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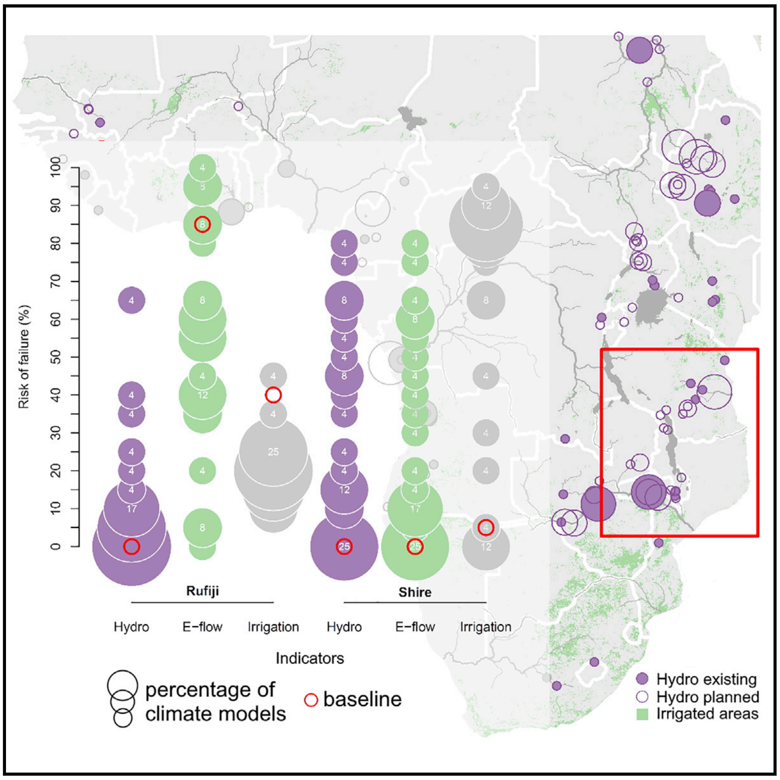
Climate variability affects water-energy-food infrastructure performance in East Africa

Graphical abstract



Highlights

- Climate variability is poorly understood in East Africa's climate transition zone
- Recurrence of a multi-year drought will stress infrastructure performance
- Variability in rainfall, amplified in runoff, is projected to increase in the region
- Contingency planning is necessary to mitigate the impact of multi-year droughts

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In brief

In sub-Saharan Africa, exposure and vulnerability to climate risk are high across crucial economic sectors. Yet, investments are still made under the assumption that rainfall or streamflow will resemble historical patterns, and most climate-impact studies focus on changes in mean climate. Our analysis identifies critical climate risks to water-energy-food infrastructure performance in two large river basins targeted for major development and highlights the need for climate risk assessments to incorporate a long view of variability.

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Climate variability affects water-energy-food infrastructure performance in East Africa

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SCIENCE FOR SOCIETY Despite awareness of climate impacts on development, climate variability and future change have received limited attention in investment decisions. We examined past and future climate variability with the aim of understanding the main source of climate risk to development plans across the water, energy, and food sectors in southern East Africa, a relatively neglected region in terms of climate science and targeted for extensive infrastructure development. Infrastructure performance shows high sensitivity to multi-year droughts that have occurred in the past, which would challenge the viability of proposed infrastructure. Contingency plans for the worst-case extremes need to be developed. Our assessment exemplifies the need for investors and donors to take a comprehensive approach to climate risk. Infrastructure design should take into consideration the potential for changes in climate variability and recognize the limitations of planning on the basis of short time series of observations or projections.

SUMMARY

The need to assess major infrastructure performance under a changing climate is widely recognized yet rarely practiced, particularly in rapidly growing African economies. Here, we consider high-stakes investments across the water, energy, and food sectors for two major river basins in a climate transition zone in Africa. We integrate detailed interpretation of observed and modeled climate-system behavior with hydrological modeling and decision-relevant performance metrics. For the Rufiji River in Tanzania, projected risks for the mid-21st century are similar to those of the present day, but for the Lake Malawi-Shire River, future risk exceeds that experienced during the 20th century. In both basins a repeat of an early-20th century multi-year drought would challenge the viability of proposed infrastructure. A long view, which emphasizes past and future changes in variability, set within a broader context of climate-information interpretation and decision making, is crucial for screening the risk to infrastructure.

INTRODUCTION

In sub-Saharan Africa (SSA), exposure and vulnerability to climate risk is high across crucial economic sectors.[1–5] Recent extreme drought and flooding events demonstrate the scale of disruption.[6–8] The 2015–2016 drought across southern Africa highlighted the cascading nature of impacts involving food insecurity, power cuts, and drinking water shortages,[6] disproportionally affecting small and medium-sized enterprises.[7] While economic development may reduce poverty and reliance on

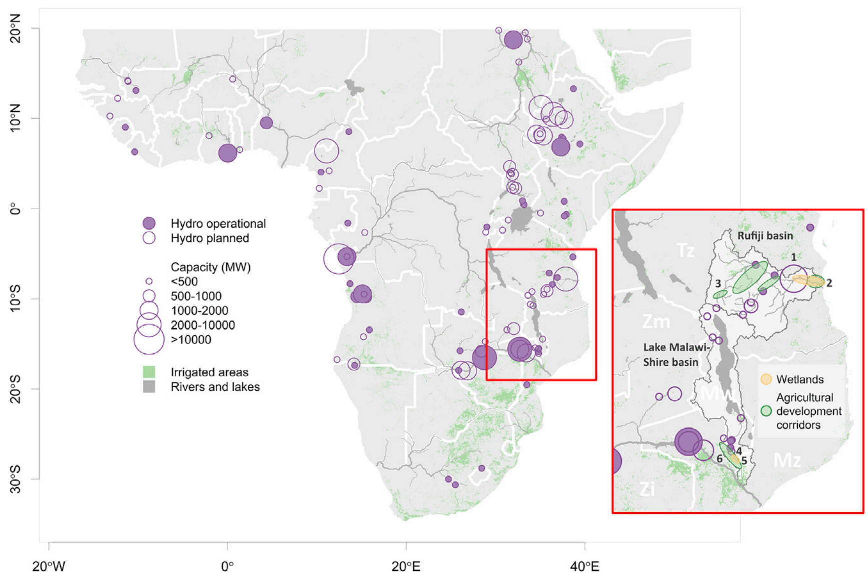

Figure 1. Existing and planned hydropower across sub-Saharan Africa and area under irrigation

Inset: Rufiji and Lake Malawi-Shire River basins with existing and new hydropower infrastructure, wetlands affected, and agricultural development corridors under consideration. (1) Julius Nyerere Hydropower Project (JNHPP), (2) Rufiji delta ecosystem, (3) upstream rice areas in the Southern Agricultural Growth Corridor of Tanzania (SAGCOT), (4) Kholombidzo Hydropower, (5) Elephant Marsh, and (6) Shire Valley Transformation Program (SVTP). Source of hydropower data: Conway et al.[3] for East and southern Africa and http://www.internationalrivers.org for central and western Africa, with capacity and operational status updated to the present day. Only hydropower plants with a capacity of more than 50 MW are presented. Irrigated areas for 2019 (at least 50% of agricultural area irrigated according to 250-m-resolution gridded data) were derived from the WaPor database (http://wapor.apps.fao.org) of the Food and Agriculture Organization of the United Nations (FAO). Planned irrigation in sEA will expand irrigation outside the traditional irrigated areas in southern and northern Africa.

climate-dependent agriculture, vulnerability to climate shocks may remain high across the tropics as assets and economies grow.[9–12]

Population and gross domestic product (GDP) growth in SSA have been among the highest globally. To support this growth, major infrastructure investments are planned,[13] including the Julius Nyerere Hydropower Project (JNHPP) in Tanzania, one of the largest hydro developments in SSA, and the expansion of hydropower on the Shire River in Malawi (Figure 1), a tributary of the Zambezi River. Agricultural land use is still increasing—in Tanzania it doubled between 2000 and 2018[14]—and in many SSA countries irrigation is strongly promoted in government programs.[15] These developments require massive investment at a time when increasing debt is a growing concern for some countries in SSA. Despite awareness of climate impacts on development,[8,16] climate variability and future change have received limited attention in investment decisions[17] and practical coordination on adaptation remains superficial and sectoral,[18] despite guidelines appearing.[19,20] Most investments in large hydropower plants are still made under the assumption that rainfall or river flow patterns will resemble historical patterns, which are often poorly characterized. This poses severe risks to performance.[21] Moreover, the vast majority of studies on future projections focus on changes in mean climate. Information on past and possible future changes in variability is typically neglected in climate risk assessments.[22]

Here, we examine past and future climate variability with the aim of understanding the main source of climate risk to development plans across the water, energy, and food sectors in the southern East Africa (sEA) region, a relatively neglected region in terms of climate science that is targeted for extensive infrastructure development. We consider the sEA region to be a "climate transition zone" in three aspects. First, regarding rainfall variability, sEA lies in a transition zone of complex responses to dominant global and regional modes of climate variability including the El Niño-Southern Oscillation (ENSO; note the opposing sign of ENSO influence across sEA; Figure 2B)[23–25] and the Indian Ocean Dipole (IOD),[26] while the magnitude of variability remains high (Figure 2A).[27–29] Second, sEA straddles the transition between the bimodal rainfall regimes of equatorial East Africa to the north and the unimodal southern African regime. Third, there is low intermodel agreement in rainfall projections (Figure 2C). This contrasts with the relatively robust projected increase (decrease) over the neighboring East (southern) Africa (see Note S3). This combination of climate features makes the region special but not unique; climate transition zones complicate development planning in regions across the world, such as in equatorial western Africa and parts of South Asia and South America. A better understanding of how to characterize risk under these conditions therefore has wider relevance.

In this paper, we adopt a comprehensive approach that integrates multiple sources of evidence and methods to develop a rounded portrayal of climate risk. We synthesize evidence from recent literature on climate processes in and around sEA's transition zone and undertake primary data analysis and hydrological impact modeling combined with detailed analysis of climate model projections. Major infrastructure proposals are identified from current policies and analyzed under historic and future climate variability with user-defined performance metrics and a suite of new robust rainfall products. The products are all based on similar underlying observational data but vary in their spatial extent, resolution, and data-assimilation techniques. For future variability, we utilize the CMIP5 archive and a bias-corrected version,[30] for which we assess the ability to simulate the dominant drivers of variability.

Climate variability and changing policy contexts

In regions where rainfall is markedly seasonal and characterized by high interannual variability, higher levels of institutional and infrastructure investment are needed to achieve basic water

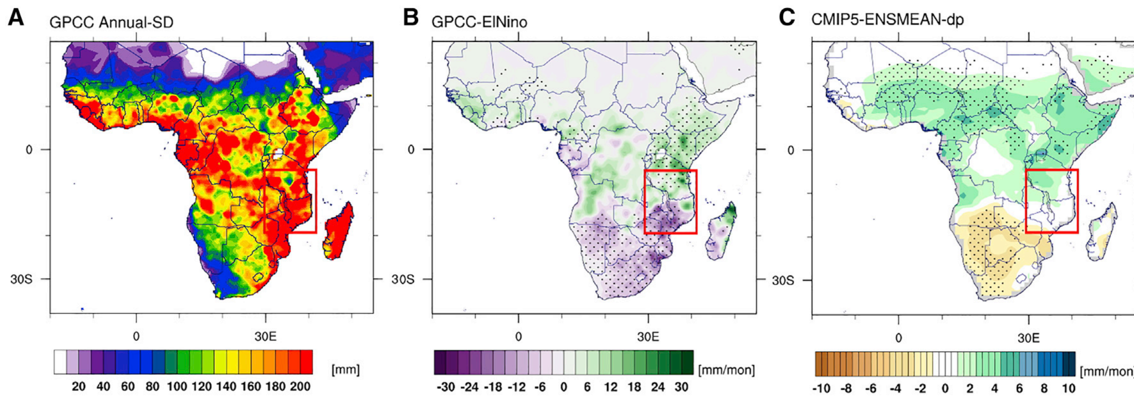

Figure 2. Three variables characterizing southern East Africa's transition zone

(A) Standard deviation of annual (July–June) rainfall (mm).

(B) Composite wet-season (October–March) rainfall anomalies during moderate and strong El Niño years (in mm/month); dots indicate regions with significant correlation with the ENSO index Niño3.4 over the period 1901–2016 ($p < 0.05$).

(C) Projected change in annual (July–June) rainfall for 2020–2050 compared with present day (1976–2005, in mm/month); dots indicate model agreement in signal (more than 66% of models) (see the experimental procedures).

security.[31] Investments in irrigation and hydropower infrastructure are often seen as necessary for socioeconomic development and in order to manage water resource variability.[32] However, in sEA, such variability is sometimes overlooked in surface and groundwater development plans, including policy commitments to increase irrigation. Furthermore, low policy coherence in the highly interdependent water, energy, and agriculture sectors is evident in both Malawi and Tanzania with regard to considerations of climate change.[18,33]

Expanding energy supply is a crucial element of economic development[34,35] in a region where half the population is still without direct access to electricity[36] and with a heavy reliance on hydropower,[37] which currently produces about 90% of Malawi's and 40% of Tanzania's electricity. Both countries experience regular blackouts and load shedding associated with dry conditions and drought, among other causes.[38] In Malawi, climate variability has contributed to substantial fluctuations in Lake Malawi levels[39] that have influenced political priorities on energy security.[40] The economic cost of power outages has been estimated at 5%–7% of the GDP for Malawi and Tanzania.[41]

Concern about overdependence on hydropower led to policy shifts in both countries toward diversifying electricity supply, including coal in Malawi[42,43] and natural gas in Tanzania.[18,44] Yet, even though declining hydropower supply is attributed to climate change, the Malawi Growth and Development Strategy[34] still aims to develop hydropower plants along the Shire River. In Tanzania, a major decision was taken in 2017 to go ahead with the JNHPP, first conceived in the 1950s, to support the country's growth and economic transition agenda.[45] When operational, it will be the third largest hydropower dam by energy-generating capacity (2,115 MW) in Africa. Both the JNHPP and Malawi's Shire River hydropower will dominate the countries' energy supply mix, concentrating risk in large infrastructure projects.

The agriculture sector is also pursuing policies that aim to increase productivity and food security with expanded irrigation embodied in a number of presidential programs, such as the Shire Valley Transformation Program and the Southern Agricultural Growth Corridor of Tanzania (SAGCOT, which is planning a quadrupling of irrigated agriculture in the basin). Together, both programs focus on the commercialization of up to 200,000 smallholder families and aim to lift millions out of poverty through enhanced rural employment in improved value chains. The aim expressed in the National Agricultural and Irrigation Policies is to absorb variation in production linked to weather variability;[46,47] however, there is little consideration of irrigation water availability under future climate conditions.

RESULTS

Characterizing historical rainfall variability

Rainfall over sEA is primarily controlled by the African rain belt, which is intensely active from December to March and predisposed to north-south fluctuations,[29] driving high interannual rainfall variability with a standard deviation (SD) of ~200 mm around a crop production-critical level (roughly 600 mm required for maize) in both basins (Figures 2A and 3). Rainfall variability over our study basins substantially reflects the control of ENSO[23–25] and the IOD[22] (Figure 3) occurring both independently[26] and through complex interactions.[48,49] Over the Rufiji basin, rainfall anomalies show a clear signal whereby El Niño or positive IOD events tend to be associated with above-average rainfall and La Niña or negative IOD events tend to be associated with drier-than-average conditions (Figure 3A). The IOD positive phase is particularly important for major wet years, e.g., 1961–1962 and 1967–1968 independent of El Niño and 1997–1998 coincident with El Niño. The Rufiji wet season, with contributions from the East African "short rains" and the southern African unimodal wet season, is rather long and has accordingly complex influences.[50]

Conversely, for the Shire basin, rainfall anomalies during the El Niño and La Niña phases of ENSO are reversed (Figure 3B). However, the association is less coherent than in the Rufiji, and La Niña events have produced both wet years (e.g., 1988–1989) and dry years (1999–2000) as the basin straddles the dipole structure of ENSO influence (Figure 2B). The IOD has

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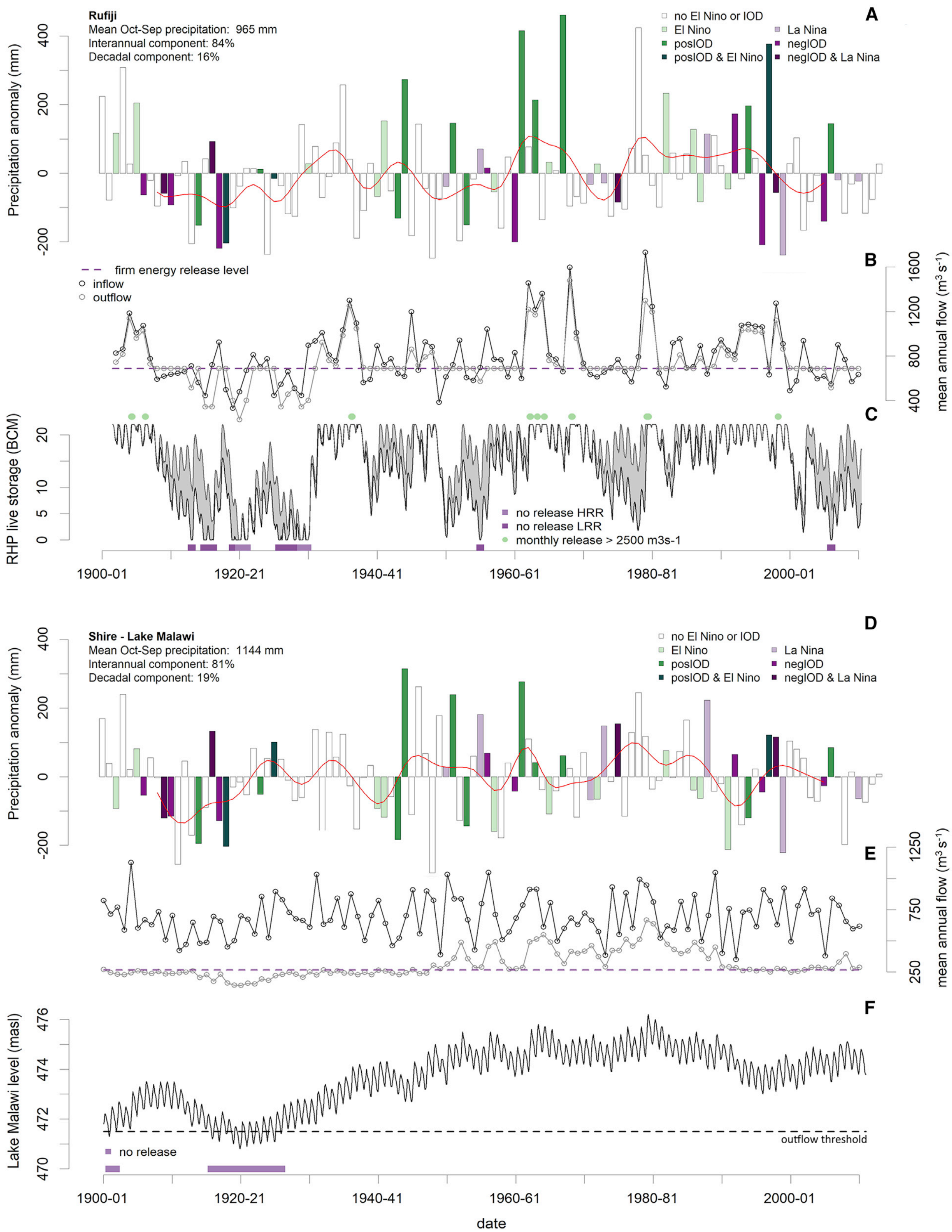

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far less control on the Shire than the Rufiji as a result of location (Note S3) and seasonality of rainfall. Furthermore, the control exerted by the IOD and ENSO on sEA rainfall is non-stationary with pronounced multi-decadal variations.[25] Major rainfall anomalies in both basins also occur in years when ENSO and IOD are inactive, during which regional controls are important (e.g., the Angola Low during the wet event of 1978–1979).

Multi-year variability is also apparent with periods of consecutive dry years, especially during the early 20th century, in both basins. More recently, the Rufiji basin experienced consecutive dry years after the 1997–1998 EL Niño, possibly associated with persistent La Niña-like conditions in the Pacific (Figure 3A).[50] Decadal variability (red lines in Figure 3) contributes 16% of overall variance in the Rufiji and 19% in the Lake Malawi-Shire. There is no significant long-term trend in rainfall, such that interannual and multi-annual variability rather than long-term changes in mean rainfall dominates the historical period.

Historical performance of recent infrastructure plans

Using hydrological models and climate data (see the experimental procedures), we examined the impact of historical climate variability on several of the large, pending investments in the two basins: expansion of hydropower (e.g., the JNHPP) and irrigation (e.g., the Shire Valley Transformation Project and SAGCOT) (see the experimental procedures for hydrological model setup). These represent "what-if" scenarios: as if the hydropower and irrigation expansion had been present from 1900 onward.

Rainfall variability translates into high variability in streamflow with persistence of wet and dry years (see Figure 3 and the coefficients of variation in Figure 5), leading to a multi-year pattern most notably in simulated Lake Malawi levels (Figure 3F). Prolonged periods of below-average rainfall during the beginning of the 20th century led Lake Malawi levels to fall below the outflow threshold.[51] Even if the Lake Malawi barrage (built in 1960) had been present, it would not have fully prevented the drop in lake levels (Figure 3F) because of the severity and duration of the multi-year drought. Similar multi-year dry conditions in the Rufiji basin (Figure 3A) would have led to the JNHPP—assuming it was built and operated to prioritize firm (reliable) electricity production (see the experimental procedures)—failing to meet its potential firm energy level for multiple consecutive years (Figures 3B and 3C).

The second half of the 20th century recorded wetter periods especially in the 1960s, similar to much of East Africa.[52] After the strong El Niño of 1997–1998, a higher frequency of years with below-average rainfall returned and contributed to hydropower disruption in smaller reservoirs in the Rufiji basin.[53] The simulation shows that under these conditions, the JNHPP would have just managed to maintain firm energy output because of its large storage size but only if upstream irrigation expansion was managed to ensure recovery of irrigation water return flows. Uncontrolled upstream irrigation expansion and greater reuse of return flows by smallholder farmers is ongoing,[54] which would put greater pressure on the performance of the JNHPP downstream (Figure 3C and the experimental procedures).

The present relatively undisturbed natural flow regime in the Rufiji comprises biennial bank overflows, which rejuvenate one of the world's largest deltaic wetland systems in the Nyerere National Park and support downstream flood recession irrigation.[55] The JNHPP dam will alter this pattern, particularly if operated primarily for hydropower purposes. In our simulation, exceedence of the peak flow threshold of more than 2,500 $m^3 s^{-1}$ during a whole month[56] (Figure 3C), required for delta flooding and regeneration, would be reduced from one in 2 years to less than one in 10 years. This would affect the delta ecosystem, fisheries, and farming, although it is possible that the JNHPP dam could be operated to mitigate this risk but at the expense of reliable energy production.

In Malawi, barrage operation aims to replicate natural outflows into the Shire River. High rainfall does not translate directly into high outflows; although the size of Lake Malawi buffers part of the interannual variability in inflows, the large surface area leads to high evaporative losses of up to 80% of total inflows and lake rainfall. While single years with low inflow can still be buffered (e.g., 1949 and 1954), consecutive or multiple years of drought within a short time span (1910s and around 1990) lead to a drop in lake levels, a sharp reduction in outflows, and a slow recovery. Our analysis shows how investments in both the Rufiji and Lake Malawi-Shire basins are strongly sensitive to multi-year rainfall variability.

Climate change and future variability risk

The Rufiji and Lake Malawi-Shire basins are located in a region of particularly high uncertainty in projected rainfall, as noted in Figure 2B. Most research has focused on projected changes in mean rainfall[57,58] or extremes.[59,60] Over sEA, climate-model projections of mean annual rainfall span wetter and drier futures (Figure 4A): performance-based model weighting does not reveal strong systematic effects on the spread of projections or their impacts and has limited effect on the range of uncertainty.[61] This range in rainfall uncertainty is both amplified and modified by hydrology. Relative changes in runoff are more

Figure 3. Hydrological impact pathways

(A and D) Annual precipitation anomalies (October–September) for the Rufiji (A) and Lake Malawi-Shire (D) basins (source: CENTRENDS); years with modest to strong El Niño or La Niña and with strong positive or negative IOD are highlighted. The red line indicates a decadal rainfall variability obtained with a low-pass Lanczos filter with 8-year frequency cutoff. Note: caution is required in interpreting the early and later parts of the series because there are very few *in situ* observations. Definitions of EN and IOD events are explained in the experimental procedures.

(B and C) Simulated mean annual Rufiji river inflows and outflows at the JNHPP reservoirs (B) and simulated monthly live storage of the Nyerere Hydropower Project reservoir (assuming it was built in 1900) (C). The simulated range in live storage represents uncertainty in the efficiency of irrigated agriculture under high (HRR) and low (LRR) irrigation return flow rates, which affects inflows into the reservoir. Risk of failure, i.e., not being able to release sufficient water to maintain firm energy flow, is indicated by the purple bars, whereas green dots highlight years with sufficient release of water to satisfy downstream flood requirements of the delta ecosystem.

(E) Mean annual inflows and outflows of Lake Malawi, assuming the barrage was present from 1900.

(F) Simulated monthly lake levels of Lake Malawi, assuming the barrage was present from 1900.

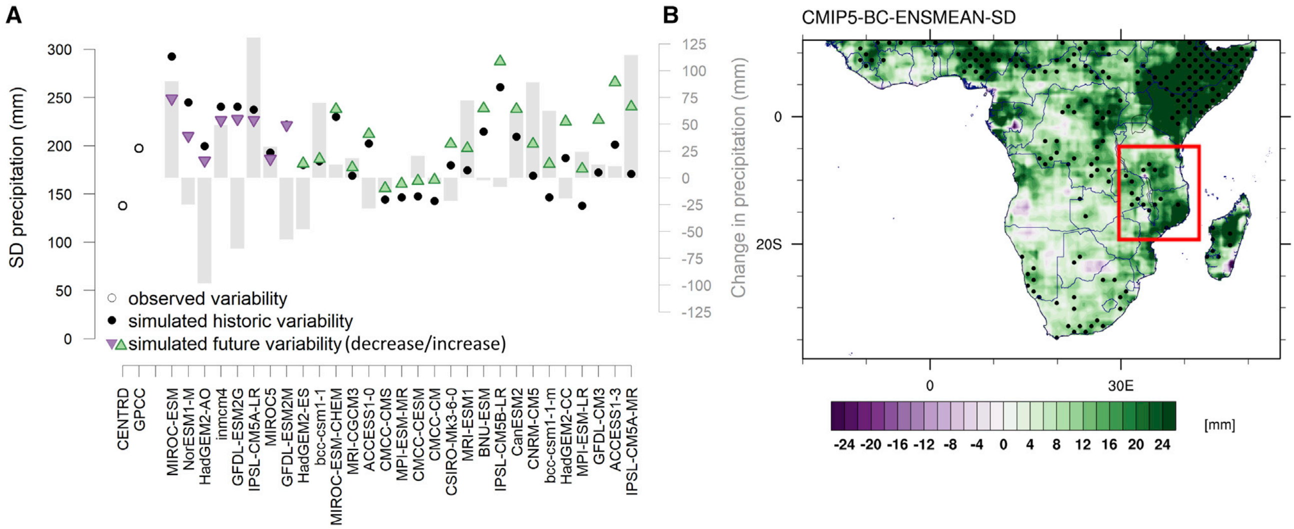

Figure 4. Projected future rainfall variability

(A) Current and future rainfall variability using the bias-corrected AMMA2050 models;[30] the absolute change in future mean annual rainfall is shown by gray bars. Green (purple) triangles indicate increase (decrease) in future variability (represented by standard deviation [SD]); also shown is the historical variability from two observational datasets (GPCC and CENTRENDS).

(B) Multi-model mean projected change in interannual rainfall variability (SD); dots indicate model agreement (>66% of models have a sign similar to the multi-model mean).

pronounced than the changes in rainfall, and there is a higher proportion of drier futures (for the Rufiji, only 3 out of an ensemble of 24 projections show a reduction in rainfall, but 9 out of 24 have lower runoff[62]), associated with increased evaporation due to higher temperatures.

Intensification of daily rainfall is emerging as a robust response to global warming resulting from thermodynamic principles.[59] Such intensification is stronger in new high-resolution convection-permitting models over much of Africa;[60] however, in these large basins, the response to changes in rainfall intensity will be dampened. It is the changes in interannual to multi-annual variability that are decision critical (Figure 3), and these will be shaped by the extent to which the local, regional, and global drivers of variability evolve under a warming climate. These remain uncertain even for ENSO,[63–65] and climate models typically have a limited ability to simulate ENSO teleconnections to sEA (Figure S5). In contrast, representation of IOD rainfall patterns in models is more reassuring (Figures S2 and S3), and a robust increase in the frequency of extreme positive IOD events has been suggested[66] (Note S3), although we note no apparent systematic relationship between the projected changes in rainfall variability over sEA and that in the IOD mode (Figure S4). Furthermore, changes in mean state and variability are likely to interact; it has been suggested that changes to mean east-west gradients across the Indian Ocean may lead to an emergent ENSO-like mode of climate variability according to CMIP5 climate model analysis,[67] capable of generating unprecedented sea surface temperature (SST) and rainfall fluctuations. With regard to the synoptic-scale weather responsible for much of the regional rainfall—tropical lows, cyclones, tropical-extratropical cloud-bands—climate models do simulate these events but with limited skill in representing their seasonality or intensities (see Note S2).[68,69]

Acknowledging the limitations of models to simulate underlying drivers, we analyzed a set of 24 bias-corrected CMIP5 model experiments for future changes in variability. There is strong agreement on the sign of projected change in future rainfall variability such that about three-quarters of the CMIP5 models suggest an increase in interannual variability (Figure 4) (irrespectively of their mean rainfall change), and all but one project an increase in daily variability (data not shown).

Changes in annual runoff variability show greater relative changes (Figure 5), leading to marked changes in risk of failure to achieve performance objectives. Hydrological amplification of changes occurs through multiple processes including an increase in rainfall events outside of the normal rainfall season in some years but not others, converting rainfall mostly into transpiration, which has higher potential due to higher mean temperature, rather than runoff.

To understand extreme, multi-annual drought conditions, we identified periods of three or more consecutive years with at least one month without lake or reservoir outflow. For the Rufiji, multi-annual drought conditions are projected by the three driest models, as well as by one model (ACCESS1-3) in which, on average, rainfall and runoff increase, indicating the risk of changes in frequency and sequencing of dry years and hinting at a higher likelihood of a recurrence of the early-20th century drought. For Lake Malawi, the likelihood of multi-annual drought was dominated by projected changes in the mean such that models projected either reduced precipitation and (semi-) permanent drought conditions or increased rainfall and runoff and no drought at all.

Simulated profiles of present and future climate risk of failure to achieve performance indicators across the water, energy, and food sectors (see the experimental procedures) are shown in Figure 6. Under near-present-day climate (1981–2010), the

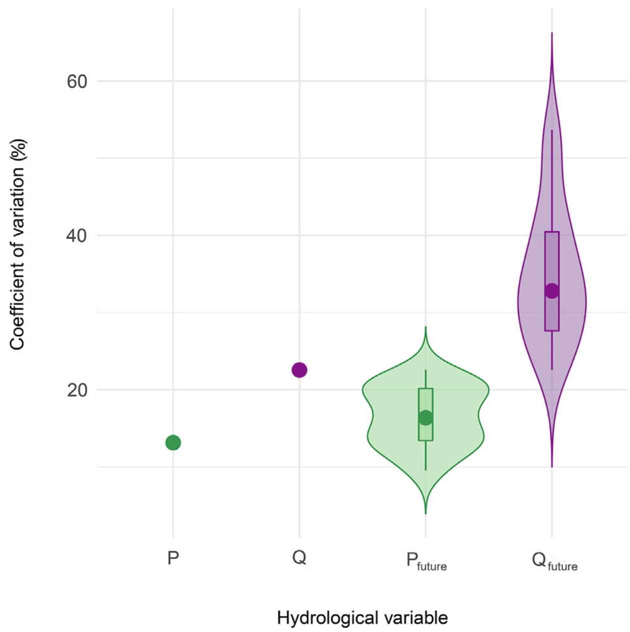

Figure 5. Amplification of rainfall variability

Annual coefficient of variation for rainfall (P) in the Rufiji basin and runoff into the JNHPP reservoir (Q) under present conditions and future projections (2020–2050).

risk of failure to meet environmental flows with the JNHPP assumed built, irrigation expanded, and no adaptive management is already substantial. With this particular indicator for ecosystem services in the Rufiji, the environmental flow failure rate could be as high as ~85% given that a period of sufficient peak releases from the JNHPP dam would have occurred only once since 1981 (Figure 3C). For irrigated agriculture in upstream rice producing areas in the Rufiji basin, sufficient water availability shows a failure rate >40%. Here, irrigation is vulnerable to climate variability because of a lack of storage. In the Lake Malawi-Shire river system, climate variations are buffered by Lake Malawi storage, but the planned irrigated demand (37–50 m^3/s; the residual of lake outflows and downstream environmental flows that have priority) is difficult to meet. In contrast, both basins show that firm-level hydropower requirements, assuming hydropower would get priority over other sectoral demands and with no ad hoc releases that could affect firm-level production, could be met reliably under present conditions and the risk of failure would be low.

Regarding future risk, our analysis demonstrates considerable uncertainty. For different reasons, risk tends to become lower for those indicators currently at high risk and higher for those currently at low risk. In both the Rufiji and Lake Malawi-Shire, for the majority of projections, the risk of hydropower failure increases. Design characteristics of the JNHPP appear to be fully optimized on limited observational river flow records of the late 1950s, 1960s, and early 1970s, a relatively wet period (Figure 3), and climate projections with drier conditions increase the risk of failure. However, because many model projections of drying also exhibit high variability in rainfall, wet years alternate with dry years and add to live storage, thereby keeping hydropower risk of failure in most projections at 15% or below. In the Lake Malawi-Shire basin, there is a more divergent effect whereby the consequences of a small selection of projections of a drier future lead to a higher risk of failure due to persistent constrained or no-outflow conditions. However, for a subset of wet climate projections (note that Munday and Washington[70] question the reliability of several of these; see also Note S2), the risk with regard to firm energy remains low in both the Lake Malawi-Shire and JNHPP hydropower systems.

Positive impacts occur for the environmental flow indicator in the Rufiji such that increased variability in rainfall and runoff increase the chance of high releases during the wet season, although considerable risk remains. Specific adaptive environmental flow management measures will be necessary to reduce the expected negative impacts, which will involve a trade-off between total energy production and environmental flows. Upstream irrigation water supply deficits in the Rufiji basin might reduce in future with high model agreement for slightly wetter future conditions in the mountainous areas to the west of the basin. In the irrigated areas planned downstream of Lake Malawi, large uncertainty about whether demand can be met remains, with projections suggesting lower water availability.

The full climate risk profile is important in advising policymakers and guiding further research; the most serious potential hydropower risk in the Rufiji basin (e.g., over 35%) occurs with just three outlier models, which, depending on stakeholder risk appetite, could be further scrutinized for their representation of regional climate drivers and teleconnections and discounted if found unsatisfactory to avoid making expensive modifications on the basis of unreliable information. Other risk profiles are characterized by either a concentration of models around a certain risk or an even spread from low to high risk, such as for the environmental flow indicators, where uncertainty is less likely to be easily constrained.

Table 1 summarizes how future risk compares with historic risk over various 30-year periods. It shows that future hydropower and environmental flow risks in the Rufiji basin are similar to those of recent decades. Future irrigation risk is lower than at any period during the 20th century. For Lake Malawi-Shire, the increase in risk for hydropower and environmental flows, though with large uncertainty, is beyond what has been experienced previously. Even during the early-20th century drought, the risk of hydropower and environmental-flow failure was lower as rainfall downstream of the lake mitigated no-outflow conditions. However, the warmer and drier conditions in several of the climate projections lead to further reduced inflow and reduced outflow and would require a permanent adjustment in managed outflows.

DISCUSSION

This analysis focuses on the sEA climate transition zone, where past and future climate signals are complex, presenting particular challenges for infrastructure development and performance. A majority of climate models project an increase in interannual rainfall variability, in line with advances in understanding plausible mechanisms for future hydrological changes. Our results also show that climate models have a mixed ability to simulate the dominant drivers of variability over sEA, underscoring the challenges in the use of model projections for local-regional-scale

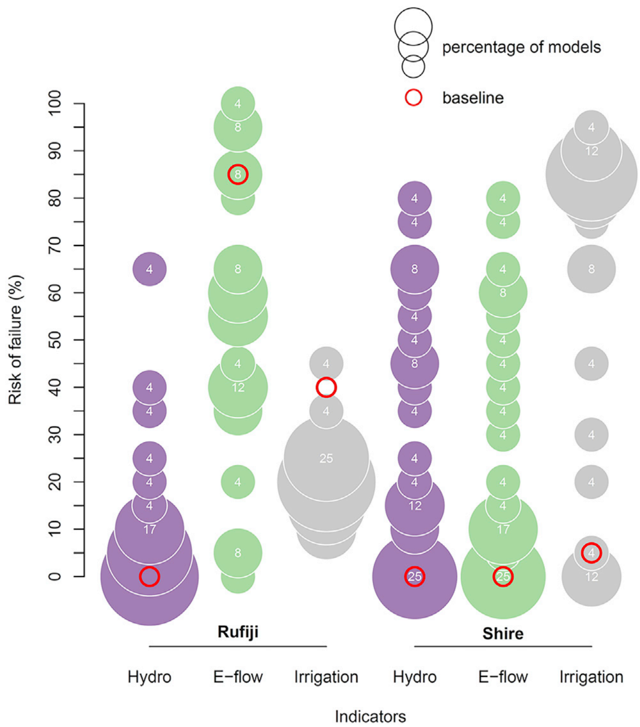

Figure 6. Climate change impacts on failure rates in three main Rufiji and Lake Malawi-Shire performance indicators in three sectors

Reliability of infrastructure is summarized under current baseline (1970–2010) and future (2020–2050) climate conditions. The size of circles and number (plotted if not overlapped by a circle) represent the percentage of climate model projections in this category of risk (total of 24 models). "Hydro" indicates the risk of not meeting firm energy requirements, "E-flow" indicates the risk of not meeting biannual flooding requirements in the Rufiji basin and average minimum flow in the Lake Malawi-Shire, and "irrigation" indicates the risk of not meeting monthly demand in both the Rufiji and Lake Malawi-Shire basins (see the experimental procedures).

future risk assessment.[22,71] Nevertheless, our climate is changing, and strategies need to be put in place now to manage existing and future climate risks as the world warms further.

Climate risk was traced in two river basins involving high-stakes, long-term major investment decisions across the water, energy, and food sectors. In both basins, which share similar climatology, infrastructure performance risk shows substantial sensitivity to multi-annual climate variability, which would challenge the viability of proposed infrastructure. Additional exposure to future risk differs between the two basins. The size of Lake Malawi buffers single-year extremes, so future risk mainly lies in projections of reduced rainfall. In the Rufiji, high interannual variability in rainfall—amplified through basin hydrology—sees the climate risk profiles for hydropower and environmental flow performance indicators stretched.

Our analysis highlights the need for climate risk assessments to incorporate a long view of variability. Infrastructure design should take into consideration the potential for changing patterns in variability and recognize possible bias if only short time series of observations are available or when using only projections of limited length. Here, we have tested infrastructure investment performance under historical variability and an ensemble of bias-corrected climate projections set within a broad understanding of the policy context. This combination of looking back and forward can better portray the infrastructure risk.[22]

Major policy and sectoral decisions require careful planning; in cases involving large investments, long lifetimes, and irreversibility, there is a strong argument to develop contingency plans for the worst-case extremes (in the past and future), for example, the development of drought management plans in both basins to handle multi-year dry conditions. These would involve sequences of decision points across years with increasingly stringent restrictions on releases after successive years of drought. Such plans require careful analysis to identify trigger points for decisions and cross-sectoral coordination, particularly between agencies responsible for water resources, energy, and agriculture.

We presented risk without considering adaptation. Through adaptive management and well-designed reservoir operating rules and improved irrigation practices, some of the risks could potentially be mitigated.[72] Greater use of groundwater, taking into consideration observed volatility in recharge events,[73] could reduce trade-offs between agriculture, energy, and the environment in dry years. The cost of building and maintaining dams often exceed their benefits[74] and alternatives or complementary options, such as solar, thermal, or wind power, which can be expanded incrementally, are rapidly becoming more cost-competitive[75] and should be considered alongside more open consultation on major infrastructure decisions. Moving beyond a region's own zone of variability, for example, when hydropower dams are integrated in regional power grids, reduces systemic risk.[3] This also offers opportunities; as the continent becomes increasingly connected through new infrastructure corridors, trade can contribute to increased income, food,[76,77] and energy security.[3]

Our study contributes new knowledge and insights across the multi-dimensional nature of climate risk. Outlining the policy context that underpins development goals highlights plans at scales and with lifetimes that will be exposed to climate conditions considerably different from those in which the plans have been drawn up. This context also allows us to identify important performance indicators that stakeholders see as being crucial for the sustainability and success of development actions. The results identify some outcomes that would be highly problematic; how exactly such information informs decisions about water-energy-food infrastructure will depend upon stakeholder risk appetite toward climate, alongside a host of non-climate considerations. Our approach demonstrates the benefits of adopting a long view of variability—of revealing areas of deep and aleatory uncertainty in model projections that can be made explicit to stakeholders in the risk analysis.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further questions about the analysis should be directed to and will be fulfilled by the lead contact, Christian Siderius (c.siderius@lse.ac.uk).

Materials availability

This study did not generate new unique materials.

Data and code availability

All used data and models are open source and can be downloaded from the references mentioned in the experimental procedures (WEAP [Water

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Table 1. Risk of failure in three performance indicators for different periods in the Rufiji and Lake Malawi-Shire basins

		Rufiji			Lake Malawi-Shire		
	Period	Hydropower	E-flow	Irrigation	Hydropower	E-flow	Irrigation
Historic risk	1900–2009	12%	78%	43%	2%	2%	28%
	1900–1929	38%	79%	51%	7%	7%	63%
	1910–1939	30%	80%	48%	7%	7%	64%
	1920–1949	10%	80%	44%	4%	4%	54%
	1930–1959	3%	87%	43%	0%	0%	32%
	1940–1969	3%	73%	41%	0%	0%	16%
	1950–1979	0%	67%	41%	0%	0%	6%
	1960–1989	0%	67%	39%	0%	0%	5%
	1970–1999	0%	87%	40%	0%	0%	6%
Present risk	1980–2009	3%	875	41%	0%	0%	4%
Future risk, mean (SD)[a]	2020–2050	4% (7%)	57% (28%)	22% (7%)	20% (26%)	15% (26%)	20% (35%)

Future risk is the multi-model average (of those plotted in Figure 6). Historic, present, and future risk is based on hypothetical simulations, which include planned investments in irrigation and hydropower that have yet to be implemented (see experimental procedures).
[a]Mean risk and SD of 29 bias-corrected climate projections.

Evaluation and Planning] model: http://www.weap21.org; LPJmL [Lund-Potsdam-Jena Managed Land] model: http://www.pik-potsdam.de/research/projects/activities/biosphere-water-modelling/lpjml/versions, together with model description). Parameter settings and calibration of the impact models are described in more detail in earlier publications.[40,78]

Time-series analysis and teleconnections

To visualize drivers of variability across the whole of Africa, we used Global Precipitation Climatology Centre (GPCC) precipitation data[79] to calculate the coefficient of variation in precipitation (Figure 2A) and the correlation with El Niño3.4 SST anomalies (Figure 2B) by using a Student's t test (significance at $p < 0.05$). Data are available in a 0.5° grid for the period 1900 to the present.

For the historic analysis of regional variability, precipitation was taken from CENTRENDS, another recent dataset with a better station coverage than the GPCC, but for East Africa only, starting in 1900.[80] For the Shire catchment, only the (important) Lake Malawi subcatchments are included because CENTRENDS does not extend further south. Trend (Student's t test), decadal variability, and interannual variability were determined. We detected decadal variability by applying a Lanczos bandpass filter[81] 8-year frequency cutoff to the annual anomalies of precipitation time series, where the interannual variability was the resultant of the decadal pattern.

Performance of different climate models in representing ENSO and IOD was based on the linear correlation between precipitation anomalies and SST anomalies of both teleconnection indices. The IOD index was calculated as the difference between the western Indian Ocean (IO) SST anomalies and eastern IO SST anomalies for the period 1976–2005. Positive and negative correlations indicate enhanced and suppressed convection, respectively (Figure S2). During positive IOD events, East Africa in particular experiences increased rainfall,[26] a correlation represented in over half of the CMIP5 models (Figure S3). We derived the ENSO teleconnection in CMIP5 models by correlating model rainfall with models' Niño3.4 SST anomalies (Figure S5).

In Figure 3, the classification of modest to strong El Niño or La Niña years was based on Wolter and Timlin,[82] complemented with the Oceanic Niño Index classification by the US National Oceanic Atmospheric Administration for the period after 2005. Strong positive and negative IOD years were based on the Dipole Mode Index (DMI), adjusted for warming trend, for the period 1900–1957. Years were classified with a strong positive or negative IOD if the DMI was exceeded by more than one SD for three consecutive months. From 1958 onward, better observational data on, for example, wind patterns have enabled the construction of more complex indices, and we used the classification by Hameed.[26]

Impact models

Model projections of precipitation, downwelling long-wave and short-wave radiation, and temperature were used to drive the hydrological model of each system to explore the range of possible impacts. Impacts were expressed as a risk of failure in three key performance indicators, calculated as the percentage of years (in a 30-year period) that each risk threshold was exceeded and visualized as the percentage of climate-model projections in each risk category. The performance indicators were defined through consultation with stakeholders.[40,72,83] They represent, in a simplified manner, key aspects of hydropower (electricity generation threshold), irrigation (defined as the percentage of months in which water demand cannot be fully met), and ecosystem services (frequency of biennial flooding). Each indicator reflects different features of the hydrological system and can respond differently to the same projection.

Water-balance input and crop production for the major food crops in the Rufiji basin were generated with a global coupled hydrology-vegetation model, LPJmL, specially adapted to the Rufiji basin.[78] The model runs at a daily time step, and the Rufiji application is schematized at 5 arcminutes (~9-km resolution at the equator). While the model proved capable of simulating runoff in upstream tributaries, large parts of the catchment remain ungauged including the Luwegu tributary from which an estimated 15%–20% of basin runoff originates, a percentage that is sensitive to the soil parameterization. Another source of uncertainty is the hydrological processes in downstream wetlands. Operational reservoir management was based on a simple order of priorities, maintaining firm energy releases until live storage is depleted, such that peak releases for environmental flows were a result of excess inflow only after the reservoir was fully filled.

For the Shire basin, the WEAP model was used to run scenarios based on stakeholder-identified infrastructural plans, performance needs, and adaptation options. The WEAP model uses a rainfall-runoff method to simulate Lake Malawi levels at a monthly time step for the period 1960–2009.[40] Lake Malawi is modeled as a "bucket" type reservoir to simulate key water balance components (inflows, outflows, and net evaporation) at a monthly time step. Although the model has shown good ability to reproduce 1960–2009 Lake Malawi levels, model calibration was challenging because of sparse streamflow observations and data gaps in lake rainfall and lake evaporation.[40] The operation of the barrage at the outlet of Lake Malawi is of critical importance for managing water resources, and although the model was capable of simulating lake levels under a number of historic management strategies, extrapolating those into future conditions represents only likely management scenarios, so our model results need to be regarded as indicative of risk without adaptation.

Meteorological input data

For the analysis of historic variability, the impact models were forced with CENTRENDS precipitation data; its monthly data were downscaled to daily time steps (the LPJmL model only; WEAP uses monthly input data) with the

Table 2. Decision-relevant water resource risk indicators

Sector	Basin	Indicator	Description
Energy	Rufiji	RP1: risk of NTF at least once per year	NTF, whereby JNHPP reservoir level falls to a level that cannot guarantee the required monthly mean turbine flow of 687 m^3/s to generate firm energy. This is expressed as a simple percentage, based on the number of years in a 30-year time period with one or more months with NTF.
	Shire	SP1: months of inadequate Shire River flow	Three run-of-the-river hydropower stations in Shire River require approximately the same river discharge of ~265 m^3/s for peak hydropower production, which falls linearly with reducing discharge. Also, if Lake Malawi levels drop below the outflow threshold, reduced Shire river discharge outside of the rainy season would affect hydropower production. These are expressed as a simple percentage based on the number of months in a 30-year time period with flow less than ~265 m^3/s.
Water (environmental flows)	Rufiji	RP2: risk of not achieving at least 2,500 m^3/s flow for 1 month every second year	Environmental flows downstream of the dam depend on sufficient peak discharge to refill the delta lakes and surrounding wetlands and to flood farmland to replenish nutrients and soil moisture, flush the delta, and buffer salinization, creating vital conditions for fisheries. Full bank flow is reached at a threshold of 2,500 m^3/s. Historically, this is exceeded once every 2 years, and 3,000 m^3/s is exceeded every 4 years. On the basis of a (limited) analysis of daily flows in the early 1970s, the duration of flows above this threshold was determined to be 32 days on average, so 1 full month.
	Shire	SP2: risk that no outflows from Lake Malawi will change seasonal flow dynamics in the Elephant Marsh	The Elephant Marsh wetland is located downstream of hydropower stations and is a designated Ramsar wetland of global biodiversity importance. However, no EFR assessment for the wetland is available. On the basis of Shire River discharge time series at Chiromo gauging station prior to the construction of the Kamuzu Barrage (1965), ~230 m^3/s is the lowest monthly discharge in the 1960–1964 period. We therefore use 230 m^3/s as a metric for EFR at the Elephant Marsh and calculate a simple percentage based on the number of months in a 30-year time period with flow less than ~230 m^3/s.
Food	Rufiji	RP3: number of months that irrigation demand for current and proposed irrigation projects is not met	Agriculture relies heavily on irrigation in several parts of the basin. Here, we plot the reliability of irrigation supply to the irrigated areas upstream of the Usangu wetlands in the Great Ruaha subcatchment.
	Shire	SP3: number of months that irrigation demand for current and proposed irrigation projects is not met	The Shire Valley Transformation Project has been formulated with defined monthly irrigation water requirements ranging from 37 to 50 m^3/s to be diverted from the Shire River. This monthly requirement is used as a metric for irrigation.

EFR, environmental flow requirement; NTF, no hydropower turbine flow.

precipitation distribution from Watch Forcing Data (WFD; available from 1901 to 2001[84]) and the Watch Forcing Data Era-Interim dataset (WFDEI; available for the period 1958–2012)[85] and adjusted for mean bias against observations. For Lake Malawi-Shire, a further correction for bias in multi-annual means was applied over the observational period (1960–2008). Temperature, wind speed, and short-wave radiation were also taken from WFD. The reported underestimation of incoming short-wave radiation in WFD due to the overcorrection of annual variations in aerosol loading[84] was corrected by the percentage difference between WFD and WFDEI during the overlapping period. Although WFD 1901–1957 should not be considered historical in terms of meteorological events (unlike WFD 1958–2001 and WFDEI), monthly-interannual variations in air temperature, precipitation, and short-wave radiation should be historically correct because of the monthly observation adjustments.[84]

To compare present with future climate through model simulations, we further refined rainfall for the Rufiji application by using CHIRPS data, which are based on an assimilation technique and observations similar to those of CENTRENDS but are spatially and temporally improved with cold-cloud-duration remote-sensing data.[86] They are available at a daily time step and at higher resolution (0.083 arc-minutes) for the period of 1981 to the present. For the Shire-Malawi application, we used historic observations per subcatchment, made available through the Second National Water Development Project (NWDP II), a study carried out by the Ministry of Agriculture, Irrigation, and Water Development of the government of Malawi in 2011. For future climate, we used the AMMA2050, a new dataset of daily data over Africa from 29 bias-corrected CMIP5 global climate models (GCMs).[30] Using a cumulative distribution function transform (CDF-t) method, AMMA2050 removes the biases with respect to the reference period (in the case of AMMA 2050, WFDEI).[30] For Figure 6, we weighed the percentage of models in each risk category by model performance and evaluated historic performance of the original GCMs against a range of indicators regarding mean state, trend, variability, and teleconnections, as described in Kolusu et al.[61]

Simulated river-basin development options

Rufiji

Exact details on planned size and operations of the Nyerere hydropower project (JNHPP) close to the Rufiji Delta are not publicly available. We derived area (1,200 km^2 up to 1,350 km^2) and live storage (22 BCM) estimates from earlier planning reports[87] and national and basin studies that often quote the planning documents of Brazilian construction firm Odebrecht from 2013 or the Power System Master Plans of the Tanzanian Ministry of Energy and Minerals.[43,45,88–90] The area-level-storage relationship was reconstructed by an overlay of the reservoir outline[45] on Shuttle Radar Topography Mission elevation data;[91] the resulting reservoir levels fluctuated between 158 and 187 masl. Nine storage turbines are expected to deliver ~2,060 MW capacity, which—if run constantly—would deliver over 18,000 GWh per year. Variable, area-based evaporation losses were derived from the LPJmL model. Because detailed information on planned operating rules was lacking, we based our risk analysis on the flow needed to maintain reported firm energy production (~6,000 GWh per year[87]), which would be achieved by running the turbines at a third of the total turbine capacity and assuming no reduction in turbine efficiency over the possible range of water-level fluctuations. We based our analysis on monthly values, thereby ignoring hourly to daily fluctuations in supply to meet peak demands.

Irrigated land use in the Rufiji basin is planned to increase 4-fold between 2010 and 2035 (an area of almost 400,000 ha[90]). We allocated this expansion per subcatchment by prioritizing cells with existing irrigated area and then cells with existing agriculture within the SAGCOT districts while ruling out expansion in game reserves or national parks and assuming that only 90% of the free area per cell could be changed. In managed irrigation schemes, the drainage system captures excess water and reroutes it back to the main river with the possibility for reuse downstream. In the Rufiji basin for current practice, the opposite occurs. Drainage return flows from large-scale irrigation schemes are often reused by smallholder farmers who surround these schemes, whereas in Indigenous smallholder schemes, water tends to be recycled until there is hardly any left without infrastructure to return drainage water back to the river.[54] Even in improved indigenous irrigation schemes, efficiency gains were found to be offset by increased overall withdrawals, facilitated by more effective water intake structures. Rather than increase downstream water availability, it further restricted it,[54] a paradox of irrigation efficiency observed in many systems in the world.[92] As our baseline, we therefore assumed a situation in which soil losses, but no canal losses, are returned to the river (return flows are 35% of irrigation withdrawal). In the future, land use and water abstractions of smallholders might be more controlled or incorporated into the designs, thereby limiting unplanned overextraction and meeting expected return flow rates (high return rate is 54%).

Shire

Irrigation and hydropower expansion plans in Malawi are still being developed. With stakeholders, we identified two key projects:[40] Kholombidzo Hydro Electric Power Plant (KHEPP) (run-of-the-river scheme) and Shire Valley Transformation Project (SVTP, with 43,370 ha canal-based irrigation). The SVTP is a World Bank-funded project[93] for which some details are available in the environmental impact assessment report[94] depending on which water requirements for the SVTP were identified. Hydropower generation capacity of KHEPP in various reports has ranged from 160 to 370 MW. Malawi stakeholders suggested that currently KHEPP is for 300 MW located between the Kamuzu barrage and the Nkula Hydropower Power Plant (HPP). Since detailed information on KHEPP plans is not available, we assume that the Shire River discharge required for peak hydropower generation is the same as that for Nkula HPP, i.e., 265 m^3/s.

Performance indicators

We used multiple stakeholder consultations to identify and prioritize key river-basin performance metrics. They involved government staff, hydrological and environmental researchers from universities, and several locally active non-governmental organizations working on sustainability and development issues.[40,72] Consultations in the Rufiji took the form of small workshops (8–20 participants) held in March 2017, March and November 2018, and July 2019, complemented by informal discussions with many individuals (from the organizations listed above) between January 2016 and July 2019. In Malawi, a similar process was conducted over the course of 2007–2019, at the end of which the WEAP model application was handed over to the Shire Basin Authority. Initial long lists of metrics were narrowed down for this analysis to three indicators representing key features of the water-energy-food nexus, for which risk of failure was calculated: one for hydropower, one for environmental flows, and one for agriculture (Table 2). Risk of failure is defined as the percentage of time and indicators that could not be met.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2021.02.009.

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AUTHOR CONTRIBUTIONS

C.S., M.C.T., and D.C. conceived the study. C.S. performed the model experiments for the Rufiji, designed the risk analysis, and drafted the article. A.B. performed the model experiments for the Shire. S.R.K. and M.C.T. analyzed the climate observations and model data, and C.C.J.R., R.J., N.C.G.H., M.C.T., and R.W. analyzed regional climate drivers. D.C., R.T.G., and J.J.H. contributed to the discussion on climate risks. D.C., A.J.D., D.D.M., K.V., J.P., and J.J.K. wrote the policy context and contributed to the performance indicators. All authors contributed to discussions and edited the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

The author list of this paper includes contributors from the location where the research was conducted and who participated in the data collection, design, analysis, and/or interpretation of the work.

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