWB will be between -0.6 and-1.7mm/year. This will increase DI by +25 to +388% and DM between +93 and +223% in the future depending on time period and scenario. These numbers may seem very high, yet similar results for DI and drought duration have been reported by Haile *et al.* (2020) for some Eastern African countries like Tanzania, which borders Malawi.

These numbers and the projected possibility of a single multi-decadal drought in the far future are quite concerning. This also underlines the crucial role of future droughts in this region. Spinoni et al. (2020) identified many regions in southern Africa including areas in Malawi to become global drought hot-spots in the future. The estimation of the drought characteristics in this study is based on the SPEI and refers to the long-term mean and variance of the MWB (see Eq. 1) for the climate normal period 1976-2005. When we consider drought events at the end of the 21st century, e.g., in the 2090s, we will then refer droughts to a "new-normal" period. This will lead to less severe SPEI values than reported in this study. However, as clearly shown by this study, the "new-normal" will be generally warmer and drier than current conditions, which may re-define our current understanding of droughts in this region. It is worth emphasizing that the drought assessments in this study are based on a drought index which also considers evapotranspiration in addition to precipitation. Several studies (e.g., Ahmadalipour et al., 2017; Mtilatila et al., 2020a) have compared drought assessments based on SPI versus SPEI and found differences in drought characteristics depending on the index used. For Malawi, drought estimations based on SPEI show higher drought magnitudes compared to drought estimations based on SPI (Mtilatila et al., 2020a). Both indices, though, show a decreasing trend from 1976 to 2013 (thus increasing drought). For other regions like in North America and Europe, and at the Horn of Africa, the direction of trend in droughts depends on the choice of the index (Ahmadalipour et al., 2017; Spinoni et al., 2014). SPEI considers the crucial role of evapo(transpi)ration which can be expected to increase given rising temperatures as projected by the GCM-RCM ensemble. However, the estimation of PET, which is needed to compute the SPEI, is not trivial and thus uncertain. For instance, PET – here estimated by the Thornthwaite method – assumes sufficient soil moisture to maintain active transpiration and tends to overestimate evapotranspiration which can temporally be water-limited (Portela et al., 2019). Potentially, this leads to an overestimation of SPEI.

The study has also shown how important it is to keep the global temperature increase below +1.5°C as stipulated in the *United Nations Framework Convention on Climate Change* (UNFCCC) - Paris Agreement (United Nations, 2015). Beyond this threshold, there is a likelihood of having 12 drought months per year if associated with a decrease in rainfall of at least -15%. All the models under RCP8.5 during 2071-2100 agree on this possibility. Since climate factors including droughts contribute to crop failure in Malawi by 53.3 % (Coulibaly et al., 2015), the more severe and longer-lasting future droughts as projected in this study will impact the agricultural sector and affect food security and the economy of the country.

From this perspective, future droughts will also impact the availability of water resources for hydropower production. Referring to Mtilatila *et al.* (2020b), who found that a temperature increase of +1.5°C combined with a rainfall decrease of less than -20% will turn the Shire River flow from perennial to seasonal, this will signify extreme hydrological drought in the country. The extreme meteorological droughts (DI<-2) that occurred in the 1990s resulted in an extreme hydrological drought on Lake Malawi that significantly reduced the Shire River flow (Mtilatila *et al.*, 2020a). During this time, the lake level of Lake Malawi was reduced by -0.9m on average and went down to -1.9m when the drought was at its peak. It was also found by Mtilatila *et al.* (2020a) that both the duration and intensity of the meteorological droughts had an impact on the strength and duration of the hydrological drought. Therefore, the future DM and DI will surely result in very intense hydrological droughts that will affect the Lake Malawi level and hence the Shire River outflow, thereby affecting the communities downstream including hydropower production (Bhave et al., 2020). The role of evaporation is essential for Lake Malawi's water balance and lake outflow to the Shire River where more than 95 % of the country's electricity productions takes place. Hydrological projections agree on a reduction in mean lake level, outflow and Shire River discharge as a consequence of climate change. In turn, future hydropower production is likely to decrease between -1% and -24% during 2021-2100 based on both RCP4.5 and RCP8.5 resulting in a reduced reliability of hydropower production due to climate change Mtilatila *et al.* (2020b).

6. Conclusion

This study analyzed the reliability of an ensemble of 16 GCM-RCM combinations from the CORDEX Africa initiative in simulating the temperature and precipitation statistics as well as drought characteristics in the GLMB, Southeast Africa. Also, the benefit of EQM bias correction of the GCM-RCM ensemble was investigated. The models have some limitations in representing the drought characteristics in the region. Therefore, the 'top-down' approach of impact assessment has been extended to the scenario-neutral 'bottom-up' method which provides the quantifiable sensitivity of drought characteristics towards the changes of temperature and precipitation. However, different from the delta approach, the sensitivity analysis in this study has taken into consideration the temporal changes of the models. Three major conclusions can be drawn from this study:

- The GCM-RCM ensemble simulates temperature dynamics better than precipitation dynamics compared to meteorological observation data, which is not a new feature of GCM results; see Bronstert et al., 2007. As such, uncertainty in rainfall projections contribute highly to the uncertainty in drought characteristics.
- Bias correction improves the ability of the GCM-RCM ensemble to reproduce meteorological conditions and – to some degree – the meteorological water balance.

However, it has only relatively small effects on the estimation of drought characteristics. This limitation reduces the -reliability of the GCM-RCM ensemble for the projection of potential future drought conditions. Therefore, the future projections of drought characteristics have been combined with a response surface approach that illustrates the outcome of a systematic sensitivity analysis of droughts towards changes in temperature and precipitation conditions. The differences in the temporal structure of the input data time series as projected by the different climate models have been preserved. Overlaying the bias-corrected future projections on the response surface for the individual drought indicators illustrates the spread of the projections, and thus the ensemble uncertainty.

Future droughts in Malawi will likely become more severe compared to the reference period (1976-2005). The entire GCM-RCM ensemble agrees that droughts will be more intense, while the number of drought events will decrease due to long-lasting future drought episodes. The degree of drought intensification depends on the scenario considered. On average, projected droughts based on RCP8.5 are 1.7 times more severe than droughts based on RCP4.5. However, the range in the projections of the individual ensemble members is also high, which illustrates the high uncertainties in the GCM-RCM ensemble. Despite the high uncertainties and therefore, the limited credibility of the climate projections, the information generated here can aid in planning and (water-) managing activities for climate change adaptation measures in Malawi. This is of particular relevance for water management issues referring hydro power generation and food production, both for rain-fed and irrigated agriculture. The study focussed on temporal changes in drought characteristics over the whole GLMB aggregated over large spatial scales. Future investigations should also establish spatially distributed change projections.

IV Susceptibility of water resources and hydropower production to climate change in the tropics: The case of Lake Malawi and Shire River Basins, SE-Africa

Abstract:

The sensitivity of key hydrologic variables and hydropower generation to climate change in the Lake Malawi and Shire River basins is assessed. The study adapts the mesoscale Hydrological Model (mHM) which is applied separately in the Upper Lake Malawi and Shire River basins. A particular Lake Malawi model, which focuses on reservoir routing and lake water balance, has been developed and is interlinked between the two basins. Climate change projections from 20 Coordinated Regional Climate Downscaling Experiment (CORDEX) models for Africa based on two scenarios (RCP4.5 and RCP8.5) for the periods 2021–2050 and 2071–2100 are used. An annual temperature increase of 1°C decreases mean lake level and outflow by 0.3 m and 17%, respectively, signifying the importance of intensified evaporation for Lake Malawi's water budget. Meanwhile, a +5% (-5%) deviation in annual rainfall changes mean lake level by +0.7 m (-0.6 m). The combined effects of temperature increase and rainfall decrease result in significantly lower flows on Shire River. The hydrological river regime may change from perennial to seasonal with the combination of annual temperature increase and precipitation decrease beyond 1.5°C (3.5°C) and -20% (-15%). The study further projects a reduction in annual hydropower production between 1% (RCP8.5) and 2.5% (RCP4.5) during 2021–2050 and between 5% (RCP4.5) and 24% (RCP8.5) during 2071–2100. The results show that it is of great importance that a further development of hydro energy on the Shire River should take into account the effects of climate change, e.g., longer low flow periods and/or higher discharge fluctuations, and thus uncertainty in the amount of electricity produced.

Mtilatila, L. *et al.* (2020) 'Susceptibility of Water Resources and Hydropower Production to Climate Change in the Tropics : The Case of Lake Malawi and Shire River Basins , SE Africa', *Hydrology-MDPI*, 7(54). doi: 10.3390/hydrology7030054.

1. Introduction

Climate is changing around the world and one of the sectors being affected most is water resources. The hydrological effects of climate change vary from region to region. For instance, altered rates and different timing of river flows are observed in high latitudes due to snow melting and increases in precipitation (Vormoor et al., 2017), while decreased flows are also noticeable in the mid-latitudes and dry tropics (Bates et al., 2008). These climate change impacts on water resources have not spared the African continent, where the frequency and intensity of droughts is rising (Shukla et al., 2019). Fourteen countries are already under water stress as water availability has decreased 2.8 times between 1970 and 1995 (Simms, 2006). In southern Africa, the highly ranked water-stressed countries are Namibia, South Africa, Lesotho, Botswana and Eswatini, while the rest of the countries in the region are rated medium or low (Luo et al., 2015). Extreme hydrological events, such as floods and droughts, are also common in Africa, and these are expected to increase under climate change, worsening the water situation in the continent (Arnell, 2004; Simms, 2006). Southern Africa is one of the most vulnerable greater regions to climate change (IPCC, 2007a) and, if the recent rate of change persists into the future, the impact on water resources will be enormous (Kusangaya et al., 2014).

A particular example of a very important but vulnerable hydro-system in the tropics is Lake Malawi and its river basin. As the fifth/ninth largest freshwater lake in the world (in terms of water volume/surface area), it is the key water resource and reservoir for hydropower generation on the Shire River, which originates at the only southern outlet of the lake. The capacity installed and electricity generated at the hydropower plants in Malawi account for 80.2% and 98%, respectively, of the country's total electricity power (Taulo et al., 2015). Lake level fluctuations affect the power production on the Shire River, for example, the below normal rainfall seasons of 2014/2015 and 2015/2016 resulted in falling lake water levels and reduced river flows, which decreased the power production by more than 50% (ESCOM, n.d.-b). Between 1915 and 1935, the outflow from the lake into the Shire River totally ceased (Shela, 2000), which nowadays would lead to a complete failure in energy supply. During the last four decades (1970–2013), droughts in the greater Lake Malawi Basin have increased in terms of duration, severity and area proportion due to both a decrease in precipitation and an increase in temperature (leading to increased evapotranspiration), which have led to declining lake levels in Lake Malawi (Mtilatila et al., 2020). Future climate projections from various studies indicate a temperature increase in the southern Africa region from 2 to 5 degrees Celsius until 2100 (Beck & Bernauer, 2011; Kusangaya et al., 2014; Mujere & Mazvimavi, 2012; Stevens & Madani, 2016; Tadross et al., 2005). Though there is uncertainty in the magnitude and direction of mean precipitation projection in the region, many studies based on climate projections have suggested decreasing trends until 2100 (Arnell et al., 2003; Beck & Bernauer, 2011; Yanda, 2010).

Hydropower will maintain its position as the main source of electricity in the short to medium term in Malawi as compared to other energy sources. There are plans to invest in even more hydropower stations along the Shire River to meet the future energy demands (Conway, 2018; GOM, 2010; Millenium Challenge Corporation, 2015). However, with reference to the recent increasing trends in both meteorological and hydrological droughts in Malawi (L Mtilatila et al., 2020), future changes in climate may further reduce river flows (Nigel W. Arnell, 2004; Harrison & Whittington, 2002; Simms, 2006) and thus affect the hydropower production, which puts the energy supply in Malawi under threat.

Although hydropower is the key energy source in Malawi, there are only a few studies that have quantified the impacts of climate change on hydropower generation, (e.g., (Kaunda & Mtalo, 2013)). Most climate impact studies on the Southern and South-eastern Africa regions focussed on water resources in general (Arnell, 2004; Gosling & Arnell, 2016; Kumambala & Ervine, 2010; Kusangaya et al., 2014; Mazvimavi, 2010), agriculture (Makungwa, 2010; Ngigi, 2012; Saka et al., 2012), health (Lotz-Sisitka, 2010) and multiple other sectors including energy, the environment and disasters (Arndt et al., 2014; Bhave et al., 2020; Simms, 2006). For the Zambezi River, reduced hydropower production has been projected for the future until the 2080s based on three General Climate Models (GCMs) (Harrison & Whittington, 2002; Yamba et al., 2011). In Malawi, reduced hydropower generation at the Lujeri Micro-Hydropower Scheme in southern Malawi during 1980–2011 was attributed to increased temperature (Kachaje et al., 2016). The decrease in Lake Malawi’s level that would potentially lead to no outflow from the lake was identified for the period 2021–2050 based on 11 out of 30 climate models (Bhave et al., 2020) and up to 2100 based on a single model (Kumambala & Ervine, 2010). This would have serious consequences for hydropower production.

So far, however, the impacts of possible changes in future climate on streamflow and hydropower productivity on the Shire River have rarely been investigated despite their crucial relevance for electricity supply in Malawi. This study (i) examines the sensitivity of the hydrological system of Lake Malawi and its basin, as well as of the Upper Shire River Basin, towards changes in key climate parameters based on dynamical hydrological modelling; (ii) estimates potential impacts of future climate change on the hydrological system by means of so-called scenario-neutral response surfaces and based on a 20-model ensemble of Regional Climate Models (RCMs); and (iii) illustrates the impacts of changes in the hydrological system on future hydropower generation in Malawi. The study is led by the following questions:

1. How sensitive are lake levels and discharge to variations in precipitation and temperature (potential evapotranspiration and lake evaporation) in the Lake Malawi Basin (including the lake) and Shire River Basin?

2. What are the impacts of future climate change projections on the water budgets of the Lake Malawi Basin and Shire River Basin? And how do these impacts translate into changes in hydropower productivity and reliability?

2. Study Area and Data

2.1. Study Area

Lake Malawi is located in south-eastern Africa along the Great Rift Valley. It is one of the southernmost lakes (Fig.IV- 1(B)) and its north-south extension is approximately 560 km, the maximum width is 75 km and the average depth is 292 m. The catchment area is 125,500 km2 including the lake surface area, which is about 29,600 km2. The lake has several inflows and only one outlet in south; the Shire River, originates at Mangochi (Fig.IV-1(A)). The Shire River, downstream of Mangochi, is 401 km long, has a catchment area of 23,500 km2, and joins the Zambezi River in Mozambique as its most downstream tributary (Fig.IV-1(B)). The middle Shire, characterized by deep gorges with steep slopes, is 80 km long and is where hydropower generation takes place (Fig.IV- 1(A)). The hydraulic gradient of 370 m provides an important potential for hydropower generation (Shela, 2000), and currently seven hydropower plants (Tab.IV- 1) are installed that contribute 98% of installed hydroelectrical power in Malawi (Taulo et al., 2015).

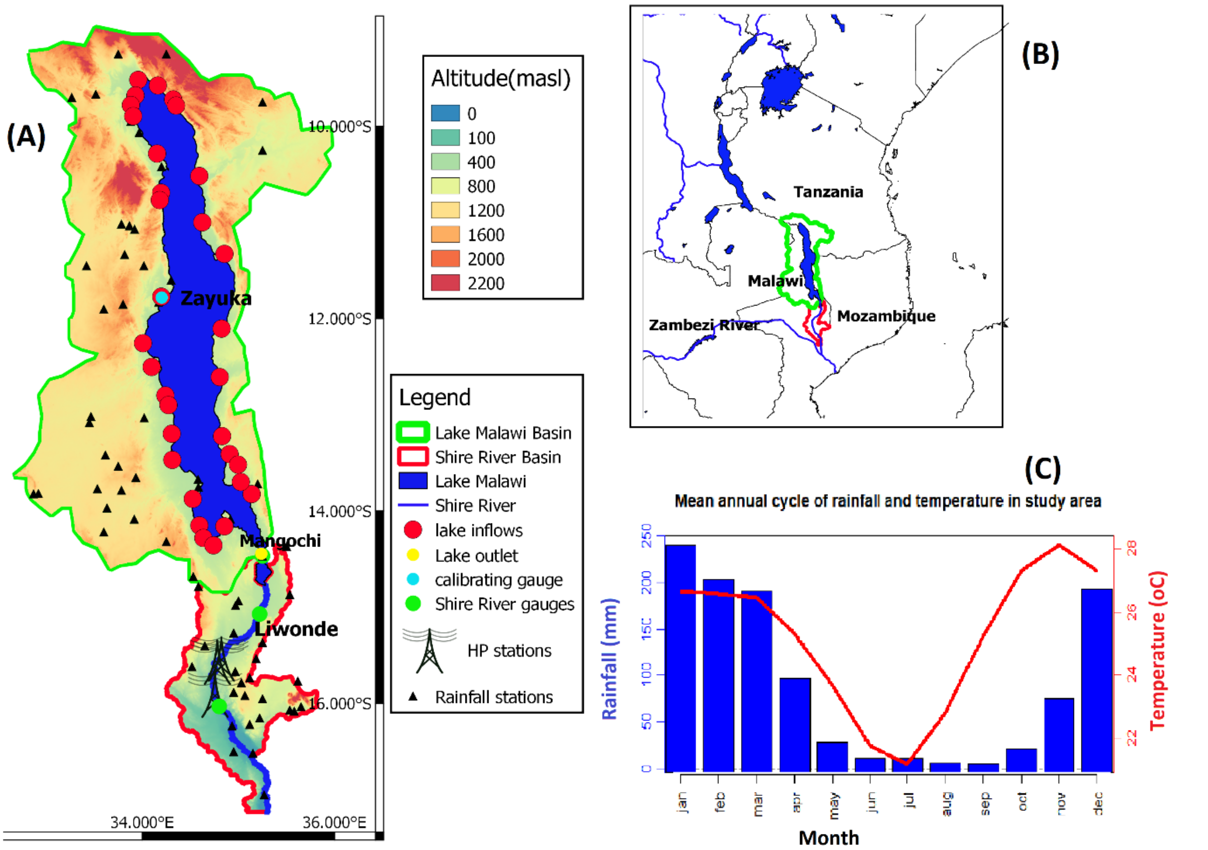


Figure IV - 1 *(**A**) The Lake Malawi and Shire River Basins, (**B**) their location in the Great Rift Valley in south-eastern Africa and (**C**) the mean annual cycles of precipitation and temperature in the study area.*

Table IV - 1 *The seven hydropower stations on Shire River in Malawi in 2020. From* *http://www.egenco.mw/page.php?slug=power-stations* *(Official site of Electricity Generating Company, EGENCO, accessed on 1 February 2020)*

Station	**Latitude**	**Longitude**	**Elevation (m.a.s.l.)**	**Installed hydropower production HPP (MW)**	**Net hydraulic head (m)**
Nkula A and B	-15.5261	34.82	~346	124	55.2
Tedzani I, II and III	-15.5594	34.7772	~291	92.7	44.8
Kapichira I and II	-15.9011	34.7531	~112	129.6	54
Total				346.3	

Lake level variability highly affects river discharge in the upper Shire River (Fig.IV- 2). For the full utilization of the installed hydropower capacity, a steady flow of ≥ 170 m³/s at gauge Liwonde (Fig.IV-1(A)) is required (Shela, 2000). In terms of runoff seasonality, high flows occur from January to May and the lowest flows usually occur during October to December (Shela, 2000). This is closely connected to the hydro-meteorological conditions in Malawi. Located in the tropics, the climate in Malawi depends on the inter-tropical convergence zone, the sub-tropical high-pressure belt further south, and its topography. There is a pronounced rainfall gradient in annual rainfall from the north (>1400 mm) to the south (<900 mm) (Mtilatila et al., 2020). The country is characterized by a prominent warm summer and rainy season between October and April (Jury & Mwafulirwa, 2002; Munthali et al., 2003), with monthly rainfall depths on average above 200 mm and an average air temperature varying between roughly 26 and 28 °C and a dry and cool winter season between June and September with very little rainfall (between 0 mm and 20 mm/month) and average an air temperature between 21 and 25 °C (Fig.IV-1(C)).

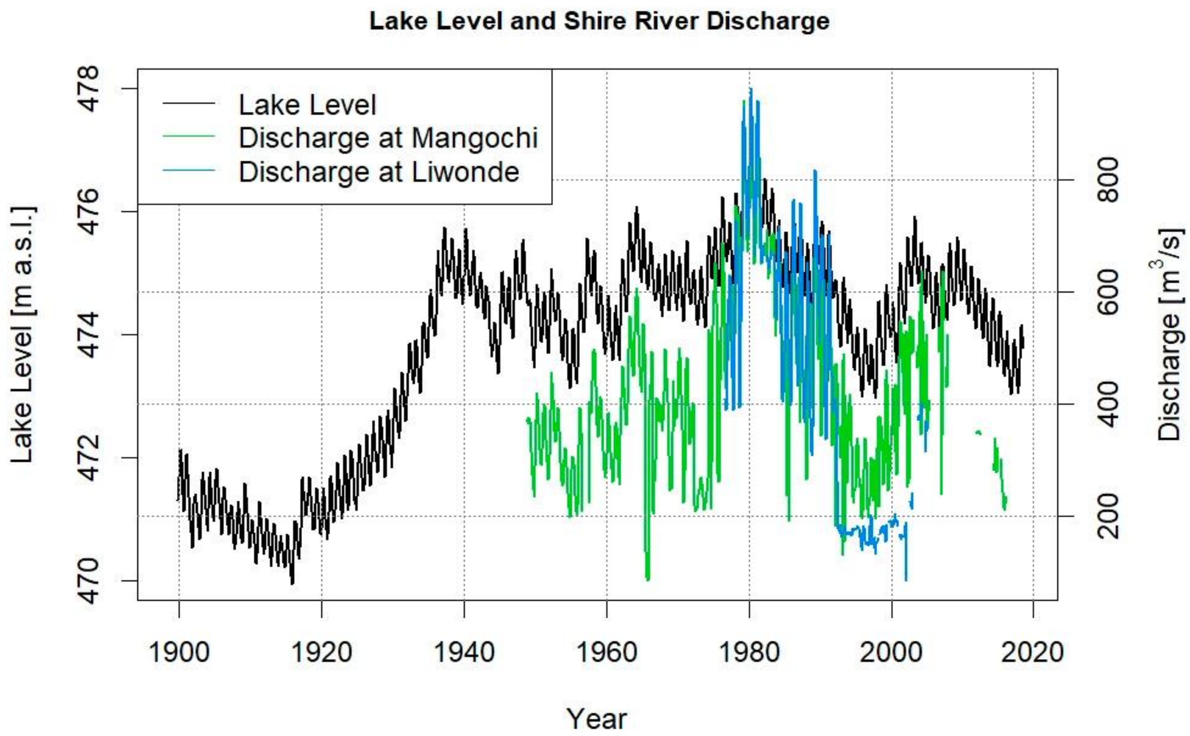


Figure IV - 2 *Monthly Lake level (from 1899 to 2018), lake outflow at Mangochi (1976 to 2004) and Shire River discharge at Liwonde (1948 to 2008).*

The dominant land cover in the Lake Malawi and Shire River basins is cultivated land. In 2005, cultivated land covered 33.7%, while forest area coverage was at 24.3%, savanna woodlands and shrubs were at 19.9% and the rest (22.1%) was covered by water (Chavula et al., 2011). Land cover is changing in the basin towards more cultivated land and less savanna woodlands and forest (Palamuleni et al., 2011). In the upper Shire River catchment, agricultural land increased by 18% from 1989 to 2002 (Palamuleni et al., 2011), while forest cover in the Lake Malawi Basin decreased from 64% in 1967 to 51% in the early 1990s (Calder et al., 1995).

2.2. Data

Monthly lake level and daily lake outflow data sets are from the Department of Water Resources in Malawi and cover the periods from 1899 to 2018 and 1948 to 2014, respectively. Daily temperature and mean relative humidity data sets are from the Climatic Research Unit (CRU) at the University of East Anglia (http://www.cru.uea.ac.uk/data) (Osborn & Jones, 2014).

Rainfall data for 65 locations is obtained from the Department of Climate Change and Meteorological Services in Malawi for the period 1960s to 2013. Gridded 0.5_ Global Precipitation Climatology Centre (GPCC) data from the German Weather Service (DWD) (Schneider et al., 2018) complement rainfall data on the Tanzanian and Mozambiquan sides of the Lake Malawi Basin. It has been shown that GPCC rainfall data represent rainfall characteristics in this region reasonably well (Mtilatila, 2010). Point data are gridded into a 0.5-degree resolution using the Inverse Distance Weighted (IDW) method by Shepard (Shepard, 1968), which has been applied successfully by many, including Bashir & Fouli, (2015) and Pai et al. (2014).

For future climate (precipitation and temperature), the Coordinated Regional Climate Downscaling Experiment (CORDEX) data for Africa are used, i.e., in order to reduce the inherent uncertainty of GCMs and RCMs, we did not to rely on the results of a single climate model but instead used the output of the model ensemble of the CORDEX Africa consortium. This is a dynamically downscaled data set (Jones et al., 2011) from Coupled Model Inter-comparison Project 5 (CMIP5) General Climate Models (GCMs) using Regional Climate Models (RCMs) at about a 50 km (0.44°) resolution. This data set has been found to simulate the historical rainfall and temperature variations over Africa satisfactorily (Pinto et al., 2016; Russo et al., 2016; Shongwe et al., 2009). In this study, only models with full simulations for both Representative Concentration Pathway 4.5 (RCP4.5) and RCP8.5 from 1976 to 2100 are used for easy comparability. RCP8.5 is almost a business-as-usual scenario (Riahi et al., 2007), while RCP4.5 is the moderately controlled scenario. RCP4.5 has moderate population growth and economic growth, while the forest area increases as the crops and grassland decline (Wise et al., 2009). Future scenarios are grouped into two periods, 2021–2050 (near future) and 2071–2100 (far future). For each period and concentration pathway considered, the simulations of an ensemble of 20 GCM–RCM combinations from CORDEX Africa are used. Tab.IV-2 provides a full overview about the various linkages of ten GCMs (columns) and five RCMs (rows) leading to the ensemble of 20 combinations from five centers. Abbreviations for the centers are described in the caption of Tab.IV-2. CORDEX data are accessed through the Earth System Grid Federation (ESGF) at https://cordex.org/data$-$access/esgf/.

The digital elevation model (DEM) and its derivatives, which are mainly used for initializing the river network in the mesoscale Hydrological Model (mHM), are taken from HydroSHEDS (https://hydrosheds.org/), while the soil database is from SOILGRIDS (https://soilgrids.org/). Land cover maps and geological information are obtained from GLOBCOVER (http://due.esrin.esa.int/page_globcover.php) and the Global Lithological Map (GLIM, https://www.geo.uni$-$hamburg.de/en/geologie/forschung/geochemie/glim.html), respectively.

Table IV - 2 *Matrix of CORDEX Africa models used in the study. The matrix consists of ten Global Climate Models (GCMs) and five Regional Climate Models (RCMs) from five centers: Swedish Meteorological and Hydrological Institute (SMHI), Sweden, Max Planck Institute (MPI), Germany, The Royal Netherlands Meteorological Institute (KNMI), Netherlands, The Danish Meteorological Institute (DMI), Denmark, and Climate Limited-Area Modeling Community (CLM), international.*

RCMs \ GCMs	CNRM-CM5-	EC-EARTH-	MPI-ESM-LR-	CanESM2-	CSIRO-Mk3.6.0-	IPSL-CM5A-	MIROC5-	NorESM1-M-	GFDL-ESM2M-	HadGEM2-ES-	Climate Centers
RCA4-	X	X	X	X	X	X	X	X	X	X	-SMHI
REMO2015-			X								-MPI
REMO2009-		X	X								-MPI
RACMO22T-		X								X	-KNMI
HIRHAM5-X											-DMI
CCLM4-8-17-	X	X	X							X	-CLM

3. Methods

3.1. Modelling Strategy

The investigation of potential climate change impacts on the hydrological system of the Lake Malawi Basin and Shire River Basin is based on a cascade of hydrological models (Fig.IV-3). This cascade consists of (i) a hydrological model upstream of the lake, the Upstream Lake Malawi Basin Model (ULMBM), i.e., for all rivers flowing into the lake in order to simulate dynamic lake inflow, (ii) a lake model that calculates the lake's water budget, including lake level changes and outflow variations (Lake Malawi Model, LMM) and (iii) a hydrological model for the upper and middle Shire River to simulate river discharge of this river system (Shire River Model, SRM) that can be translated into hydropower productivity (HPP). The hydrological models are realized by adjusting the mesoscale Hydrological Model (mHM) for the respective catchments (details in Section 3.2). The SRM takes the outflow computed from the LMM (details in Section 3.3) as inflow into its upper boundary, i.e., the origin of the Shire

River. All parts of this model cascade are calibrated and tested for independent time periods. The sensitivity of the hydrological system of the Lake Malawi and Shire River basins, as well as potential climate change impacts on hydropower productivity, are assessed by systematically varying the meteorological inputs, i.e., precipitation and temperature. The following subsections describe the individual components of the model cascade and the sensitivity experiments in detail.

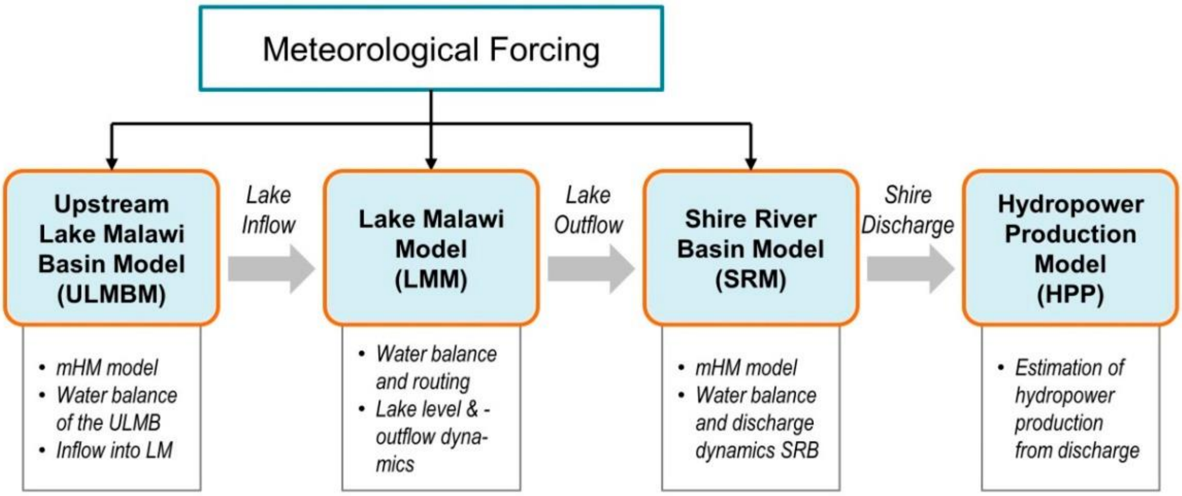


Figure IV - 3 *Conceptual overview of the hydrological model cascade applied in this study. The Mesoscale Hydrological Model mHM is used to dynamically simulate hydrological flows for the upstream Lake Malawi Basin (Upstream Lake Malawi Basin Model, ULMBM) and the upper and middle Shire River Basin (Shire River Model, SRM). A lake model (Lake Malawi Model, LMM) has been developed to dynamically simulate the water budget, lake levels and outflow dynamics of Lake Malawi. The models are driven by meteorological forcings, and model outputs from previous steps in the model cascade serve as inputs for lower model chain components. The hydropower production model (HPP) estimates hydropower generation on the Shire River.*

3.2. Mesoscale Hydrological Model (mHM)

The mesoscale Hydrological Model (mHM) is a spatially distributed, partly process-based model that treats grid cells as unique hydrological units. It comprises hydrological processes such as interception, snow accumulation and melting, infiltration, soil water dynamics, groundwater recharge and storage. The generated discharge of a model cell consists of direct runoff, baseflow and slow and fast interflow, which, after aggregating its components, is routed through the model domain using the Muskingum-Cunge flood routing algorithm (Chow et al., 1988; Toddin, 2007). By using the multiscale parameter regionalization technique (Kumar et al., 2013; Samaniego et al., 2010), the mHM directly accounts for the sub-grid variability of the physiographic characteristics. In the mHM, the model parameters are estimated in a preliminary step at the lowest possible input resolution of the physiographic variables. In case of the ULMBM and SRM, these grids are 1/128 degrees x 1/128 degrees (or ~867 m x 867 m). In step two, effective parameters at mode a resolution of 0.5 degrees _ 0.5 degrees are estimated by applying particular upscaling operators. This technique makes the mHM scale- and location-independent because it connects effective parameters to physiographical inputs (Kumar et al., 2013). Having such a scalability feature means better control over equifinality of the model with a more restrained parameter space. Plus, the mHM also has a satisfactory performance over a wide range of catchments sizes (4 to 530,000 km2) and contrasting climatic regimes (Europe, Asia, North America, South America, Australia and Africa (West and Horn of Africa) (Eisner et al., 2017; Kumar et al., 2013; Kumar et al., 2013; Poméon et al., 2018; Rakovec et al., 2016; Samaniego et al., 2010, 2011), hence chosen as the hydrological model for our analysis.

We apply the mHM at a 0.5-degree (~55 km) grid resolution at daily time steps on the Lake Malawi and Shire River Basins. The model is adjusted to the catchment upstream of Lake Malawi (ULMBM; Fig.IV-3) to simulate daily inflow into the lake, and to the catchment of the upper and middle Shire River (SRM; Fig.IV-3) to simulate discharge, from which hydropower productivity can be derived. Lake inflow is simulated for 33 rivers (red points around the lake in Fig.IV-1a). Due to the rather coarse spatial resolution opted for the ULMBM, some inflow points fall into the same grid cell, so these points are aggregated, which results in a total of 23 inflow points. Attributable to the best daily (continuous) discharge data availability (in terms of temporal coverage and data quality), the calibration of the ULMBM is performed at Zayuka gauge on the Luweya River (blue point in Fig.IV-1a) for the period November 1988 to October 1995. The calibration for the SRM is performed at Liwonde gauge, which provides the comparatively good hydrological data integrity in this section for the period November 1985 to October 1991. The model calibration uses the Dynamical Dimensioned Search (DDS) (Tolson & Shoemaker, 2007), which is a global optimization algorithm for the calibration of multiple-parameter models. DDS finds best fit parameter sets based on a user-defined maximum number of model calls. We use 3000 model runs to separately calibrate the ULMBM and SRM. The Kling-Gupta Efficiency (KGE) (Kling et al., 2012), which combines the bias, the correlation and the variability between simulated and observed discharge, is used as the objective function. The KGE is given as:

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\beta_s}{\beta_o} - 1\right)^2 + \left(\frac{\overline{s}}{\overline{o}} - 1\right)^2} \qquad \text{(Equation IV-1)}$$

where r is the correlation coefficient, $\frac{\bar{s}}{\bar{o}}$ is the bias ratio, in which $\bar{S}$ and $\bar{O}$ are the mean values for simulated and observed values, respectively, $\frac{\beta_S}{\beta_O}$ is the variability ratio between simulated and observed discharge with β as the coefficient of variation, where $\beta_s = \delta_s/\bar{s}$ and $\beta_o = \delta_o/\bar{o}$, and δ_s and δ_o are the standard deviations for simulated and observed datasets, respectively. The combination of the three parameters provides a good insight into the model performance, as temporal discharge dynamic is captured by *r* and the flow duration curve is captured by the bias and variability terms (Kling et al., 2012). In turn, KGE = 1 represents the best model, which means all the three parameters r, $\frac{\beta_s}{\beta_o}$ and $\frac{\bar{s}}{\bar{o}}$ are unity. The calibrated ULMBM and SRM are tested for the independent time periods November 1985–October 1988 and November 1977−October 1982, respectively.

3.3. Lake Malawi Model (LMM)

For our study area, lake water budget plays a prominent and crucial role within the whole hydrological system. Therefore, we develop a model that accounts for the water balance including the lake level and outflow dynamics of Lake Malawi. The lake model applies a reservoir routing method, which is basically based on the lake water balance dynamic and an empirical relationship between lake level and outflow volume. The basic lake water balance equation reads as follows:

$$\frac{dS_L}{dt} = P_L + Q_{in} - E_L - Q_{out} \qquad \text{(Equation IV-2)}$$

where $\frac{dS_L}{dt}$ is the change in storage that can be translated into lake level change and groundwater exchange. Groundwater exchange is, however, neglected due to an unavailability of adequate data in this area (Kumambala & Ervine, 2010). Q_{in} and Q_{out} are lake inflow and outflow, respectively, P_L is the precipitation on the lake and E_L is the water loss due to lake evaporation. Based on Equation IV-2, we estimated daily water fluxes within the lake reservoir. Daily Q_{in} is dynamically simulated by the ULMBM (c.f. section 3.1), and daily P_L is taken from the interpolated daily precipitation grids described in Section 2.2. Lake evaporation (E_L) at daily time steps is estimated using the Penman formula for open water bodies (Penman, 1948). The Penman formula for open water is based on energy balance on the Earth's surface. The formula, modified by the Food and Agriculture Organisation (FAO), assumes heat flux density into the water to be zero at daily periods so that the final version is composed of a radiation term (a) and a wind term (b) (FAO, 1998).

$$E_L = c\left[\underbrace{\frac{\Delta}{\Delta+\gamma}R'_a}_{(a)} + \underbrace{\frac{\gamma}{\Delta+\gamma}\ 2.7f(u)(e_a - e_d)}_{(b)}\right] \qquad \text{(Equation IV-3)}$$

The radiation term (a) is comprised of R'_a, which is the equivalent net radiation (incoming solar radiation minus the budget of long wave radiation), and Δ is the slope of the saturation vapor pressure curve, estimated using

$$\frac{4098\left[0.6108exp\left(\frac{17.27T}{T+237.3}\right)\right]}{T+237.3^2} \qquad \text{(Equation IV-4)}$$

where T is average temperature and γ is a psychrometric constant derived from $\frac{c_p P}{\varepsilon\lambda}$ (c_p is specific heat at a constant pressure, P is atmospheric pressure, ε is the ratio of the molecular weight of water vapor to dry air and λ is the latent heat of vaporization). The wind term (b) includes a function f(u) which is estimated by $1+0.864u_2$ and u_2 is the surface wind speed at 2m. The term (e_a–e_d) is the vapor pressure deficit, as e_a is the saturated vapor pressure at temperature T_a and e_d is the prevailing vapor pressure. Finally, c is a dimensionless adjustment factor (FAO, 1998). The variation of wind speed over monthly periods is relatively small so that wind speed is assumed to be steady at 2 m/s, which is the average wind speed found at over 2000 weather stations around the world (FAO, 1998). Evaporation from the lake plays a crucial role within the hydrological system of the lake since previous estimates for Lake Malawi report only 16.3 % to 19.5 % of the annual water received into the lake is transposed to outflow, the rest is lost by evaporation (Drayton, 1984; Kidd, 1983; Neuland, 1984).
Referring to Kumambala and Ervine (Kumambala & Ervine, 2010), the lake outflow at Mangochi (Q_{out}) is a power law function of lake level that refers to the following relationship:

$$Q_{out} = 30.285(L - 470.8)^{1.9145} \qquad \text{(Equation-IV-5)}$$

where $L - 470.8$ is the effective lake level above the crest of the Shire riverbed sill at the lake outlet, i.e., 470.8 m a.s.l., which indicates the level at which no outflow into the Shire River occurs. The factor and the exponent are calibrated and adjusted based on outflow and lake level data to best match lake outflow and observed discharge at Mangochi, the gauge at the outlet of the lake ($R^2 = 0.97$) (Kumambala & Ervine, 2010).

In the late 1960s, a barrage was installed at Liwonde to control discharge into the Shire River within the lake level range of between 473.2 and 475.3 m a.s.l. Lake outflow (in m^3/s) is regulated as follows (Shela, 2000):

$$Q_{out} = \begin{cases} Q_{out},\ if\ L > 475.32\ m\ a.s.l. \\ 237(L - 471.37) - 411,\ if\ 473.82 < L < 475.32\ m\ a.s.l. \\ 170,\ if\ 473.22 < L < 473.82\ m\ a.s.l. \\ Q_{out},\ if\ L < 473.22\ m\ a.s.l. \end{cases} \quad \text{(Equation IV-6)}$$

The developed lake model takes these operation rules into account, although observed discharge data at Liwonde suggest that these rules have not always been completely followed (Drayton, 1984) (see Fig.IV- 2).This agrees with Shela (2000), who indicated that a temporal rule was introduced following the massive 1992 drought to control water flow between 155 to 200 m3/s whenever the lake level is above 473.22 m a.s.l., otherwise the gates are opened. The dynamic estimation of lake level (changes), based on lake inputs (river inflows and rainfall) and outputs (Shire River outflow and water loss due to evaporation), is crucial for the water budget of the lake. The lake model has been tested for the period 1976–2013 by comparing simulated lake level and lake outflow with observations. The dynamic lake model has been implemented in R (Team R Core, 2020).

3.4. Estimation of Hydropower Production

Hydropower production (HPP) is a function of gravitational acceleration g, efficiency of the system μ, net hydraulic head h of the power station, density of water ρ and river discharge Q.

$$HPP = g\rho\mu hQ \quad \text{(Equation IV-7)}$$

As g and ρ are constants and μ and h are known and assumed constant for each individual power station (see Tab.IV-1), Q is the missing variable which we infer from the simulations of the SRM (Fig.IV-3). The power calculated here is an ideal, i.e., power production breaks or reduction due to, e.g., maintenance or repair works at the power stations are not considered. The energy production is estimated at the three main power station groups on the Shire River: at Nkula, representing Nkula hydropower stations A and B, at Tedzani (I, II and III) and at Kapichira hydropower station (I and II) (see Tab.IV-1). As Nkula and Tedzani are located only 7 km apart from each other and no tributaries enter into the Shire in this section, the energy of those two groups is calculated with the same river discharge Q at this river stretch. The production of all seven stations is then added to obtain the overall energy production on the Shire River. The total installed hydropower on the Shire River at all seven hydropower stations is 346.3MW, which yields a maximum daily production of 8,304MWh per day (Tab.IV-1), assuming the turbines are running with full capacity and the efficiency of the system of 90% ($\mu = 0.9$). To fully utilize this capacity, a firm flow of $\geq 170\ m^3/s$ at Liwonde is required (Shela, 2000).

3.5. Sensitivity Analysis and Response Surfaces

To illustrate the sensitivity of the overall Lake Malawi/Shire River hydro-system towards variations in the most important hydro-climatological drivers, we systematically perturb the input variables temperature and precipitation, and run the whole model cascade with these perturbed time series. The perturbation is applied to reference period of 1976 to 2005 at daily time steps. Observed daily time series of the crucial meteorological variables temperature (To) and precipitation (P_o) are linearly scaled within a given range of allowed change:

$$T(i) \mapsto T_o(i) + X_t \qquad \text{(Equation IV-8)}$$

$$P(i) \mapsto P_o(i) X_p \qquad \text{(Equation IV-9)}$$

where X_t and X_p are the perturbation factors which incrementally scale the observed input data (additive for temperature; multiplicative for precipitation) and *i* indicates the daily time step. Daily temperature time series are systematically perturbed up to +5°C with +0.5°C increments, leading to ten different model realizations. Precipitation time series are perturbed within −20 % to +30 % with 5 % increments, also leading to ten different model realizations. We then compare the simulated time series generated with the perturbed input data to the reference simulation that is generated by the original input data (T_o and P_o). This sensitivity test is applied to all the three model parts, the ULMBM, LMM and SRM (Fig.IV- 3), to highlight the sensitivity of the hydrological system towards changes in the hydro-meteorological drivers. The target variables of the simulations are lake level, lake outflow and Shire River flow dynamics. By linearly scaling the temperature and precipitation, the monthly, seasonal and annual cycles are conserved.

To estimate the potential impacts of climate change (i.e., changes in temperature and precipitation) on lake level, discharge and hydropower productivity in the upper and middle Shire River, we generate so-called response surfaces. Response surfaces are generated by summarizing the response of lake level and discharge towards changes in the climate system estimated by a systematic sensitivity analysis in a two-dimensional matrix. In this study, the entire hydrological model chain (Fig.IV- 3) is run with all possible combinations of perturbed daily temperature and precipitation time series generated for the sensitivity analysis (Equations IV-8 and IV-9), and the result of each combination (i.e., the mean impact) is plotted as one single realization (i.e., one pixel) of possible climate change impacts in a two-dimensional domain (i.e., the response surface with 11 X 11 = 121 realizations, thus including the reference pixel, i.e., the realization with non-perturbed, original input data). This so-called scenario-neutral approach was introduced by Prudhomme et al. (2010) and has been applied for various purposes (Keller et al., 2019; Vormoor et al., 2017). In that way, this approach differs from top-down approaches that apply an ensemble of (locally adjusted) GCM–RCMs as inputs into the hydrological model. Still, the spread and the mean of an ensemble of climate projection can be visualized by overlaying the climate change signals from the GCM–RCMs over the response surfaces, which provides an intuitive illustration of the uncertainties of the impact response: the wider the spread, the larger the uncertainties. In turn, the response values that are covered by the spread of the ensemble show the range of possible impacts (Wetterhall et al., 2011).

In this study, we apply simple linear scaling to the meteorological input data, as shown in Equations (IV-8) and (IV-9), although this neglects possible modifications of the temporal structure of the input and response data due to climate change (Keller et al., 2019; K. Vormoor et al., 2017). This limitation is similar to the criticism raised against delta change approaches for statistical downscaling in top-down approaches (Sunyer et al., 2012). However, since we are interested in the mean long-term impacts of climate change on runoff and hydropower productivity, simple linear scaling is a reasonable approach for the generation of the response surfaces. The spread and the mean of the ensemble climate projections (cf. 2.2) are overlaid on the response surfaces to indicate the physically projected climate change in the greater Lake Malawi Basin/Shire River Basin.

4. Results

4.1. Calibration and Verification of the Hydrological Model Chain

The three components of the hydrological model chain are calibrated and verified independently. Each calibration includes a warm-up period of two years for stabilizing the soil moisture in the model. We use seven years (1988–1994) and six years (1985–1990) for the calibration of the mHM for the ULMBM and SRM, respectively. In comparison, the mHM has been successfully applied in the existing literature with calibration periods ranging from 3 to 20 years (Kumar et al., 2013; Nijzink et al., 2016; Poméon et al., 2018; Rakovec et al., 2016; Samaniego et al., 2010, 2011, 2013). Fig.IV- 4 presents the hydrographs simulated by the ULMBM and SRM in comparison with runoff observations for the respective calibration and verification periods, including the KGE estimates which are used as a goodness of fit measure. Regarding the ULMBM, which simulates inflow into Lake Malawi, the calibrated model slightly overestimates low flows but matches the seasonal cycle and peak flows rather well.

The skill determined by the KGE for the calibration period is 0.8. Applying the calibrated ULMBM to a three-year verification period (1985–1988), the skill drops by only 3.75% (KGE = 0.78). Here, the model partly underestimates high flows but matches low flows relatively well. In turn, some water inflow into the lake, e.g., by groundwater, might be missed by the model. However, the volumetric bias is low (7.0%), and this rarely affects the simulation of lake level dynamics (see Fig.IV-5 upper panel).

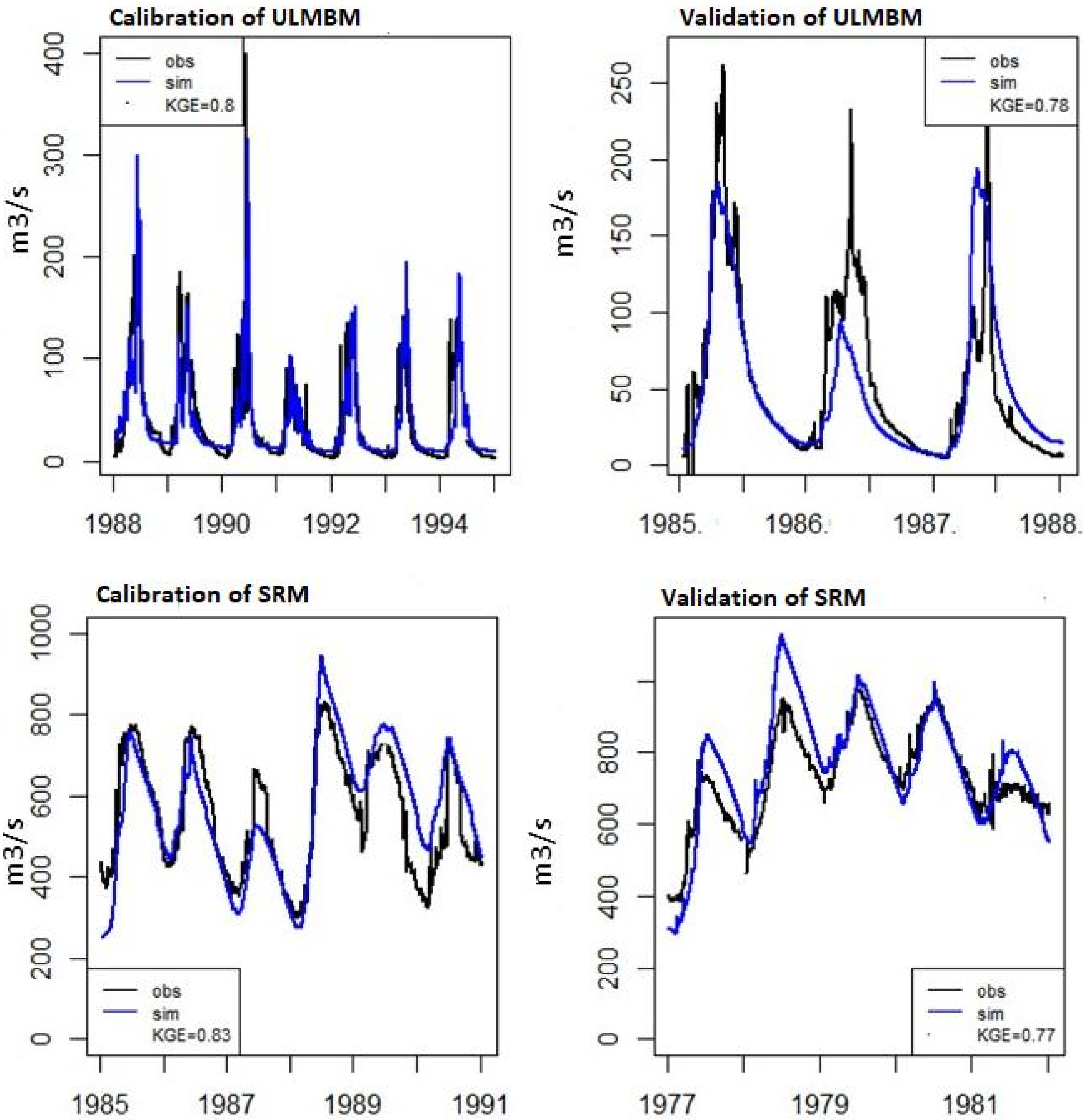


Figure IV - 4 *Simulated vs. observed hydrographs for the calibration and verification periods (columns) obtained by the mHM for the Upstream Lake Malawi Basin Model (ULMBM) and the Shire River Model (SRM) (rows).*

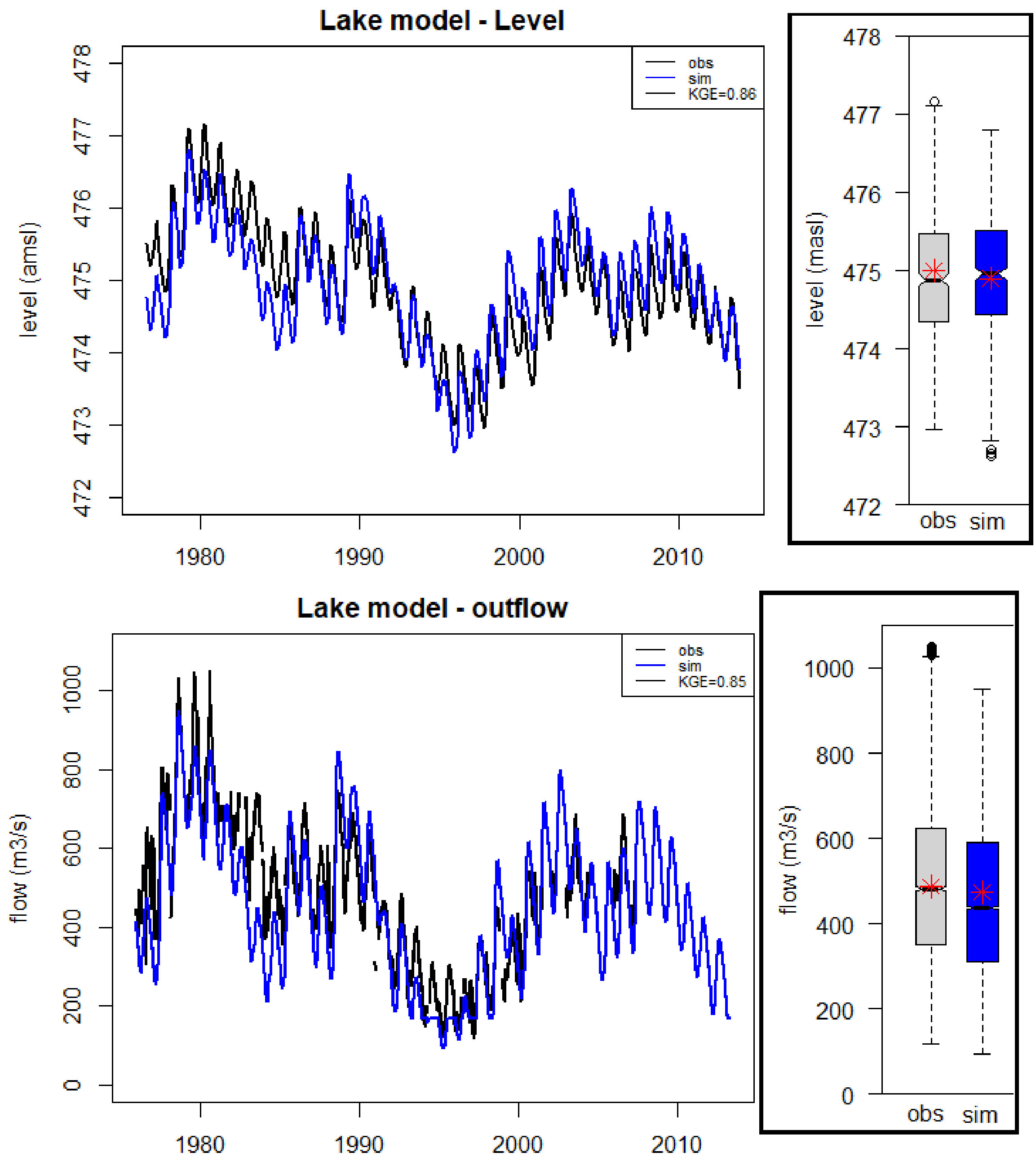


Figure IV - 5 *Simulated time series and boxplots for lake level (upper) and lake outflow (bottom), as simulated by the Lake Malawi Model (LMM) for the period 1976−2013 against observations.*

The calibrated SRM, which takes outflow from the lake model as input, is able to reproduce discharge observations on the Shire River, particularly for the first half of the calibration period. In the second half of the calibration period, the model systematically overestimates river runoff. This is also the case for the first two years of the 5-year verification period (1977–1982), while the latter three years show better matches with observations. The skill of the SRM determined by the KGE for the calibration and verification period is 0.83 and 0.77, respectively. Note that the calibration and verification of the SRM is done using Liwonde, which is the only gauge with adequate data. However, the gauge at Liwonde is located downstream of the barrage (c.f. Section 3.3), and streamflow is regulated according to operation guidelines illustrated in Section 3.3. Since these guidelines were apparently not strictly followed during a severe drought period in the 1990s, we restrict the calibration to the time before 1992 (Section 3.3). Applying the model to periods after 1992 leads to non-systematic mismatches, mainly due to undocumented barrage operations at Liwonde that cannot be captured by the model. For illustration, the mismatch between simulated vs. observed mean flow at Liwonde prior 1992 is +4.4% (647.1m3/s vs. 619.5m3/s); for the period from 1977 to 2007, this mismatch is +27.3% (538m3/s vs. 422.7 m3/s). The behavior of the model prior to 1992 is satisfactory enough to warrant its application to hydrological changes in the Shire River Basin.

The lake model, developed for this study and linked between the ULMBM and SRM, is tested for the periods 1976–2013 (lake level) and 1976–2008 (lake outflow) (Fig.IV-5). The model represents the observations regarding both lake level and outflow considerably well, though there are occasional non-systematic mismatches where the model either overestimates or underestimates observations. The KGE estimates are 0.86 and 0.85 for lake level and outflow, respectively. The model's simulated lake level matches well with observations (474.9 vs. 475 m.a.s.l.), where the difference is only 10 cm, while the comparison between simulated and observed lake outflow is +2.8% (487.2 vs. 473.9 m3/s). In addition to the KGE, the boxplots in Fig.IV- 5 show that the model represents the distribution of lake dynamics satisfactorily. Lake level simulations are slightly better than lake outflow simulations, which are slightly underestimated by the model.

4.2. Sensitivity Analyses

Before applying the hydrological model chain for the investigation of potential climate change impacts, the sensitivity of the reduced model chain towards systemic alterations in precipitation and temperature is tested. Since Lake Malawi is a key component in the hydrological system of the greater Lake Malawi Basin, it is crucial to understand how the lake system reacts to systematic changes in the hydro-meteorological drivers. The effects of systematically changing precipitation, P (at T_o) and temperature, T (at P_o) (as main drivers for catchment evapotranspiration and lake evaporation) input time series from 1976 to 2005 on the simulations of lake level and lake outflow are shown in Fig.IV-6.

Changing precipitation and temperature considerably affect lake levels and corresponding lake outflows. However, the lake level never drops below the No Outflow Level (NOL) of 470.8 m.a.s.l., neither by the most extreme change in precipitation (-20%) nor by the most extreme change in temperature (+5°C) considered here (Fig.IV-6 (A), (B)). An increase in temperature of 5°C reduces the lake level by 1.42 m as compared to the simulations with no modifications in the temperature input data (reference; T_o, P_o). This translates to a decrease rate of about 0.3 m per 1°C temperature rise. The impacts of changing precipitation input are more pronounced than changing temperature. Here, lake level changes range from -2.28 m (ΔP of -20% in precipitation) to +4.39 m (ΔP of +30% in precipitation). The mean changes in lake level due to precipitation change are larger with increasing precipitation (+0.7 m per +5%) than decreasing precipitation (-0.6 m per -5% change).

Corresponding to changes in lake level, the outflow from Lake Malawi is considerably altered by systematically varying precipitation (at T_o) and temperature (at P_o) inputs. Compared to the reference mean outflow of 481.2 m3/s, as simulated with the original input data sets (reference; T_o, P_o), outflow decreases by 59.8% with a 5°C temperature increase (52.5% for +4°C; 43.2% for +3°C; 30.5% for +2°C; 17.1% for +1°C) (Fig.IV-6(C)). The firm flow of ≥170 m3/s (Maximum Flow for Hydropower Production (MFHPP); green line, Fig.IV-6(C)) already occurs in less than 5% of the days during the reference period. With increasing temperature, the proportion of days below the MFHPP increases up to 58% for +5°C (43% for +4°C; 30% for +3°C; 19% for +2°C; 9% for + 1°C).

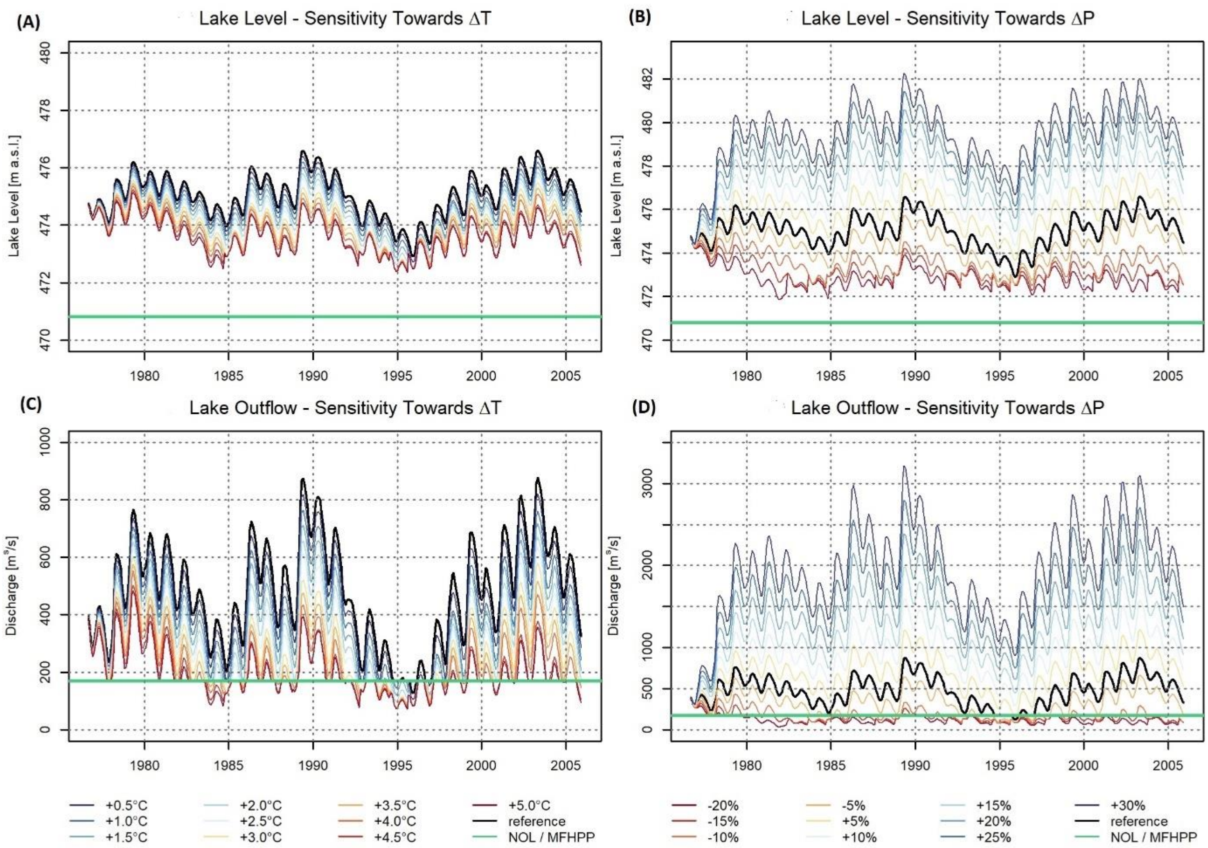


Figure IV - 6 *The sensitivity of lake level (**(A)**,**(B)**) and outflow (**(C)**,**(D)**) to systematical changes in temperature with constant precipitation, Po (column 1) and precipitation with constant temperature, To (column 2) based on Equations IV-8 and IV-9. Green lines in (A) and (B) mark the effective lake level of 470.8 m a.s.l. (i.e., No Outflow Level, NOL), while in (C) and (D), green lines mark the flow required for maximum hydropower generation (170 m3/s) (i.e., Maximum Flow for Hydropower Productivity, MFHPP). Black curves in each plot mark the reference simulations (i.e., with no changes in temperature and precipitation).*

Changes in mean river flow are even larger with changing precipitation. Precipitation increases of 5% and 30% lead to increases in mean river flow of 47% and 312%, respectively. In turn, river flow decreases by -32% (329.8 m3/s) and -77% (112.5 m^3/s), with a decrease in precipitation of 5% and 20%, respectively. The frequency of days below the MFHPP increases by 19% and 93% for a 5% and 20% decrease in precipitation input, respectively. That is, changes in precipitation have a stronger impact on the likelihood of going below the MFHPP than changes in temperature.

It is shown here that an increase in temperature and a decrease in precipitation affect both lake level and lake outflow from Lake Malawi. However, it is also shown that lake outflow never completely ceases with neither a temperature increase of up to 5°C nor a precipitation decrease down to −20 % alone. The effects of combining changes in temperature and precipitation on river flows and corresponding hydropower generation are illustrated in Section 4.4.

4.3. Climate Change Projections for the Greater Lake Malawi Basin

Climate change signals for the near (2021−2050) and far future (2071−2100) scenarios, as they are projected by the considered GCM−RCM combinations (Tab.IV-2) from the CORDEX Africa project for the Lake Malawi Basin and Shire River Basin, are summarized in Fig.IV-7. Change signals refer to the reference period 1976 to 2005.

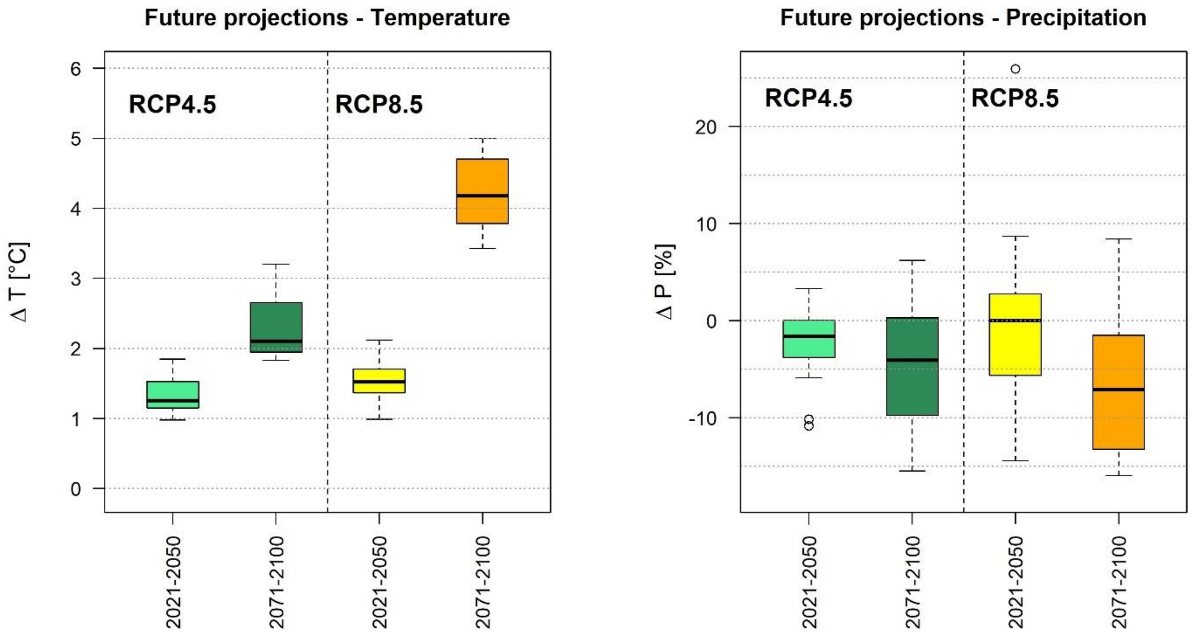


Figure IV - 7 *Climate change signals for temperature (**left**) and precipitation (**right**) as projected by an ensemble of 20 GCM–RCM combinations from the CORDEX Africa project based on the RCP4.5 and RCP8.5 for a near (2021–2050) and far future (2071–2100) period with reference to the 1976 to 2005 period.*

For the near future period, the ensemble projections indicate an average increase in temperature of 1.32°C (range: 0.98, 1.85) and 1.55°C (0.99, 2.12) for the RCP4.5 and RCP8.5, respectively. For the far future period, the ensemble projections indicate an average increase in temperature of 2.3°C (1.8, 3.2) and 4.2°C (3.4, 5.0) for the RCP4.5 and RCP8.5, respectively. The spread of the ensemble projections, which indicates the ensemble uncertainty, is considerably larger for the far future period than for the near future period irrespective of the concentration pathway considered.

Projections for changes in precipitation are not as definite as for temperature, although the ensemble mean for all considered periods and concentration pathways indicate a decrease in future precipitation. For the near future period, the ensemble projections indicate an average decrease in precipitation of -2.2% (range: -11, +3) and -0.63% (-14, +26 (outlier); +9 (upper whisker)) for the RCP4.5 and RCP8.5, respectively. For the far future period, the ensemble projections indicate an average precipitation decrease of -4.6% (-15, +6) and -7.1% (-16, +3) for the RCP4.5 and RCP8.5, respectively. As indicated by the range of the projections, the ensemble of GCM–RCM combinations does not entirely agree on the direction of change: at least one model (far future; RCP8.5) and a maximum of nine model (near future; RCP8.5) projections indicate an increase in precipitation rather than a decrease, while four and five models for RCP4.5 (near) and RCP4.5 (far), respectively, indicate a positive increase. The uncertainty is larger for RCP8.5 than RCP4.5 for the near future. In general, the spread of the ensemble is larger for precipitation than for temperature.

4.4. Climate Change Impacts on Water Budgets and Hydropower Productivity

Here, we combine the insights of the sensitivity analysis (c.f. Section 4.2) with the projected changes in temperature and precipitation (c.f. Section 4.3) to investigate the potential impacts of climate change on lake level, Shire River discharge and corresponding hydropower productivity and reliability by means of response surfaces. Each pixel in the response surface indicates the simulated impact (color coded) of a certain combination of changes in mean annual temperature and precipitation (ΔT, x-axis; ΔP, y-axis) on the specific target variable. The reference pixel (i.e., no change in hydro-climatological conditions; ΔT = 0, ΔP = 0) is marked by an "R". Overlaid, colored symbols illustrate the mean climate change signal from the CORDEX Africa ensemble projections for both periods and RCPs considered (same colors as in Fig.IV-7). The corresponding hollow symbols refer to the climate change signals from the individual ensemble members and illustrate the ensemble range (i.e., the uncertainties in the projections). That is, the reader can easily assess likely future changes (impacts) as projected by the climate models within the domain of the response surface.

4.4.1. Lake Level

Fig.IV-8 shows the response surfaces for absolute and relative changes in lake level as simulated by the ULMBM and the LMM using all the combinations of perturbed meteorological input data. The figure shows the relative changes with reference to the simulated mean lake level based on observed temperature (T_o) and precipitation (P_o) (R-labelled pixel in Fig.IV-8) for the period 1976–2005.

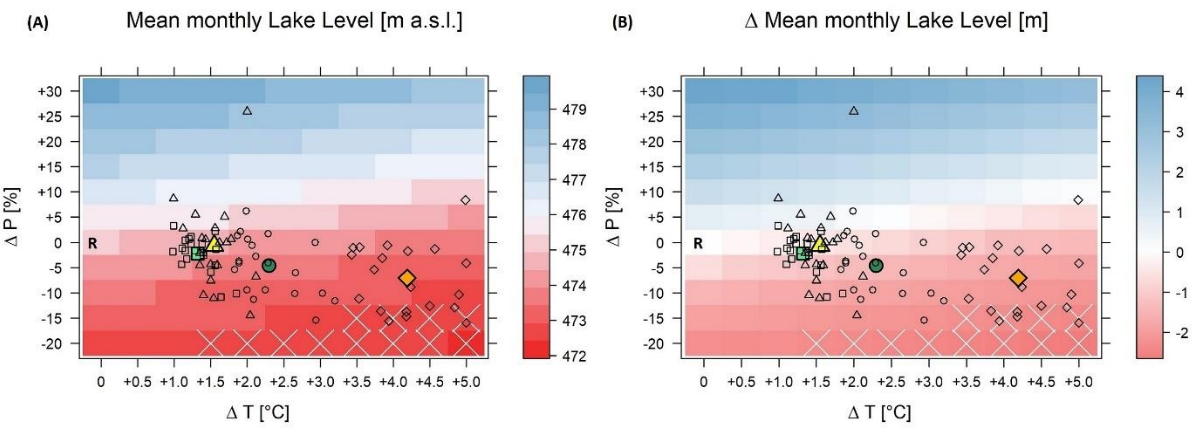


Figure IV - 8 *Response surfaces showing absolute (in m a.s.l., (A)) and relative (deviation from reference level, (B)) changes in the water level of Lake Malawi as simulated by the ULMBM and the LMM using systematically perturbed precipitation (y-axis) and temperature (x-axis) data as input. The points added to the response surface indicate the hydro-climatological change as projected by the 20 GCM−RCM combinations indicated in Tab.IV-2. The different symbols refer to different periods and scenarios (rectangles/circles: RCP4.5 near/far future; triangles/diamonds: RCP8.5 near/far future). The colored symbols reflect the mean of the climate model ensemble for the respective periods and scenarios (same color code as in Fig.IV-7). Pixels marked by an "X" indicate combinations of ΔT and ΔP where outflow from Lake Malawi temporally ceases (i.e., lake level temporally falls below 470.8 m a.s.l.). R is the reference pixel (ΔT = 0; ΔP = 0).*

The response surfaces demonstrate that the estimates for mean lake level range between 472.4 (ΔT +5°C; ΔP -20%) and 479.4 m.a.s.l. (ΔT 0°C; ΔP +30%) (Fig.IV-8(A)) which refers to relative changes of -2.6 m and +4.4 m (Fig.IV-8(B)) compared to the reference mean (ΔT 0°C and ΔP 0%) lake level of 475 m.a.s.l. (1976–2005). Both decreasing annual precipitation and increasing temperature lead to a decrease in the mean water levels of Lake Malawi. The influence of scaling precipitation on lake level changes is slightly larger than scaling temperature, although temperature scaling alone already accounts for a decrease in mean lake level of 1.4 m (ΔT +5°C; ΔP 0%)). For the combinations of scaling precipitation and temperature by ΔP -15% (-20%) and ΔT 3.5°C (1.5°C), the simulations indicate that lake level decreases to an extent so that the level is temporally below 470.8 m.a.s.l. (crossed pixels in Fig.IV-8) during some days of the year and this leads to a temporal absence of outflow from Lake Malawi into the Shire River. It is noteworthy that this situation does not occur when only one parameter is scaled, as shown by the sensitivity analysis (cf. Section 4.2 and Fig.IV-6).

The ensemble means of the climate projections (colored symbols) indicate that the mean lake level in the near future period (2021–2050) is projected to decrease by/to 1.1 m/473.9 m.a.s.l. (RCP4.5) and 0.5 m/474.5 m a.s.l. (RCP8.5). In the far future period (2071–2100), lake level is projected to decrease by/to 1.5m/473.5ma.s.l. (RCP4.5) and 2.1m/472.9ma.s.l. (RCP8.5) (summary in Tab.IV- 3). The spread of the models (different symbols), though, is rather large and some individual climate models even suggest an increase in lake level for some periods and scenarios considered. However, seven GCM–RCM combinations for the far future period and RCP8.5 indicate changes in mean annual temperature and precipitation sums, which will lead to a temporal absence of outflow from Lake Malawi.

Table IV - 3 *Summary of the GCM–RCM results. Ensemble mean changes in temperature, precipitation, lake level, flow, electricity production and electricity reliability compared to the reference period (1976–2005).*

Period	**2021-2050**				**2071-2100**			
Scenarios	**RCP4.5**		**RCP8.5**		**RCP4.5**		**RCP8.5**	
	Ensemble change	**range**	**Ensemble change**	**range**	**Ensemble change**	**range**	**Ensemble change**	**range**
Temperature mean change (° Celsius)	+1.32	+0.98, +1.85	+1.55	+0.99, +2.12	+2.3	+1.8, +3.2	+4.2	+3.4, +5
Precipitation mean change (%)	-2.2	-11, +3	-0.63	-14, +26	-4.6	-15, +6	-7.1	-16, +3
Lake level mean change (m)	-1.1	-1.9, +0.5	-0.5	-2.1, +3.3	-1.5	-2.2, +0.2	-2.1	-2.4, +0.2
Flow mean change at Liwonde (%)	-49	-70, +24	-23	-76, +203	-59	-78, +7	-75	-82, +4
Electricity production mean change (%)	-2.5	-13, +0.1	-0.7	-24, +0.1	-5	-29, +0.07	-24	-38, -0.07

4.4.2. Shire River Discharge at Liwonde

Fig.IV-9 presents response surfaces illustrating the absolute and relative changes in Shire River discharge at the Liwonde gauge derived by the entire hydrological model chain using systematically perturbed meteorological observations as input.

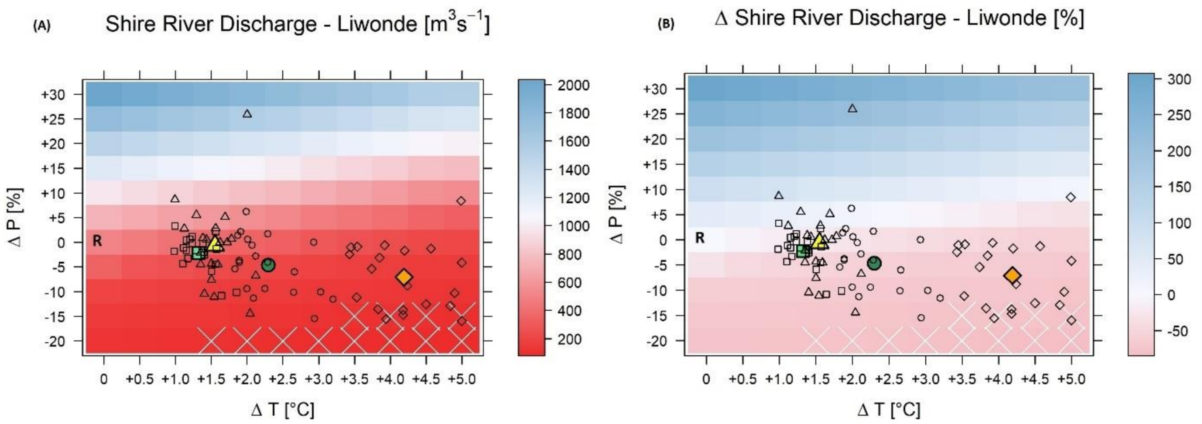


Figure IV - 9 *Same as Fig.IV-8 but for mean discharge at Liwonde gauge generated with systematically perturbed meteorological observation data as input to the hydrological model chain. Absolute (in m3/s, (**A**)) and relative (in % deviation from reference mean discharge, (**B**) mean change*

In terms of absolute river discharge, that the mean annual discharge at Liwonde ranges from ~75 m3/s (ΔT +5°C; ΔP -20%) to ~2000 m3/s (ΔT 0°C; ΔP +30%). This refers to relative changes of -84% to +307% respectively (Fig.IV-9(B)). With increasing temperature (as a proxy for increasing evapotranspiration) and decreasing precipitation sums, river discharge in the Shire River decreases. As expected, the lowest discharge values are found for the combinations of lowest precipitation and highest temperature changes, while the largest discharge values are found for the opposite combination. Changes in river discharge are predominantly driven by scaling precipitation.

4.4.3. Hydropower Productivity

Fig.IV-10 presents the response surfaces illustrating absolute ((A); in MWh) and relative changes ((B); in % differences from reference mean) in agglomerated mean hydropower production in the middle Shire River (in terms of mean daily produced electricity). Hydropower production is estimated based on discharge simulations derived by the hydrological model chain driven with systematically perturbed meteorological observation data as input. Hydropower reliability (Fig.IV-10(C)) indicates the number of days with hydropower productivity below 346.3 MW (maximum production) per year.

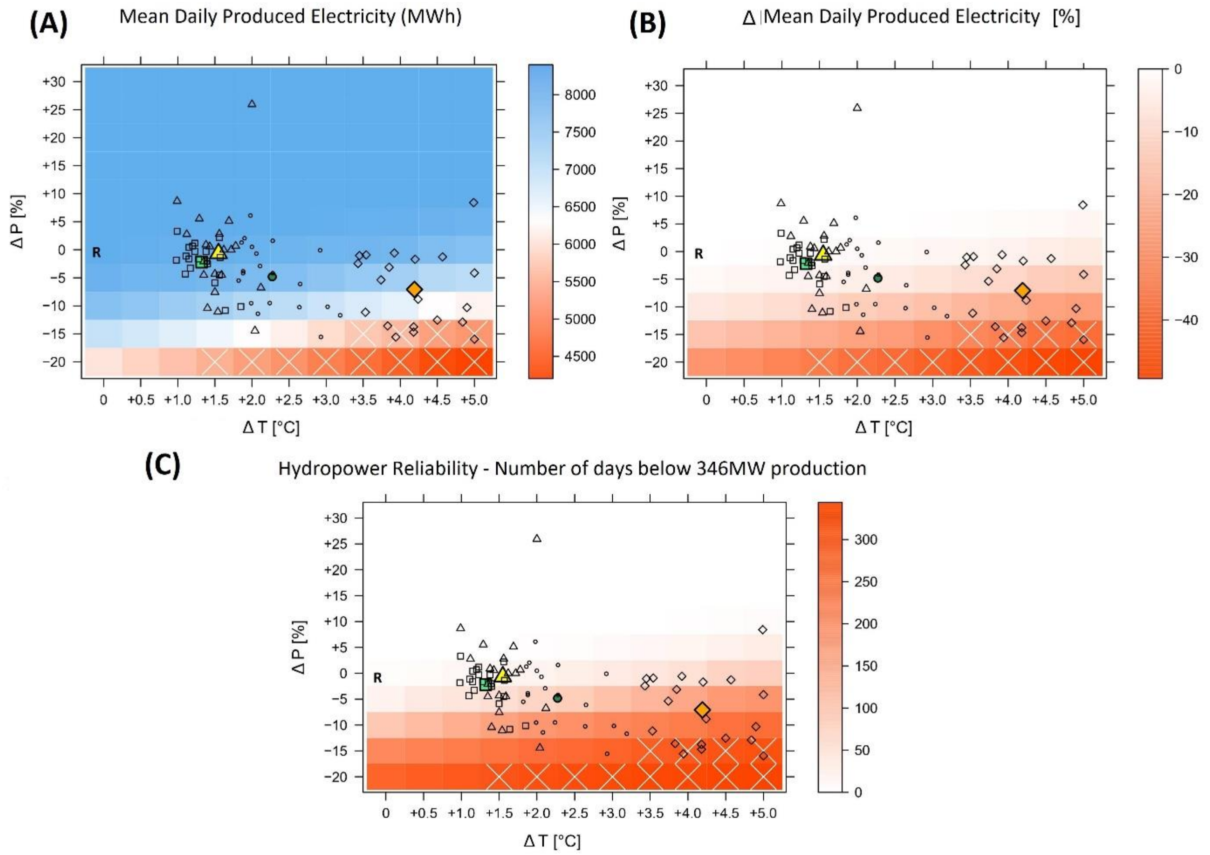


Figure IV - 10 *Same as Fig.IV- 8 but for (**A**) absolute and (**B**) relative changes in mean daily produced electricity and (**C**) the number of days with hydropower productivity below 346 MW (hydropower reliability) summarized for all hydropower plants along the middle Shire River. Hydropower productivity is inferred from discharge simulations by the hydrological model chain driven by systematically perturbed meteorological input data.*

As long as the river discharge is above the MFHPP threshold (see Fig.IV-6(C) and (D)), the installed maximum daily hydropower production is 8310 MWh. That is, with the currently installed hydropower infrastructure, no more hydropower can be produced even if the discharge in the Shire River increases. However, the mean daily hydropower production (as simulated by the hydrological model chain) for the reference period (T_o and P_o) is 8304 MWh, indicating that the impacts of climate on hydropower production are already manifesting themselves. However, when the precipitation increases by 5%, the maximum production is realized as long as the temperature increase remains less than 2°C (thus $\Delta P \geq +5\%$; $\Delta T \leq 2°C$) or when the precipitation increases by 10% and the temperature increase is below 5°C (thus $\Delta P \geq +10\%$; $\Delta T \leq 5°C$). This situation makes the number of days without maximum electricity production, which is currently at 4 days (T_o, P_o), reduce to zero days (Fig.IV-10(C)). For all the other combinations of changes in temperature and precipitation, hydropower productivity decreases up to 4206 MWh (ΔT +5°C; ΔP -20%) which is a reduction of -49%. This results in a considerable decline in hydropower reliability: 344 days per year when the daily maximum electricity production of 346.3MW is not reached. The mean of the ensemble climate projections (colored symbols) consistently indicates a decrease in hydropower productivity and reliability for all the periods and scenarios considered. For the near future period, the decrease in mean production is by/to -2.5%/8046 MWh (RCP4.5) and -0.7%/8244 MWh (RCP8.5). This corresponds to 46 (RCP4.5) and 16 days (RCP8.5) without maximum electricity production per year (Tab.IV-3). For the far future period, the decrease in production indicated by the ensemble climate mean projections is about -5%/7879 MWh (RCP4.5) and -24%/6291 MWh (RCP8.5). This corresponds to 89 and 259 days without maximum hydropower production (Tab.IV-3). Again, we need to emphasize the marked uncertainty in this regard, i.e., the spread of the models includes individual model projections which suggest no decrease in hydropower productivity and reliability and several projections which indicate a decrease much larger than those suggested by the ensemble means. For instance, seven GCM–RCM combinations for the far future period and RCP8.5 indicate a decrease in hydropower productivity between 33 and 38% (5535 MWh and 5138 MWh) and a corresponding hydropower reliability between 300–318 days (production below currently installed capacity).

5. Discussion

5.1. Sensitivity of Water Resources to Changes in Precipitation and Temperature (Evapotranspiration)

Our analyses have shown that lake level and outflow are highly sensitive to changes in precipitation and temperature. As expected, the influence of changing precipitation on lake level and outflow is stronger than the influence of changing temperature. However, the decrease of 0.3 m in lake level and 17% in lake outflow per 1°C temperature increase clearly demonstrates the important role of evapotranspiration in the hydrological system of the Lake Malawi Basin. The effects of evapotranspiration are also detected in the Shire River discharge and corresponding hydropower productivity. They are, however, not as large as for the hydrological parameters of the lake system. The effects of altered evapotranspiration on the Shire River can rather be seen as a translation of such effects on lake outflow downstream to the Shire River. This underlines the particular role of (changing) lake evaporation, including its relevance to lake outflow, which is substantial for water supply and energy production on the Shire River. Note, however, that these statements are based on changing temperature as a single driver for altered evapotranspiration. The detection of actual changes in evapotranspiration would require more detailed, physically based analyses which should also consider changes in radiation budget, e.g., through altered cloud cover and/or the feedback effect of air humidity, for instance, which may amplify or dampen the effects. Still, the increasing relevance of lake evaporation due to increasing temperature agrees with findings in other regions such as Lake Victoria (Vanderkelen et al., 2018b, 2018a).

As shown by the response surface generated in this study, the combination of decreasing precipitation and increasing temperature would lead to even more severe impacts on lake level, outflow, river discharge and energy production. Here, we found that 12 out of 121 hydrological model simulations project temporally ceasing outflow from Lake Malawi into the Shire River, which will transform the upper Shire River from a perennial to a seasonal river. As we have shown that temporally ceasing outflow may already occur for temperature increases from +1.5°C, this highlights the importance of the global warming limit of 1.5°C, as agreed by the United Nations Framework Convention on Climate Change (UNFCCC) in 2015 (United Nations, 2015). The transformation of the Shire River to a seasonal river would have serious consequences on fresh water supply, irrigation, river ecology and hydropower generation further downstream. For 2071–2100, seven out of 20 climate projections suggest such a situation, which highlights that there is a real risk of such a scenario. Here, we refer to Bhave et al. (2020), who detected in 11 out of 30 climate projections with a seasonal instead of perennial outflow from Lake Malawi from 2020 to 2050. However, they used bias-corrected CMIP5 GCM projections and not CORDEX Africa data, and they considered the no outflow threshold for lake level to be 471.5 m.a.s.l.; i.e., 0.6 m higher than the threshold suggested by Kumambala & Ervine (2010), which is used in this study. Moreover, Bhave et al. (2020) investigated the risk of lake level going below the no outflow threshold primarily by changes in precipitation (and land evapotranspiration) assuming constant lake evaporation. Given the sensitivity of the hydrological system towards changes in lake evaporation as sketched out by our study, the risk of temporally ceasing lake outflow is presumably even larger than reported by Bhave et al. (2020) based on their model setup. Another remarkable difference from the study of Bhave et al. (2020) is that we could identify only very few scenarios which may lead to an increase in mean lake level, while Bhave et al. (2020) identified nine out 30 climate models leading to such a situation. This generally highlights the sensitivity of climate change impact studies towards the choices made during the setup of model chains.

5.2. Climate Change Impacts on Hydropower Productivity

The mean ensemble projections of temperature and precipitation changes for 2021–2050 and 2071–2100 indicate gradually increasing temperature and decreasing precipitation for both scenarios considered. These combinations lead to a considerable decrease in Shire River discharge, and thus also in hydropower productivity. The hydropower production is under threat due to these changes, with a reduction between -1% and -24% depending on the period and scenario. That is, the critical flow of 170 m3/s, which is required for a maximum utilization of the installed hydropower capacity, is sometimes not met by all ensemble means considered in this study. Extreme scenarios even suggest a reduction in hydropower productivity up to 38%, with 318 days per year without maximum production, which coincides with a temporal lack of outflow from Lake Malawi. This will seriously endanger the reliability of electricity supply in Malawi and even risk more occasional power blackouts in the country.

The differences between the RCP4.5 and RCP8.5 scenarios and the spread of the individual ensembles (i.e., the uncertainties in the climate projections) are large. Still, water management and hydropower companies need to include likely variations in river discharge due to climate change in their future planning, e.g., by expanding hydropower capacity to meet current and future demands, or by introducing annual and diurnal optimization of electricity production responding to demand variations. Already, power deficits occur occasionally (Brailovskaya, 2018; World Bank, 2011) and our simulation indicates that the present hydropower reliability is at 4 days per year (4 days when maximum hydropower production is not reached). Therefore, decreasing hydropower production will have large implication for the economy in Malawi since energy is the main driver for economic development. Already, recent power supply deficits have had negative impacts on the economy and development. Referring to Brailovskaya (2018), about 25% of daily business profits are lost due to power outages, and the country loses more than 6% of its annual GDP due to these power cuts (World Bank, 2011). Therefore, future plans for hydropower development need to incorporate measures for sustaining electricity production in times of climate change.

Around the globe, there are a number of watersheds where related conditions or problems are similar, e.g., where uncertainty in future hydropower productivity may increase due to changes in climate. For example, such conditions are also projected in some regions of Brazil, such as the Sao Francisco basin in central Brazil (De Jong et al., 2018) or in the Amazon region(Stickler et al., 2013). In the latter, the problems are exacerbated by ongoing heavy deforestation

(Stickler et al., 2013). However, the case of Malawi is particularly interesting (and possibly vulnerable) because the ratio between lake surface area and the surrounding catchment area is rather large, probably among the largest in the world. This is why open water (i.e., lake surface) evaporation is important in this case and makes this coupled hydro-system rather unique.

5.3. Limitations and Uncertainties

This study faces several limitations and uncertainties, which request some assumptions in the study design and need to be taken into account when evaluating the results. First, there are some constraints regarding the hydro-meteorological observation data for the Lake Malawi and Shire River basins in terms of spatial and temporal data coverage. As illustrated in Section 2.2, we needed to take into account the gridded GPCC data sets for the Tanzanian and the Mozambican parts of the Lake Malawi Basin due to the unavailability of meteorological station data. In addition, inflow into Lake Malawi is rarely gauged at the tributaries of the lake. Gauge Zayuka on the Luweya River, which we used for the calibration of the ULMBM, provides the best data quality in terms of reliability and temporal coverage. Still, it is hardly possible to calibrate and verify the ULMBM at gauges in other tributaries. This limits the confidence in the hydrological model to simulate all aspects of lake inflow sufficiently well at intra-annual timescales. The estimation of lake evaporation as a key process within the lake model is prone to notable uncertainties because of limited data to assess energy budgets. For instance, we used maximum and minimum temperature to estimate net radiation. Moreover, evaporation estimates cannot be verified against observation data due to the unavailability of direct measurements of evaporation from the lake surface. However, the calibration and verification of all the three components of the hydrological model chain show good matches with available observations, which underline the suitability of the proposed approach for our study purpose.

In our model setup, we implement the operation guidelines for the barrage at Liwonde, which controls lake outflow and discharge in the upper Shire River. Observation data, though, indicate that these operation rules are often violated, presumably to allow for sufficient river discharge in the Shire River during severe drought situations (e.g., in the 1990s). This limits the time periods which can be used for the calibration and verification of the SRM. For the future scenarios in this study, we assume the operation guidelines to be active as proposed, although it is likely that barrage operation will adapt to lower lake levels in the future.

The response surfaces are generated using the simplest way of perturbing the meteorological input data, which does not account for possible changes in the temporal sequencing of climate input data (i.e., the annual, seasonal and day-to-day variability). This criticism is similar to the disadvantage of using delta change approaches for statistically downscaling climate model data (Sunyer et al., 2012). Several alternative response surface approaches are published that (partly) take changes in temporal sequencing into account (Vormoor et al., 2017). However, since we are interested in changes in long-term mean values of the water budget, the issue of changes in the temporal sequencing of the meteorological input data is considered less important, as suggested by Bronstert et al. (2007).

This study investigates the potential impacts of changes in climate conditions and does not consider changes in land use and land cover or water abstraction for irrigation. However, changes in land cover and expansion in irrigation farming in the course of the socio-economic development in Malawi, as has happened in the recent past can be expected to continue/expand in the future, that will also influence the hydrological system of the basin (Calder et al., 1995; Chavula et al., 2011; Palamuleni et al., 2011).

Lastly, the estimation of changes in the hydrological system of the basin are based on only one hydrological model using one best fit model parameter set for each component within the model chain. To explore the uncertainty of the hydrological projections in more detail, a more comprehensive model setup including more model structures and parameter sets would be necessary.

6. Conclusions

In this study, we assessed the sensitivity of the hydrological system of the Lake Malawi and Shire River basins to estimate potential impacts of future climate on key hydrologic variables and on hydropower generation on the Shire River. We have adapted the mesoscale Hydrological Mod (mHM) to the catchments of the Lake Malawi and Shire River basins. A lake model was developed and linked between the hydrological models of the upper Lake Malawi Basin (ULMBM) and the Shire River Basin (SRM). This lake model accounts for reservoir attenuation effects and dynamic lake water balances, such as rainfall on the lake, inflow from the upper Lake Malawi catchment and evaporation losses, yielding lake level and lake outflow dynamics. This calibrated and verified hydrological model chain was used to estimate the sensitivity of water levels of Lake Malawi and the corresponding discharge and hydropower production on the Shire River to systematic changes in temperature and precipitation by means of response surfaces. Reconsidering the three guiding research questions of this study, we can draw the following conclusions:

1. *The role of lake evaporation is essential for changes in lake level and lake outflow*. Note that, currently, lake evaporation clearly exceeds rainfall over the lake. Although the effects of projected future rainfall changes on lake level and outflow were slightly larger than the effects of temperature changes, the sensitivity analysis identified the particular role of lake evaporation for the hydrological system of Lake Malawi. Evapotranspiration effects (temperature increases as a proxy) on Shire River discharge are not as high as for the lake surface area, and they might be seen as the inherited influence of outflow sensitivity from the lake.

2. *Climate projections agree that gradually increasing temperature and decreasing precipitation lead to a reduction in mean lake level, outflow and Shire River discharge*. Depending on the time period and scenario considered, mean lake level and Shire River discharge are projected to decrease in the range of 0.5 m to 2.1 m and 23% to 75%, respectively. However, extreme scenarios even suggest a decrease in lake level, which would lead to a temporally ceasing outflow from Lake Malawi into the Shire River, bringing along serious ecological and economic threats. These results demonstrate that this tropical hydro-system is particularly vulnerable to climate change impacts. Since water resources are crucial for the economic development of Malawi, this may have serious socio-economic consequences for the country.

3. *Based on the currently installed capacities, hydropower productivity and reliability decrease for all future scenarios considered. The degree of these decreases, however, strongly depends on the time periods and scenarios considered.* On average, projections for hydropower production losses vary between -1% and -24% (thus for 16 to 259 days per year, the maximum electricity production will not be reached). In part, the adverse effects of reduced Shire discharge on electrical production can be counteracted by installing additional hydropower stations along the middle Shire and/or the seasonal and diurnal optimization of hydro-electric production. This strategy is currently followed in Malawi, as some new power stations are under construction or planned (Conway, D. Curran, 2018; GOM, 2010; Yanda, 2010). Still, extreme scenarios, which coincide with a temporal offset of outflow from Lake Malawi, even suggest a productivity loss by -38%, with 318 days per year without maximum production. This would seriously endanger the domestic energy supply in Malawi.

For all climate change projections, though, we need to emphasize that the uncertainties are large. Still, decision makers need to be cautious and develop reasonable adaptation strategies to secure future water and energy demands based on the detected possible outcomes highlighted in this study.

V Conclusions

1. Introduction

1.1 Climate-Water-Energy Nexus

Climate-Water-Energy Nexus (Fig.V-1) describes the intricate relationship of the global resources that drive the planet. The unsustainable exploitation of any of the component affects the other thereby threatening the ecosystem. In this study, Climate-Water-Energy Nexus represents the conceptual presentation of the world to understand the environment we leave in and therefore link with the Sustainable Development Goals (SDGs) (Tab.V-1). It also supports the understanding that some sectoral issues require the inclusion of various components for effective utilisation and management of resources. In practical terms, the nexus is complex and can include as many components and not only the three presented here. However, many studies including Lange (2019) and Teotónio et al. (2020) have also looked at these three components over the Mediterranean region, Middle East and North America.

This study has looked at the cascading effect of climate on water resources and then how the water affects energy production in return (climate → water → energy arms of the nexus). However, climate can also influence energy dimension directly (climate → energy) for example, during very hot conditions the demand for cooling services is high hence increasing the electricity consumption (Lange, 2019). With the anticipated temperature increase in the future the demand for cooling services is expected to be higher. Climate is also a potential benefit to the production of some renewable energy sources from the climate parameters such as wind- and solar- apart from hydro energy being discussed here (USGCIRP, 2014). On the other hand, non-renewable energy sources such as petroleum fuels, biomass, coal affect the climate (energy → climate) that is why the whole world is currently concerned about the global warming and GHG emissions that result into climate change (Holthaus, 2018). But energy also supports the pumping and purification of water for consumption and irrigation as well as used in waste management and sanitation processes (energy → water) (Mohammed Wazed et al., 2018) While water bodies modify the climate around them (water → climate) (Eichenlaub, 1987), the drying of some lakes in the world is also affecting the climate in its locality as the case of Lake Poopó in Bolivia (Perreault, 2020).

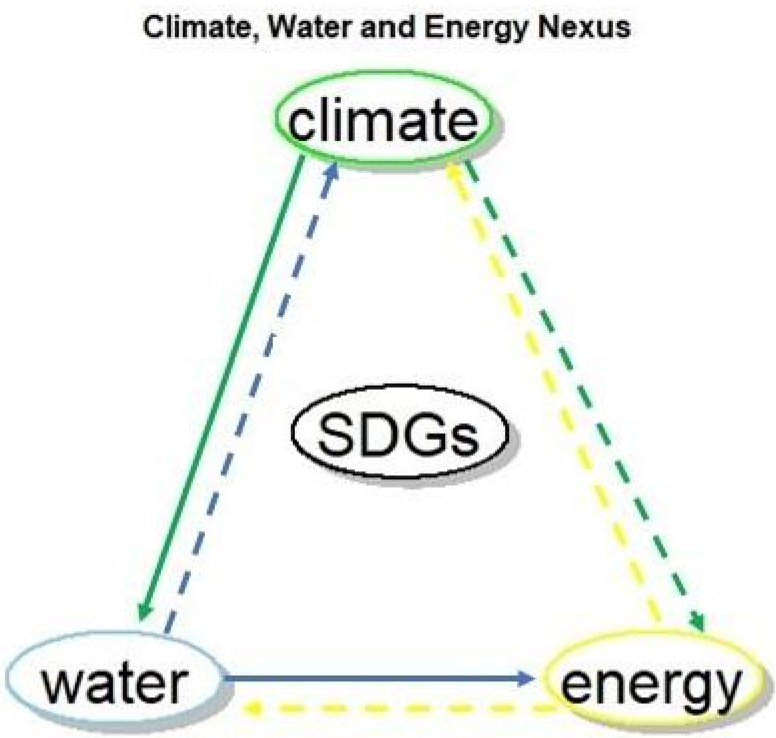


Figure V - 1 *Climate-Water-Energy Nexus and its influence on the Sustainable Development Goals (SDGs). This study focused on* ***climate*** → ***water*** → ***energy*** *arms of the nexus in the Greater Lake Malawi Basin (GLMB). '**Green**' are those connectors from climate, '**blue**' from water and '**yellow**' from energy. The dashed arrows are those arms that are not studied in this project.*

Though the Fig.V-1 has shown the possible two-way interactions of the three thematic areas, the project has mainly looked at the impacts of climate change on droughts and water resources and how these will affect the hydropower production in Malawi. The study has established the interlinkages between the three thematic areas that are crucial for the management of water and energy resources in Malawi. Using the present climate and future CORDEX climate model outputs as inputs into hydrological models to simulate lake inflow, lake level, lake outflow and Shire River discharge; the present and future drought dynamics, future water resource changes and hydropower generation impacts are evaluated.

1.2 The Climate Change Protocols and Agreements

The issue of climate change is not new as it begun in 19th century (Rodhe et al., 1997), but it is only around 1980s that it begun to be given some serious attention (Holthaus, 2018). The climate change that is attributed to global warming due to greenhouse gas (GHG) emissions has resulted into the birth of the Intergovernmental Panel on Climate Change (IPCC) under the United Nations in 1988 to provide the scientific view of climate change and its political and economic impacts (IPCC, n.d.). This led to the establishment of the United Nations Framework

Convention on Climate Change (UNFCCC) in 1994 that was designed as a platform for consensus decision making (Kuyper & Schroeder, 2018). By 2018, there were 196 countries as well as European Union (EU) that were party to UNFCCC (Kuyper & Schroeder, 2018). Apart from making decisions and agreements, the parties to UNFCCC also review the implementations of the convention under the Conference of the Parties (COP) which is the supreme decision-making body of the UNFCCC. The COP meets annually since 1995 and currently there have been 26 COP meetings. Over the years, the COP objectives have shifted from focussing on GHG mitigation only to the combinations of mitigation, adaptation and finance (Kuyper & Schroeder, 2018).

Under UNFCCC, there have been the formulation of protocols and agreements to support the mitigation, adaptation and finance such as Kyoto Protocol and Paris Agreement (United Nations, 1998, 2015). The Paris Agreement adopted in 2015 and entered into force in 2016 is a legally binding international treaty aiming at limiting global warming below 2° Celsius, preferably 1.5° Celsius compared to pre-industrial levels (United Nations, 2015). The 1.5°C limit is the socially, economically, politically and scientifically safe threshold for global warming by the end of the century (History.com Editors, n.d.). The agreement requires the countries to reach the global peaking of GHG emissions as soon as possible thereby achieve the climate neutral planet by mid-century (United Nations, 2015). The Paris Agreement works on a 5-year cycle where countries are tasked to submit their plans for climate action in the nationally determined contributions (NDCs) in which the increasingly ambitious climate actions are presented (United Nations, 2015).

But, despite all these protocols and conventions, it is noted that GHG concentrations in the atmosphere are not slowing down, actually the carbon dioxide emissions have increased by 81% since 1988 despite the increase uptake of renewable energy sources (Holthaus, 2018) and zero carbon solutions mainly in energy and transport sectors (Clairand et al., 2019; Grantham Research Institute on climate change and the environment, 2018; Holthaus, 2018; Potočnik, 2007).

The United Nations have laid down 17 Sustainable Development Goals (SDGs) to be achieved by 2030 (Tab.V-1). It is noted that the achievement of most of these SDGs is contributed by water, climate and energy. For instance, the availability of water resources supports the achievement of Goals, such as the eradication of poverty (SDG 1) and hunger (SDG 2). While the attainment of good health and wellbeing (SDG 3), gender equality (SDG 5) affordable and clean energy (SDG 7), decent work and economic growth (SDG 8), resilient infrastructure and sustainable industrialization (SDG 9), sustainable cities and communities (SDG 11), sustainable consumption and production patterns (SDG 12), sustainable utilisation of the oceans, seas and marine resources (SDG 14) and conserved terrestrial ecosystem (SDG 15) can also only be realized if water is available and accessible. Actually, SDG 6 that calls for access to safe and affordable clean water is the primary link to all the above goals. "Water is life" and nothing on earth can survive without water. However, as much as we would like to keep water on earth to sustain life, only 2.5% of water on earth is fresh and only 1.2% of the fresh water is accessible because some is stored in glaciers, ice caps and deep groundwaters (Oki & Kanae, 2006; Shiklomanov, 1993). There is also uneven distribution of this available water resource in both space and time as such more than two billion people live in water-stressed areas (Oki & Kanae, 2006). Currently, there are 14 countries in Africa which are water-stressed and 11 more will likely join in the next 25 years (Simms, 2006).

Table V - 1 *The Sustainable Development Goals(SDGs). Source: (United Nations, 2018)*

Goal	Agenda	Description
1	No poverty	End poverty in all its forms everywhere
2	Zero hunger	End hunger, achieve food security and improved nutrition and promote sustainable agriculture
3	Good health and well-being	Ensure healthy lives and promote well-being for all at all ages
4	Quality education	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all
5	Gender equality	Achieve gender equality and empower all women and girls
6	Clean water and sanitation	Ensure availability and sustainable management of water and sanitation for all
7	Affordable and clean energy	Ensure access to affordable, reliable, sustainable and modern energy for all
8	Decent work and economic growth	Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all
9	Industry, innovation, and infrastructure	Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation
10	Reduce inequality within and among countries	Reduce inequality within and among countries
11	Sustainable cities and communities	Make cities and human settlements inclusive, safe, resilient and sustainable
12	Responsible consumption and production	Ensure sustainable consumption and production patterns
13	Climate action	Take urgent action to combat climate change and its impacts
14	Life below water	Conserve and sustainably use the oceans, seas and marine resources for sustainable development
15	Life on land	Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse
16	Peace, justice, and strong institutions	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive

The global water cycle is influenced by the climate; hence the changing climate shifts the global water distribution as a result there are big water reservoirs including Lake Chad, Lake Eyre, Lake Urmia and Lake Poopó in west-central Africa, Australia, Iran and Bolivia that are drying respectively. And apart from the water retention upstream of the tributaries and large water abstraction, climate change is also playing a role on the loss of waters from these lakes. (Cockayne, 2021; Gao et al., 2011; Perreault, 2020). This brings to the fact that climate is essential for the global water cycle, hence climate change can also impede the achievement of the most of the SDGs mentioned above including poverty (SDG 1), gender equality (SDG 5), water and sanitation (SDG 6) and energy (SDG 7) (Ansuategi et al., 2015).

Much as climate is known to affect energy production, it is also found that energy industry contributes to 60% of climate change globally[5] mainly due to coal power generation which is the global primary cause of GHG and toxic airborne emissions. The emissions are largest in United States of America (USA), China and Russia as they cumulatively contribute over 45% of the GHGs emissions[6]. USA alone contributes 24.56%, and comparatively Malawi's contribution is negligible. All in all, the main sources of these GHGs in Malawi are transport that contributes about 43.2%, followed by power generation at 21.6%, then other sources are at 13.5%, industry and buildings are at 10.8% each (Crippa et al., 2019). But, Crippa et al. (2019) did not include the emissions from biomass, land use change and forestry in their analysis. And yet over 3 billion people in the world use biomass[7] and in Malawi 88.5% of the population use this energy source mainly for cooking (Kambewa & Chiwaula, 2010) which is about 93% of the country's total energy needs (Chimulu et al., 2015). As the highest GHG emission contributor is power generation in the world, Oberschelp et al. (2019) estimated that 10% reduction of polluting coal power plants can reduce GHG emissions by 16% and hence improve human health by 64%.

The SDG 7 is encouraging the investment of renewable energy sources including solar, wind and thermal, which was at 20% in 2015. Not only does the SDG7 promotes use of renewable

[5] https://www.mw.undp.org/content/malawi/en/home/sustainable-development-goals/goal-7-affordable-and-clean-energy.html

[6] https://ourworldindata.org/co2/country/united-states?country=USA~DEU#what-share-of-global-cumulative-co2-has-the-country-emitted

[7] https://www.mw.undp.org/content/malawi/en/home/sustainable-development-goals/goal-7-affordable-and-clean-energy.html

energy but it also calls for the energy to be affordable[8]. While the SDG 13 calls for climate action that includes the raising of level of ambition as one way of reducing the GHGs emissions. Otherwise, the achievement of SDGs will be compromised if countries go for low-ambition level of agreements (Ansuategi et al., 2015). The high-ambition level is related to levels that will limit the global temperature below 2°C increase with reference from pre-industrial period which is associated with RCP4.5 scenario, while the low-ambition level is linked to business-as-usual scenario (RCP8.5) (Ansuategi et al., 2015).

The Paris Agreement is enhancing the SDG 13 considering that climate change is increasing the severity of climate extremes such as heatwaves, heavy precipitation, droughts, tropical cyclones and floods (IPCC, 2021). Every country on the planet is being affected but Africa continent is affected the most due to the limited capacity to adapt (Simms, 2006). Being in Africa, Malawi is also affected by the climate change, and the impacts of this changing climate on water resources, hydropower and drought are evaluated in this study. Therefore, this section summarises the results based on the three studies and literature review that are divided into three subsections as follows: Climate change in Malawi; Effects of climate change on water resources in Malawi; Effects of climate change on meteorological droughts; and Effects of climate change on energy in Malawi. Though the study has looked at Lake Malawi and Shire River Basins, the assumption is that the findings are true for the whole Malawi nation since over 94% of Malawi is covered by these two basins.

2. Climate Change in Malawi

2.1 Temperature and rainfall changes

Despite the efforts to mitigate the global GHG emissions for the past 26 years, the temperature is still on the rise and year 2020 and 2016 are equally the hottest years since the modern record keeping begun on earth. The past seven years have also been the hottest and the temperature has increased more than 2° Celsius comparing with 1880 records and 1.8° Celsius more than 1950-1980 reference period globally (NASA, 2021). With this trend, the world is in the trajectory towards the increase of 4 to 5° Celsius by the end of the century (United Nations, 2020) hence failing to achieve the Paris Agreement, which will result into the irreversible consequences on earth's surface (History.com Editors, n.d.).

[8] https://www.mw.undp.org/content/malawi/en/home/sustainable-development-goals/goal-7-affordable-and-clean-energy.html

The study has found that in Malawi the temperature is increasing at 0.02°C per year (based on 1970-2013 period) and it is very likely to continue into the future; and with this trend, it means the increase of about 0.8°C in 40 years or 2°C in 100 years. But considering the findings from this study based on future climate scenarios; the increase is much higher than that. For instance, the noted increase in temperature with the moderately controlled RCP4.5 scenario that is associated with high-level ambition (according to Paris Agreement) is between 0.8 and 1.4°C during 2021-2050 period. The increase is below the global limit of 1.5°C, however, with the current trajectory of business-as-usual, RCP8.5 (low-level ambition) then the possibility of reaching 1.5°C is at 37.5%. The temperature increase for the models ranges from 0.9 to 1.8°C during this period. But during 2071-2100 period, the increase is between 1.7 and 4.5°C, indicating high possibility for temperature to rise beyond 1.5°C limit. While the chance of temperature increases beyond 2°C is 100% and 50% for RCP8.5 and RCP4.5 respectively. It should be noted that the changes are with reference to 1976-2005 period otherwise if pre-industrial period is considered then the changes could be larger.

On the other hand, annual rainfall change is not definite but the decrease is noticeable even during 1976-2005. There is high uncertainty amongst the models but declining trend seems more likely. The model agreement towards the rainfall declining during 2021-2050 is between 62.5 to 75%. While the range of declining trend during 2071-2100 is between 81.3 to 87.5%. The high uncertainty warrants caution in the use of these scenarios in terms of rainfall. However, though the results show high uncertainty among the models, but the study has shown that the bias-correction reduces their spread and the magnitude, otherwise without bias correcting the models' performances may be weak (Warnatzsch & Reay, 2019) in Malawi more so with rainfall.

2.2 Meteorological water balance (MWB)

The study has found that the current meteorological water balance (precipitation-PET) in the GLMB which is at ~+4mm annually is in the peripheral of turning into negative and the chances of this happening in the near future is at 94% otherwise 100% in far future for both scenarios. Despite the model disagreements in the direction of change of rainfall projections, they all agree on the decrease in water balance in the GLMB. This signifies the role of temperature (evapotranspiration) in the water balance of the basin. During the 2021-2050, the annual decrease in meteorological water balance is ranging from 0 to -0.3mm per year while during 2071-2100 is in the range of -0.3 to -2mm per year. There is high uncertainty in the magnitude, but on average the moderately controlled scenario (high-level ambition) which is unlikely to happen (considering the current trajectory of temperature increase) has a potential decrease of water balance of -0.1mm per year during 2021-2050 while the business-as-usual scenario (low-level ambition) which is likely is at -0.3mm per year (3 times more than high-level ambition). Otherwise, the mean decrease during 2071-2100 is -0.6 and -1.7mm per year for RCP4.5 and RCP8.5 respectively.

It is also found that the increase of temperature by either 1.5°C or 2°C will decrease the meteorological water balance by –0.4mm or -0.6mm per year in Malawi respectively (Tab.V-2). If this temperature is combined with decreasing rainfall, then the impact will be larger than what is found in this study. The negative net water balance in Malawi is a threat to various sectors including water, agriculture, energy, fishing and forestry industries and is also a catalyst of more severe droughts. For instance, decrease in water balance increases soil moisture stress hence affecting vegetation cover. Chisale et al. (2021) alleged that erratic rainfall and high temperatures reduce the availability of forest products in some forest reserves in Malawi. Therefore, with temperature increase anticipated in the future, the forest cover will be highly affected. Similar effects are also noted on biodiversity; e.g. the 3°C permanent increase in temperature (heat wave) reduces the development time, body mass and immune parameters of butterflies in Malawi (Fischer et al., 2014). The effect of climate change on biodiversity will be enormous bearing in mind that population growth alone is putting about 25-50% of Africa's biodiversity at risk (Boko et al., 2007).

Table V - 2 *The effects of temperature increase beyond global limit of 1.5°C and 2°C on Lake Malawi level, Shire River flow, Hydropower production (HPP) and its reliability on Shire River, meteorological water balance (MWB), drought intensity (DI) and drought months (DM) per year. This assumes that rainfall remains the same as reference period (1976-2005)*

Global ΔT	Δlake level (m)	ΔShire flow (%)	ΔHPP (%)	ΔHPP reliability (days)	ΔMWB (mm/yr)	ΔDI (%)	ΔDM/year
1.5°C	-0.45	-23.6	-0.7	+12.1	-0.4	+50	+5
2.0°C	-0.6	-30.5	-1.1	+16.6	-0.6	+81.2	+6

Effects of climate change on agriculture come in various scenarios. For example, increase in temperature and reduction in rainfall does not always mean reduction in agricultural production as it also depends on the timing of the rains if they occur at the critical stage of the crop. Therefore, the maize yield declining due to climate change in Malawi by 2050 was found by Arndt et al. (2019) to be about -2%. But could reach -20% during 2061-2070 if no adaptation measures are considered otherwise the reduction could only be -0.1% with proper adaptation practices (Kachulu, 2018). Subsequently, the yield reduction will lead into increased number of food insecure population in Malawi as was found by Stevens & Madani (2016) where about 12% of population will likely be food insecure by the end of the century in Lilongwe District due to climate change. The future climate change is also anticipated to decline the suitable area for the production of some crops such as macadamia (cash crop) by either 18% (RCP4.5) or 21.6% (RCP8.5) in Malawi (Zuza et al., 2021) leading to economic losses. Similarly, tea production will also require some adaptive measures to maintain its sustainability and quality in the future due to climate change in Malawi (Mittal et al., 2021) which will for sure come at a cost. The temperature rise will also increase the breeding grounds for some crop pests. This will increase the usage of pesticides that will not only make the production expensive but also negatively affecting the biodiversity and aquatic life (Donga et al., 2020).

The effects of climate change on health is noted on malaria prevalence which is associated with high temperature and PET hence low-lying areas have higher risk than highlands in Malawi (Kazembe et al., 2006). And high temperature increase will increase favourable areas for vector breeding hence increasing the malaria incidences (Kumambala, 2010). The tuberculosis (TB) prevalence is also seasonal as high cases are noted during hot months in September and October just before rainfall onset (Kirolos et al., 2021). Indicating that high temperatures being projected in the future could lead to suitable environment for these diseases. On the contrary, temperatures greater than 28°C are associated with lower invasive salmonella disease in Malawi (Thindwa et al., 2019).

Though this is like this, in general, the increase in temperature and changes in rainfall are unlikely to be net beneficial to most African countries including Malawi (Arndt et al., 2019) as the country has less adaptative capacity (Chisale et al., 2021; Suckall et al., 2017). All these negatively affecting the accomplishment of the SDGs more particularly, SDG1, SDG2, SDG3, SDG4, SDG14 and SDG15 (Table V-1).

3. Effects of Climate Change on Droughts in Malawi

As the increase in temperature is very likely in Malawi, the study has established that these changes will impact drought characteristics. The temperature increase enhances evapotranspiration (PET) and hence with reduced rainfall, meteorological water balance of the GLMB is also reduced. That is why drought estimates based on SPEI tend to be more severe and longer lasting than those that use SPI signifying the important role of PET on meteorological water balance in Lake Malawi and Shire River Basins.

Droughts are common and are also increasing in Malawi in both severity and area coverage. As all the models agree on the decreasing trend of meteorological water balance, similarly, they all also agree on increasing meteorological droughts in future. It is found that future meteorological droughts will be more intense and longer-lasting that will result into severe hydrological droughts in the GLMB. It was further found that the response of the hydrological drought from meteorological drought is delayed by more than 24 months due to the attenuation effect of Lake Malawi. And the possibility of having moderate hydrological drought is high during 2021-2050 that will turn into severe and extreme during 2071-2100.

Considering the global temperature limits of 1.5°C and 2°C, the DI increases by +50% and +81.5% while drought months increase by +5 and +6 months per year respectively. This assumes that rainfall remains the same as reference period, otherwise with rainfall decrease the severity of drought will be enormous (Tab.V-2).

The study has also introduced the new hydrological drought index, lake level change index (LLCI), that has proved to determine the hydrological drought based on lake level. The index is calculated in a similar way as SPI and hence is comparable with both SPI and SPEI. Changes in lake level depends on rainfall characteristics, evapotranspiration in the catchment including lake evaporation and lake outflow. Therefore, lake level change is assumed to be the end result of all the processes in the basin. That means, at longer time scales, the water received in the catchment will be transferred to lake outlet if it is not lost by evapotranspiration.

The recurrent of drought affects crops, livestock, environment, health, water, education and migration in Malawi (Becerra-Valbuena & Millock, 2021; Munthali et al., 2003; Pauw et al., 2010; Phiri & Saka, 2008) and hence impacting the economy of the country (Pauw et al., 2010). This makes the adaptation difficult for the subsistence farmers in Malawi whose crop production falls by 32.34% under the 25-year return period drought. This worsens the poverty by 16.9 percentage points which translates into 2.1 million more people falling under the poverty line (Pauw et al., 2010). For instance, one of the worst droughts of 2015/16 resulted into food deficit to about 40% of the Malawi population (Mutenje, 2018), and lack of water and folder for animal feed threatens livestock production in Malawi (Munthali et al., 2003). However, the annual increase in poverty is 1.3 percentage points thus 154,000 more people being more poor every year due to drought (Pauw et al., 2010). Climate stressors like drought cause rises in food prices (e.g. 2015/16 drought; the price went up by 50% in Malawi) and declining labor wages that results in high migration to urban centers in Malawi hence rising unemployment among non-skilled workers in cities (Mutenje, 2018; Pauw et al., 2010). This creates pressure in urban areas and results into city crime rate increase (Tambulasi & Kayuni, 2008).

The effect of drought on health is undeniable as food insecurity results into malnutrition and other disease outbreaks such as diarrhoea, kwashiorkor and marasmus (Munthali et al., 2003). Similarly, food and water scarcity lead to high school dropouts (Munthali et al., 2003; Mutenje, 2018) and the higher dropouts are usually girls than boys (Eldridge, 2002). Considering the increase in drought expected in the future more and more people will be affected negatively in Malawi and hence affecting the achievement of SDGs including SDG1, SDG2, SDG3, SDG4, SDG5, SDG6, SDG8, SDG14 and SDG15 (Tab.V-1).

4. Effects of Climate Change on Water Resources in Malawi

Considering the uncertainty of future climate change scenarios, the study has used a sensitivity approach of possible range of future climate to understand the impact of climate change on water resources in Malawi including Lake Malawi.

Water resources such as lake level, lake outflow and Shire River flow are very likely to be affected by the changing climate in the GLMB. The study has demonstrated that climate change is contributing towards the declining of Lake Malawi level (which was at 475m.a.s.l.. 1976-2005) at -0.025m per year, that means -1 m and -2.5 m in 40 and 100 years respectively. The study has demonstrated the sensitivity of the GLMB to climate change, and such that the temperature increase of +1°C reduces the lake level by -0.3 m. The global temperature limit of 1.5°C and 2°C alone reduces the lake level by -0.45m and -0.6 m (Tab.V-2). While the change of rainfall by +0.5/-0.5% increases/decreases lake level by +0.7/-0.6 m. The combination of temperature increase and rainfall decrease has enormous effect on lake level, for example, the increase of temperature of +1.5°C and reduction of rainfall by -20% reduces the lake level by -2.28 m (472.72 m.a.s.l.). The climate models, indicate the average decrease ranging from -0.5 (474.5 m.a.s.l.) to -1. 1m (473.9 m.a.s.l.) during 2021-2050 period, and between -1.5 (473.5 m.a.s.l.) and -2.1m (472.9 m.a.s.l.) during 2071-2100.

The impact of climate change on Lake Malawi level is noted but with the vastness of the lake the impact appears small, however, if it were a small lake like Lake Chirwa the effects would have been highly noticeable. Lake Chirwa level fluctuates a lot due to meteorological water balance between rainfall and evaporation. The lake has gone through 12 severe recessions since 1879 and the recent was in 2012 (Nagoli et al., 2017). With the anticipated increase in temperature and likely decrease in rainfall, the Lake Chirwa will be highly affected, and certainly affect the livelihood of more than 10000 people who rely on the lake (Nagoli et al., 2017).

Changes in climate variables such as temperature, wind speed and rainfall results into not only lake level changes but also loading and recycling of nutrients thereby disrupting the physical and chemical conditions of the lake. This alters the water quality, invertebrate productivity and life history of fish (Ogutu-Ohwayo et al., 2016). Much as overfishing, pollution, habitat degradation, and invasive species are declining the fishes on Lake Malawi (Ogutu-Ohwayo et al., 2016), climate change is also contributing to the dwindling of Tilapia (chambo) fish on the lake (Makwinja & M’balaka, 2017).

The influence of evapotranspiration on Shire River flow is not as high as that on lake level and the effects may be inherited from the lake. But still the effect is large enough to affect the firm flow of 170 m^3/s (Maximum Flow for Hydropower Production (MFHPP)) required for maximum hydropower production. It is found that +1°C increase in temperature also reduces the Shire River flow (outflow from the lake) by -17% and increases the number of days where the flow is below MFHPP by +9%. Considering the global temperature limits 1.5°C and 2°C, the Shire River flow decreases by -23.6% and -30.5% respectively (Tab.V-2). While the reduction in rainfall by -5% increases the frequency of MFHPP by +19%. The combination of temperature increase and rainfall reduction affects the flow highly. It is noted from the study that the Shire River flow turns into seasonal with the temperature increase of only +1.5°C (which is likely during 2021-2050 at 37.5% probability) if it is accompanied by the decrease in rainfall of -20%, similarly, with the temperature increase of +3.5°C (which is likely during 2071-2100) in combination with rainfall decrease of -15%. The study has established that 35% of the models project the possibility of this happening during 2071-2100 period, though other studies have predicted this happening earlier during 2021-2050 period (Bhave et al., 2020).The ceasing of Lake Malawi outflow is not new, records show that in 1920s the Lake Malawi outflow stopped completely. Though the reasons are not well known, some speculate that rainfall reduction could be one of the reasons (Shela, 2000).

The effect of climate change on some rivers in Malawi is also noted. For instance rainfall reduction decreased the river discharge by 1.58 m^3/s during 1980s-1990s on Wamkurumadzi river a tributary to Shire River (Nkhoma et al., 2021). Some big rivers such as Bua, Dwangwa and Lufira are also facing flow decline during dry seasons (Kumambala, 2010).

The study has only looked at climate change effects on water resources, but it is understood that land use change is also playing a role on these changes. Calder et al. (1995) found that the decrease in forest cover increased lake level by 1m during the 1992 Southern African drought. And in view of forest cover declining at 0.84% per year (GOM, 2005), it provides the picture that the lake level changes being noted are being compensated by the depletion of land cover which is encouraging the surface and subsurface flows to the lake and less replenishment of groundwater (Kelly et al., 2019; Kumambala, 2010). And yet the groundwater is main source of water to 60% of Malawi's population (Mapoma & Xie, 2014) as many rivers are turning into seasonal (Kumambala, 2010). On another hand, the fast flowing of surface runoff into lakes enhances the loss of water through evaporation, as volume of water loss by evaporation depends on surface area of the lake (Hassan et al., 2020).

The demand for agricultural land and increasing energy needs due to population increase are the main cause of forest depletion in Malawi (Kumambala, 2010). The negative feedback of population growth on water resources is noted. The rising population expands the quest for agricultural land and energy needs that lead to forest cover declining which encourages the surface runoff and less groundwater replenishment resulting into inadequate water for the increased population during the dry season. Therefore, the groundwater declining (Kelly et al., 2019) is exposing more people to water stress conditions in Malawi. As a country, Malawi is already water-stressed based total per capita water availability (USAID, 2009). And this will be exacerbated by climate change (Kumambala, 2010) as the number of people under water scarcity in the sub-Saharan countries is likely to double by 2050 (Mutunga et al., 2012). This will limit agricultural production and access to improved water and sanitation (USAID, 2009), hence increasing poverty, hunger and poor human health in Malawi. Thereby affecting the achievement of most of the SDGs particularly SDG1, SDG2, SDG3, SDG4, SDG5 and SDG6 (Tab.V-1).

5. Effects of Climate Change on Hydropower Production in Malawi

The effect of climate change on Shire River flow reduces the discharge to below MFHPP, thereby affecting the hydropower production. There is high likelihood for the hydropower production to decrease during 2021-2050 even with the moderately controlled scenario (RCP4.5) where the mean reduction is at -2.5% with reliability (days without maximum power production per year) of 46 days. Otherwise, some individual models have the reduction to the extent of -13% and the related reliability of 190 days. During the 2071-2100, the RCP4.5 (the high-ambition scenario) has the mean/extreme model decline of -5%/-29% with reliability of 89/284 days. Otherwise, the business-as-usual (low-ambition scenario) during the same period the mean/extreme model hydropower production reduction is at -24%/-38% and the reliability is 259/318 days. The hydropower reduction associated with seasonal Shire River flow where 35% of models project during 2071-2100 is between -35 to -38% with reliability between 300 and 318 days hence risking more power blackouts in the country. And also, the global temperature increase alone of either 1.5°C or 2°C reduces the hydropower production by -0.7% or -1.1% respectively which translates into +12.1 or +16.6 more days without maximum electricity production.

The reduction in the hydropower production will not only affect the achievement of SDG 7, but also those that are energy dependant such as SDG3, SDG4, SDG5, SDG6, SDG8, SDG9 and SDG12 (Tab.V-1). The plan to achieve 100% sustainable energy in Malawi by 2030 will be affected as populations will continue using unsustainable sources such biomass hence continue degrading the environment (Taulo et al., 2015). Women and girls will be affected highly as they are the ones who will be spending longer hours searching for firewood (GOM, 2017) as such failing to participate in developmental agendas. The use of petroleum fuels as backup during power failure will also increase and yet the petroleum procurement alone consumes almost 10% of the Malawi foreign currency reserves for importation (GOM, 2003), that means with the anticipated increase in power blackouts the importation will also increase relatively. The current failure to meet the electricity demand affects 2 to 3% of Malawi's GDP (Millenium Challenge Corporation, 2010) thereby affecting the human development index (HDI) which is correlated with per capital electricity consumption (Taulo et al., 2015) hence the achievement of Decent work and economic growth; Industry, innovation, and infrastructure; Sustainable cities and communities; Clean water and sanitation goals (Tab.V-1) will be compromised. All these supports economic development which increases the adaptation capacity hence withstanding climate change effects.

6. Recommendations and Conclusions

The study was designed to investigate the impacts and sensitivity of climate change on water resources, droughts and hydropower productivity in Malawi especially the Greater Lake Malawi Basin (Lake Malawi and Shire River Basins). The findings have been linked to global policies more particularly the UNFCCC's Paris Agreement and the UN's SDGs, and how the failure to achieve these goals will affect Malawi. The work which has been divided into three studies have provided an additional knowledge of the impacts of climate change in Malawi. And failure to adhere the restriction of temperature increase below the global limit of 1.5°C will affect the water resources in Malawi consequently impact the hydropower production. In the end the achievement of the SDGs will be compromised.

The objective of the first study was to assess the drought dynamics of Lake Malawi Basin (LMB) and Shire River Basin (SRB) both from a meteorological and hydrological perspective from 1970 to 2013. The study has attempted to establish the relationship between meteorological and hydrological droughts in Lake Malawi Basin. It has also introduced the lake level change index (LLCI) as the hydrological drought indicator. The impact of temperature on evaporation on Lake Malawi was also investigated. The second study focussed on future climate change impacts and sensitivity on drought severity, more particularly drought months (DM), drought events (DE) and drought intensity (DI). It also evaluated the capacity of climate models to predict drought characteristics. While the third study has also tested the sensitivity of climate change on water resources (lake Malawi level and Shire River discharge) and consequently establish their impacts on hydropower production on Shire River.

The information generation is important for decision making more especially supporting the climate action required to fight against climate change. The frequency of extreme climate events due to climate change has reached the climate emergency as saving lives and livelihoods require urgent action. The following are the recommendations derived from the study:

Remaining open questions

1. *The temperature increase beyond 1.5°C will have serious repercussions on water resources in Malawi.* And this will have serious impacts on hydropower production and hence affecting the achievement of SDGs. The study recommends on conducting similar sensitivity tests for other sectors including agriculture, health and biodiversity.

2. *Water balance between rainfall and evaporation is important on Lake Chirwa which has no outlet.* The lake has faced 12 serious recessions since 1879. So, the study is required to understand the changes of lake surface area which are essential for lake users more especially fishermen. Furthermore, sensitivity tests similar to those conducted on Lake Malawi and Shire River Basin should be extended to Lake Chirwa. The findings will provide guidance on what temperature and rainfall threshold results into these recessions. And with temperature increase in the future, it will be important to establish how frequent and serious will the future recessions be, and if anything, also determine the possibility of total lake dryness.
3. *Temperature increase will increase the frequency of future heatwaves.* However, there is need to understand further their impact on human health in Malawi. Being in the tropics, Malawi experiences high temperatures, but it is not known as to what extent does temperature increase or heatwaves affects the human health in this region.
4. *The study has looked at climate change impacts on water resources, droughts and hydropower generation only*. But further studies are required that will include land use change impacts on water resources, droughts and hydropower generation.

Policies

5. *Considering the sensitivity of hydropower to climate change, there is need to diversify energy sources in Malawi.* Not only does the hydropower generation faces challenges under climate change but the capacity is also not adequate to meet the growing demand of electricity in Malawi. The expansion of hydropower on the same Shire River (which is in the plans) will still face the similar reliability challenges due to climate change in the future. If the SDG 7 is to be realised, then there is need to consider other renewable energy sources such as solar and wind to complement hydropower. Malawi has abundant solar energy potential that is under deployed. And adequate renewable energy sources will also reduce use of fossil powered generators for electricity backup and also reduction on biomass energy reliance. The adaptative capacity of the country depends on its economic status and economic status also depends on energy. Therefore, Malawi should invest adequately on energy diversification. In that way the adaptative muscle will be enhanced.
6. *The adherence of mitigation policies including the Paris Agreement is essential for the development in developing countries such as Malawi.* Malawi has low adaptive capacity, and yet is caught up in vicious circle, where climate extremes are affecting its developmental agendas, thereby further weakening the adaptative power. Therefore,

the dangers that will come with temperature increase beyond 1.5°C on water resources in Malawi will impede further the economic growth. It is a plea to the whole world to adhere to Paris Agreement and mitigate the GHG emissions in the atmosphere.

In conclusion, the study has outlined and added knowledge on the impact and sensitivity of climate change on water resources, drought and hydropower in Malawi. The climate change intervention requires integrated approach as it affects all sectors. Otherwise getting sector specific solutions creates problems or conflicts in another sector. Here we have shown the linkage between climate, water and energy, but there is also need to include other important sectors such as food security.

The information has been generated to support informed decision making, implementation of policies and development of relevant policies in water and energy sectors. Malawi energy sector requires reform and strategies to enhance access and affordability of electricity. The findings from this study which will later be developed into policy briefs will be shared at various platforms such as Climate Change Technical Committee, Early Warning Cluster and Parliamentary Committee on Climate change and Natural Resources in Malawi.

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