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Working Paper: Climate change impacts on Southern Africa's low-carbon electricity system

Climate change is expected to significantly impact the electricity system of Southern Africa. In this study, the authors examine the potential impacts of climate change on electricity demand, hydropower energy availability, and thermal and solar power generation in the region's electricity system from 2020-2045. System-level impacts are assessed by comparing cost-optimal energy generation mixes, costs, and carbon emissions of systems planned and operated assuming historical weather conditions with those under four future climate scenarios from the Coupled Model Intercomparison Project Phase 6 (CMIP 6).

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Climate change impacts on Southern Africa's low-carbon electricity system (Working paper)

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Abstract

Climate change is expected to significantly impact the electricity system of Southern Africa, a region serving 40% of the African continent's population and expecting to double its electricity demand over the next two decades. In this study, we examine the potential impacts of climate change on electricity demand, hydropower energy availability, and thermal and solar power generation in the region's electricity system from 2020-2045. To assess these impacts, we compare the energy generation, costs, and carbon emissions in a base scenario that assumes historical weather conditions with four future climate scenarios from the Coupled Model Intercomparison Project Phase 6 (CMIP 6). Under climate change conditions, rising temperatures drive increases in electricity demand. If the effects of climate change are not incorporated in electricity planning, system costs increase by up to 3% and carbon emissions by up to 13% by 2045. More importantly, up to 4% of demand is curtailed because of a lack of availability of generation capacity. If electricity infrastructure is planned under a low-carbon cap of 100 $MtCO_2$ by 2045, the impacts on system costs and demand curtailment are less because climate change impacts on renewable energy generation are expected to be much lower than on thermal power generation. If electricity infrastructure is planned by incorporating the potential effects of climate change (CC), investments in new wind and solar capacities increase compared to the base scenario in most CC-planned scenarios. On the contrary, natural gas generation capacity decreases in most CC-planned scenarios because of temperature rise-driven decrease in availability of generation capacity. Because of these impacts on thermal generation capacity, even new hydropower capacity increases in many CC-planned scenarios in spite of lower annual average energy availability for hydropower plants. However, in CC-scenarios with increased drying, decreases in hydropower generation are compensated by wind, solar, and thermal power generation. Incorporating climate change impacts in electricity system planning increases costs by up to 4%, similar to scenarios that do not incorporate climate change impacts in planning, but also avoids demand curtailment. The modest system cost increases show that policy and decision-makers should incorporate climate change impacts in electricity system planning to maintain system reliability.

1. Introduction

Climate change is expected to severely impact electricity systems (Cronin, Anandarajah, and Dessens 2018; Chandramowli and Felder 2014). On the supply side, rising temperatures and cooling water availability will affect the efficiency and availability of thermal power plants (McFarland et al. 2015; Craig et al. 2018; van Vliet et al. 2016). Changing precipitation and temperature patterns will also affect availability of hydropower energy (van Vliet et al. 2016). Climate change is also expected to affect renewable energy generation—solar generation through decreased efficiencies with high temperatures and changing cloud patterns, and wind generation driven by changing wind patterns (Craig et al. 2018; Kozarcanin, Liu, and Andresen 2019). However, significant uncertainties remain in the direction of the impacts on renewable energy (Craig et al. 2018). On the demand side, rising temperatures will also increase electricity demand because of both, greater adoption and increased usage of cooling appliances (McFarland et al. 2015).

Impacts of climate change on electricity supply and demand will be acute in developing regions like the Southern African region, which are expected to experience large increases in temperature and changing precipitation patterns and at the same time, significant economic growth and rising incomes (Falchetta and Mistry 2021). The Southern African Power Pool (SAPP), consisting of twelve countries—Angola, Botswana, Democratic Republic of the Congo, Eswatini, Lesotho, Mozambique, Malawi, Namibia, South Africa, Tanzania, Zambia, and Zimbabwe— accounts for 40% of Africa's electricity demand and is expected to double its demand by 2040. Eight of the twelve SAPP countries are dependent on hydropower for more than half of their electricity generation, while several additional hydropower projects are under construction or proposed (Zarfl et al. 2015). South Africa, responsible for three-quarters of the region's electricity demand and supply, has the African continent's largest coal power plant capacity, which is vulnerable to climate change (Conway et al. 2015).

Most research focused on the Southern African region and elsewhere has mainly focused on climate change impacts on only one or a few aspects of the electricity system and have not comprehensively incorporated these impacts into electricity system planning and operations (Craig et al. 2018). Previous studies have highlighted several risks that hydropower projects in the Southern African region may face due to future climate variability (Beilfuss 2012; Falchetta et al. 2019). Some studies have quantified potential reductions in hydropower outputs for large regions including the Southern African region using data from global climate models (van Vliet et al. 2016), but the results are at a coarse resolution that may not be suitable for energy systems planning. Other studies have examined the spatial interdependencies of the impacts of climate variability on hydropower dams (Conway et al. 2017), but not simulated the expected generation outputs of these projects and how those outputs should be incorporated in and impact energy planning. No studies have comprehensively incorporated climate change impacts into electricity planning in Southern Africa.

Table 1: Business-as-usual (BAU) scenario with historical climate and four future climate change scenarios. Scenario names are shortened to indicate shared socioeconomic pathways with drying or wetting effects in major basins of Southern Africa. Main regions that have the most hydropower capacities include Kwanza South, Congo East, Congo Central, Zambezi Northwest, and Zambezi Northeast. Weather in the last modeling investment period (2045) is assumed to be the same as average weather or weather in the lowest and highest precipitation years across 20 historical years (1996-2016) or future climate years (2036-2055). Highest and lowest precipitation years for each climate scenario vary due to interannual variation in precipitation. Anomalies in annual hydropower availability from historical mean for climate change scenarios show highest and lowest precipitation years in Figure 14.

Climate scenario	**Lowest precipitation year**	**Average**	**Highest precipitation year**	**Climate variability**
BAU - Historical	2005	Average temperature and precipitation across 20 years	2008	Weather same as historical
RCP 4.5 CNRM CM6.1 (RCP4.5A)	2042		2045	More drying across main regions
RCP 4.5 INM CM5.0 (RCP4.5B)	2051		2045	Less drying across main regions
RCP 8.5 CNRM ESM2.1 (RCP8.5A)	2038		2046	More drying across main regions
RCP 8.5 INM CM5.0 (RCP8.5B)	2055		2052	Less drying across main regions

In this study, we compare a base electricity system scenario under historical weather conditions with four future climate scenarios, selected from the Coupled Model Intercomparison Project Phase 6 (CMIP 6). Two of the future climate scenarios correspond to representative concentration pathway (RCP) 4.5 (“RCP 4.5 INM CM5.0” and “RCP 4.5 CNRM CM6.1”) and two represent RCP 8.5 (“RCP 8.5 INM CM5.0” and “RCP 8.5 CNRM ESM2.1”) (Table 1). These scenarios represent general drying and wetting in the main subregions of Southern Africa but in each of these scenarios, precipitation varies across the region (Table 1). For each climate scenario, we select average, dry, and wet precipitation conditions over a 20-year period (1997-2016 for historical and 2036-2055 for climate change conditions). These 15 scenarios ((1 historical + 4 RCPs) x 3 precipitation) represent distinct combinations of plausible future changes in temperatures and precipitation patterns in Southern Africa. We use the changes in temperatures and precipitation patterns to drive changes in electricity demand, hydropower energy availability, thermal power plant availability, and solar PV generation efficiencies from 2020 to 2045. We then evaluate the effects of these demand and supply changes using a detailed electricity system planning and operations model in two steps. First, we develop cost-optimal investments in generation, storage, and transmission assets assuming historical weather data. Second, we fix these investments but apply the demand and supply changes to the model and examine the cost, emissions, and demand curtailment effects of these changes until 2045. Third, to understand the economic implications of incorporating effects of climate change within electricity planning, we develop cost-optimal investments in electricity infrastructure for each of the climate scenarios. We examine these electricity pathways for Southern Africa with and without imposing a low carbon emission target.

2. Results and Discussion

2.1. Climate change effects on demand and generation

Across Southern Africa, annual electricity demand is expected to increase by 2-5% (2.5±0.1%—RCP4.5A, 4.4±0.1%—RCP4.5B, 5.9±0.1%—RCP8.5A, and 2.1±0.1%—RCP8.5B) because of higher temperatures in 2045 compared to demand under historical weather conditions (Figure 1). Across all climate scenarios, electricity demand increases mainly in the summer months (Figure 5, 6, and 7). Annual availability of thermal power plants decreases by about 1% (0.6.±0.03%—RCP4.5A, 0.35±0.02%—RCP4.5B, 0.98±0.03%—RCP8.5A, and 0.46±0.02%—RCP8.5B) (Figure 1). Availability of natural gas power plants decreases more compared to coal power plants (Figures 15).

Our results for all climate scenarios indicate that climate change is likely to reduce future streamflow (Figure 12), and thus hydropower production (Figure 13), particularly during the wet season, in almost all river basins. The annual hydropower production for Southern Africa is likely to be less than historical in almost each of the future years between 2036-2055 across all climate scenarios (Figure 14). This suggests a strong likelihood of the drying impact of climate change on Southern African hydropower systems, which was also reported in several previous studies (van Vliet et al. 2016, Conway et al. 2017). Average annual hydropower generation reduces across all climate scenarios by 2-8% (7.32±0.24%—RCP4.5A, 4.17±0.28%—RCP4.5B, 6.18±0.30%—RCP8.5A, and 2.34±0.18%—RCP8.5B) (Figure 1).

Similar to electricity demand, availability of thermal power plants and hydropower energy generation is affected more in summer months compared to winter months (Figures 11, 12, 14, and 16). Lastly, solar PV capacity efficiencies and resulting loss of generation is relatively small (less than 1%) compared to thermal generators (0.52±0.02%—RCP4.5A, 0.65±0.02%—RCP4.5B, 0.91±0.03%—RCP8.5A, and 0.46±0.02%—RCP8.5B) (Figure 1).

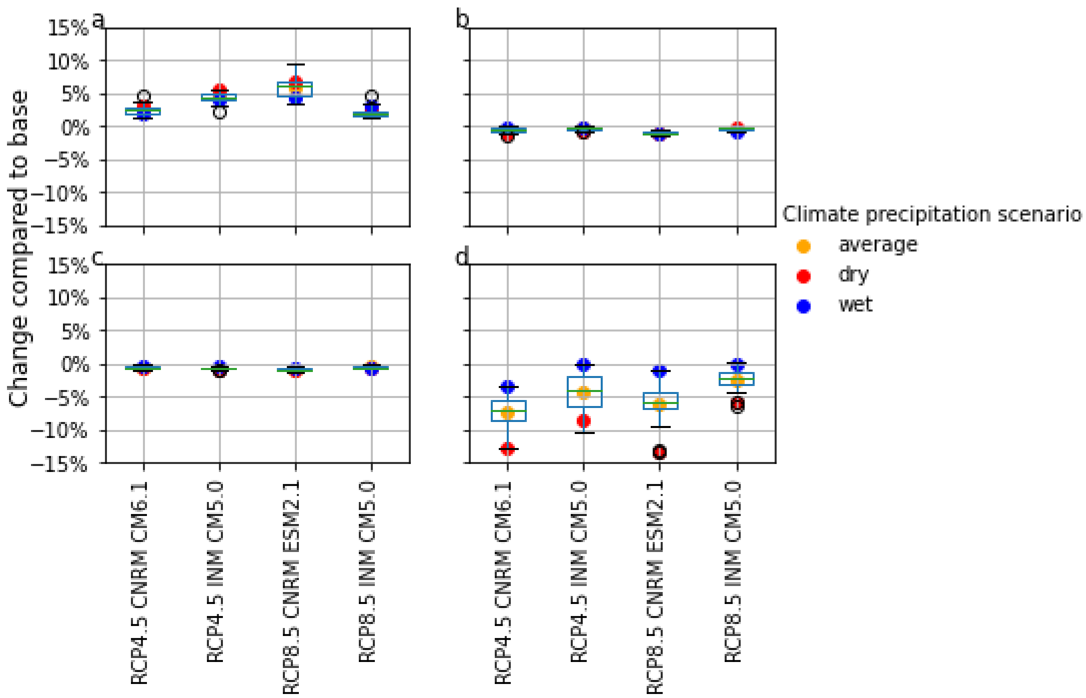

Figure 1. Changes in annual average A) electricity demand, B) available capacity of thermal power plants, C) available capacity of solar PV, and D) hydropower generation in the climate change scenarios for 2036-2055 compared to the base scenario with historical weather conditions.

2.2. Impacts on system costs, emissions, and curtailment

If the effects of climate change are not incorporated in electricity planning, i.e., infrastructure investments are made based on historical weather conditions, then costs of operations mostly increase across all climate scenarios. Without a carbon target, annual average system costs in 2045 vary from -0.7 to 1.5 USD per MWh or -1.2 to 2.6% under climate change conditions compared to the BAU scenario. An annual carbon target of 100 $MtCO_2$ by 2045 results in similar changes in annual average system costs— -0.7 to 1.3 USD per MWh or -1.2 to 2.1% (Figure 2). However, these costs do not include penalties for electricity demand curtailment (Figure 3). Under climate change scenarios, new and existing generation capacity is unable to meet electricity demand increases in some hours of the year. Demand curtailment ranges from 0-4.0% and 0-2.8% without and with the carbon target in 2045, respectively.

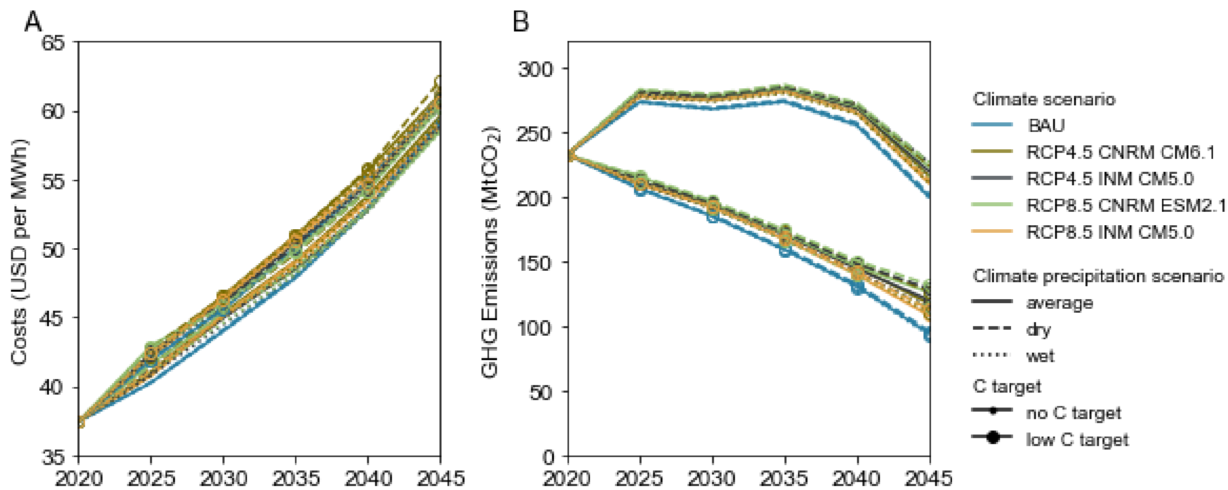

Figure 2. A) Annual system costs and B) greenhouse gas emissions for historical weather (business-as-usual or BAU) and climate change scenarios across 2020-2045 with and without a carbon target. Generation, storage, and transmission investments are based only on historical weather without considering effects of climate change.

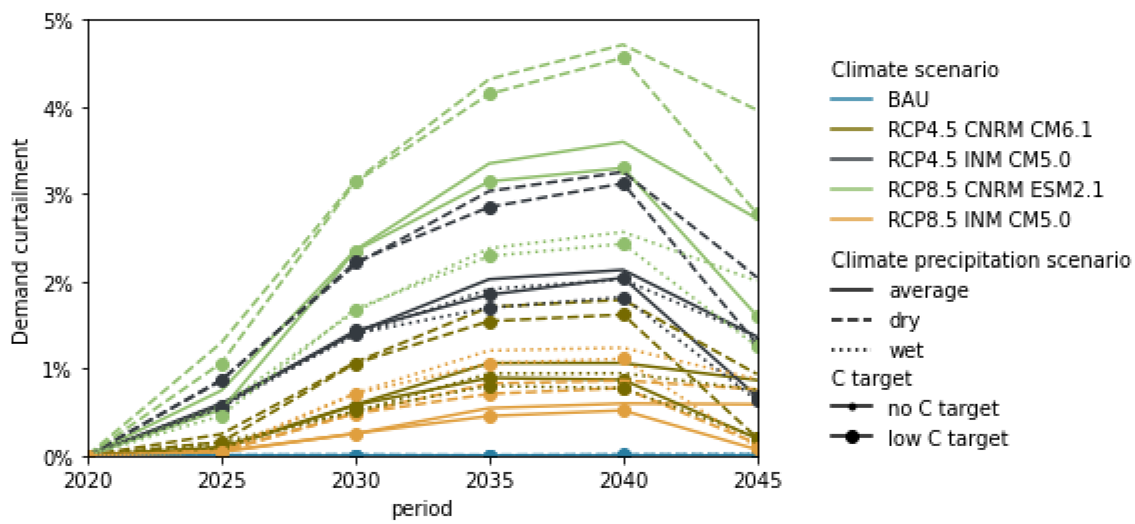

Figure 3. Unserved energy for historical weather (business-as-usual or BAU) and climate change scenarios across 2020-2045 with and without a carbon target. Generation, storage, and transmission investments made using only historical weather and without considering effects of climate change.

Annual average GHG emissions mostly increase in scenarios both without and with the low-carbon target compared to their corresponding scenarios that assume historical weather conditions. These differences from BAU range from -1 to 27 $MtCO_2$ per year (0 to 13%) and -1 to 38 $MtCO_2$ per year (-1 to 40%) without and with the carbon target in 2045, respectively (Figure 2).

2.3. Incorporating climate change effects in system planning

When we assume weather conditions under climate change in electricity system planning (CC-planned scenarios), no demand is curtailed. Changes in annual system costs are mostly positive (increases)--- -0.2 to 2.3 USD per MWh (-0.3 - 3.8%) compared to the BAU scenario (Figure 4). Annual GHG emissions in 2045 change from -3 to 37 MtCO2 per year (-1 - 18%).

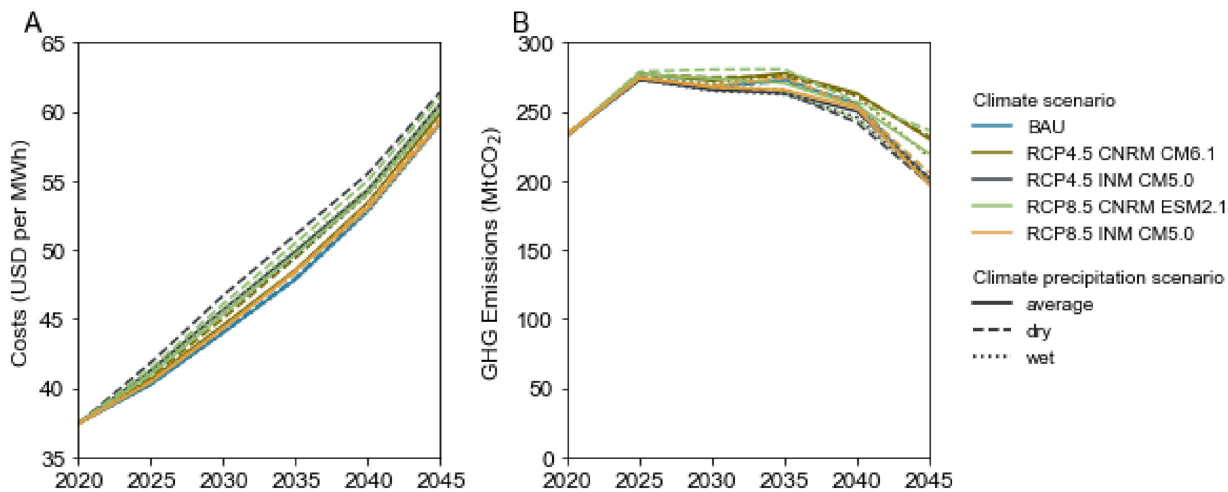

Figure 4. A) Annual system costs and B) greenhouse gas emissions for historical weather (business-as-usual or BAU) and climate change scenarios across 2020-2045 with and without a carbon target. Cost-optimal generation, storage, and transmission investments are based on both historical weather and climate change conditions.

Investments in new wind and solar capacities increase compared to BAU in most CC-planned scenarios, except RCP4.5A scenarios. On the contrary, investments in natural gas generation capacity decrease across all CC-planned scenarios, mainly because the temperature rise-driven derating (or availability) of existing and new installed capacity makes these investments less attractive compared to BAU (Figure 5). Derating of installed capacity means less capacity is available to generate electricity.

No new coal capacity is installed in the BAU scenario. However, in a few scenarios under drying conditions, some additional coal capacity is installed compared to BAU because of greater derating for gas power plants compared to coal. In spite of lower average energy availability for hydropower plants across most climate change scenarios, hydropower capacity increases in CC-planned scenarios, largely due to a decrease in the available capacity of natural gas power plants under climate change conditions (Figure 5).

In all CC-planned scenarios, electricity generation increases to meet additional electricity demand driven by rising temperatures under climate change conditions (Figure 6). Gas and coal generation increases in climate scenarios that experience increased drying whereas hydropower generation increases in scenarios with increased wetting (Figure 6). Wind and solar generation increases in the RCP4.5B and RCP8.5A scenarios.

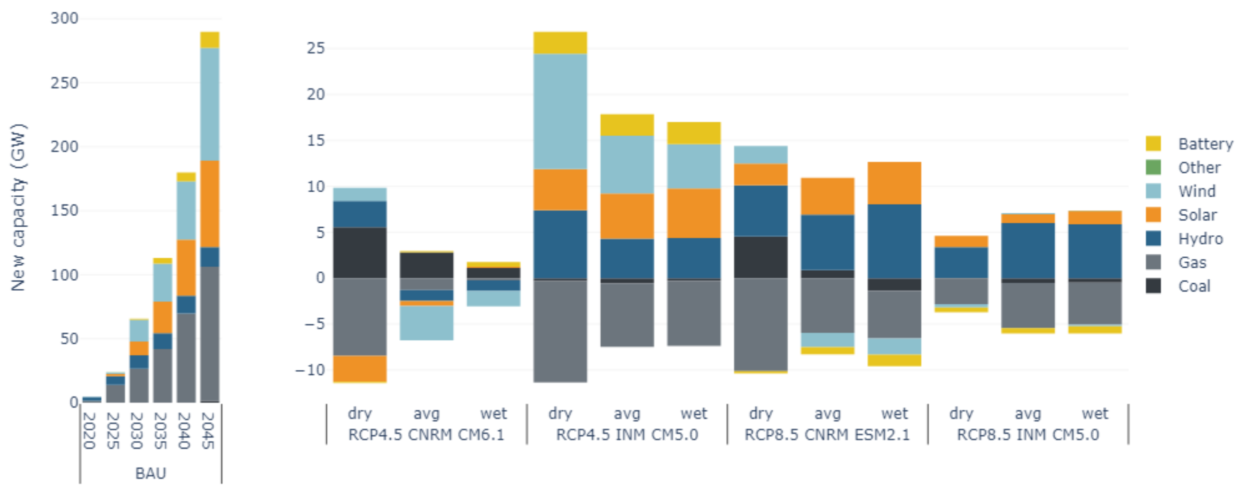

Figure 5. A) New generation capacity investments by technology under business-as-usual (BAU) assuming historical weather conditions across 2020-2045. B) Differences in new generation capacity investments in climate change scenarios assuming climate change conditions compared to the BAU scenario. No carbon target imposed.

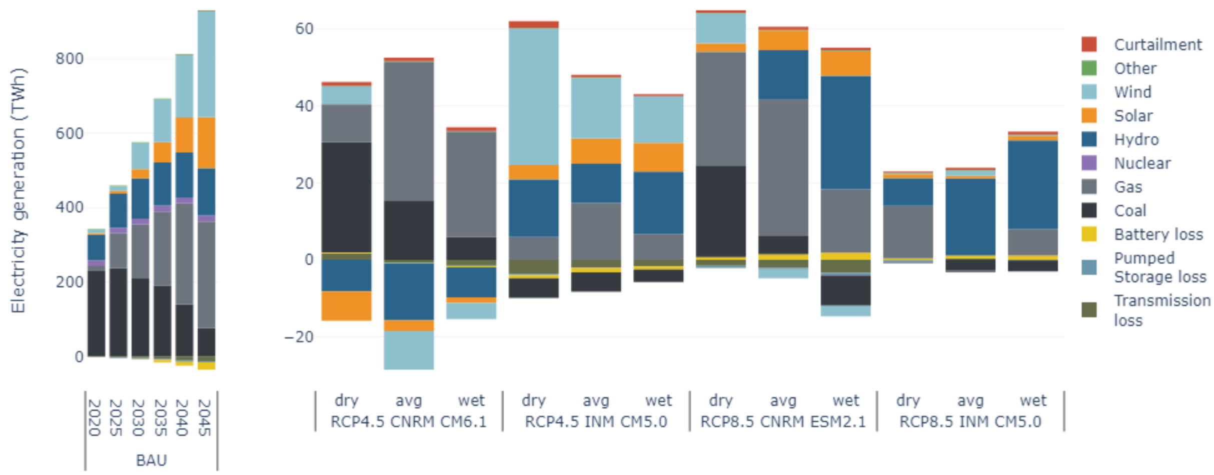

Figure 6. A) Electricity generation by technology under business-as-usual (BAU) assuming historical average weather conditions across 2020-2045 in Southern Africa. B) Differences in energy generation in climate change scenarios compared to BAU. No carbon target imposed.

3. Methods

3.1. Climate change modeling scenarios

We selected four climate scenarios from an ensemble of Global and Regional Climate Models of the Coupled Model Intercomparison Project Phase 6 (CMIP6). Two of the selected climate change scenarios—“RCP 4.5 INM CM5.0” and “RCP 4.5 CNRM CM6.1”—represent the Shared Socioeconomic Pathway (SSP) scenario SSP2-4.5, a “middle of the road” pathway corresponding to a Representative Concentration Pathway (RCP) 4.5 with a nominal radiative forcing level of 4.5 W/m2 by 2100. The other two climate scenarios—“RCP 8.5 INM CM5.0” and “RCP 8.5 CNRM ESM2.1” represent the SSP5-8.5, a high-fossil fuel development pathway corresponding to RCP 8.5, resulting in a nominal radiative forcing of 8.5 W/m2.

We selected individual model simulations to preserve the spatial coherence of the climate change signal. To select these scenarios, we first calculated the differences (deltas) between future (2021-2050) and historical (1990-2020) mean annual temperatures as well as the ratios of future and historical annual rainfall. We then selected the model scenarios based on the clustering of the temperature differences and precipitation ratios to capture the range of climate change signals.

3.2. Electricity demand projections

Hourly time series of electricity demand are based on actual 2018 data linearly extrapolated across investment periods assuming growth rates from the SAPP Plan (SAPP 2017). Using the 2018 data, we applied a linear regression to quantify the relationship between temperature and demand.

$$log\left(l_{c,t}\right) = \beta_1 T_{max,c,t} + \beta_2 T_{max,c,t} + \beta_3 T^2_{max,c,t} + \beta_4 T^2_{min,c,t} + \beta_5 \bullet w_t + \sum_{m_t=1}^{11} \beta_m \bullet m_t + \beta_0$$

Where l_t is the daily demand in country *c* at time *t*; $T_{max,c,t}$ is the population-weighted average of the daily maximum temperature (°C) in country *c* at time *t*; $T_{min,c,t}$ is the population-weighted average of the daily minimum temperature (°C) in country *c* at time *t*; w_t is a dummy variable for the weekdays at time *t*; m_t is the dummy variable for months at time *t*; β_1, β_2, β_3, β_4, β_5 and β_m are the regression coefficients; β_0 is the regression intercept.

The average climate impacts on daily demand is therefore calculated as

$$G_{cc,c,m,y} = \beta_1 \overline{T_{max,c,m,y}} + \beta_2 \overline{T_{min,c,m,y}} + \beta_3 \overline{T_{max,c,m,y}}^2 + \beta_4 \overline{T_{min,c,m,y}}^2$$

$$G_{ncc,c,m,y} = \beta_1 \overline{T_{max,c,m,2020}} + \beta_2 \overline{T_{min,c,m,2020}} + \beta_3 \overline{T_{max,c,m,2020}}^2 + \beta_4 \overline{T_{min,c,m,2020}}^2$$

$$l^{cc}_{c,h,m,y} = l_{c,h,m,y} \frac{(1+G_{cc,c,m,y})}{(1+G_{nc,cc,m,y})}$$

Where $G_{cc,c,m,y}$ is the temperature effects on country *c*'s demand in month *m*, year *y* under climate change; $G_{ncc,c,m,y}$ is the temperature effects on country *c*'s load demand in month *m*, year *y* under no climate change; $\overline{T_{max,c,m,y}}$ is the monthly average of the population-weighted daily maximum temperature in country *c* in month *m*, year *y*; $\overline{T_{minc,,m,y}}$ is the population-weighted monthly average of the daily minimum temperature in country *c* in month *m*, year *y*; $l_{h,c,m,y}$ is the demand of country *c* at hour *h*, month *m*, year *y* under no climate change; $l^{cc}_{h,c,m,y}$ is the demand of country *c* at hour *h*, month *m*, year *y* under climate change.

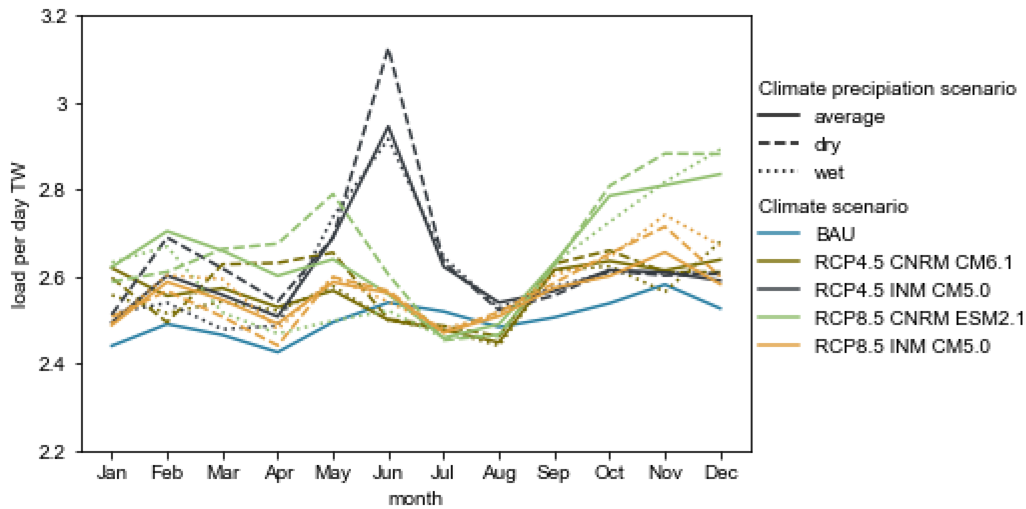

Figure 7. Electricity demand (TWh) on a representative day for January to December in 2045.

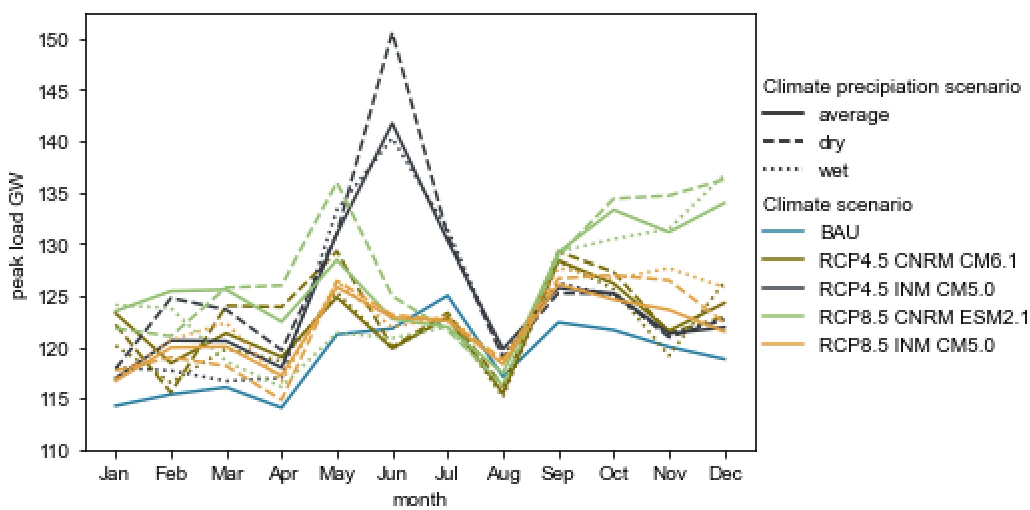

Figure 8. Peak electricity demand (GW) on a representative day for January to December in 2045.

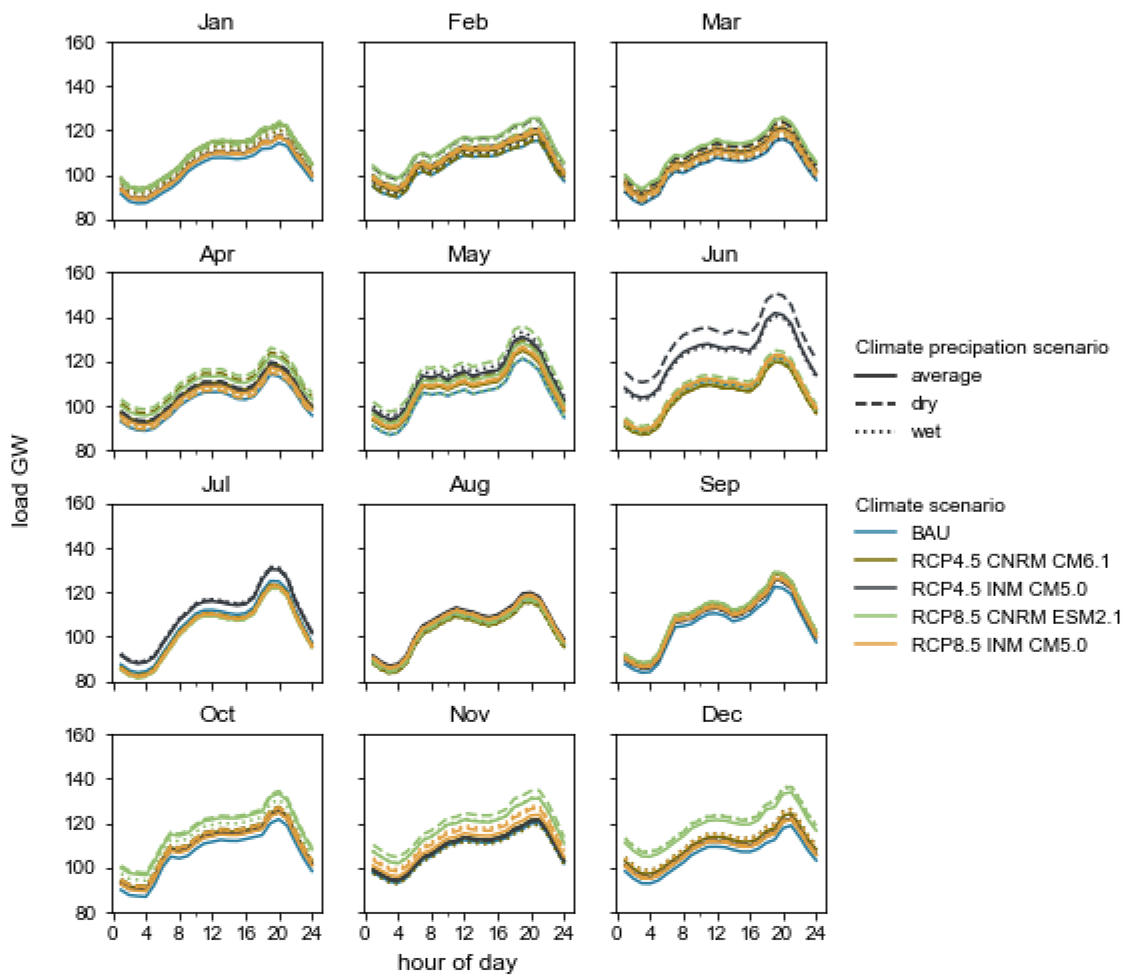

Figure 9. Electricity demand temporal profiles on a representative day for January to December in 2045 under different climate change scenarios.

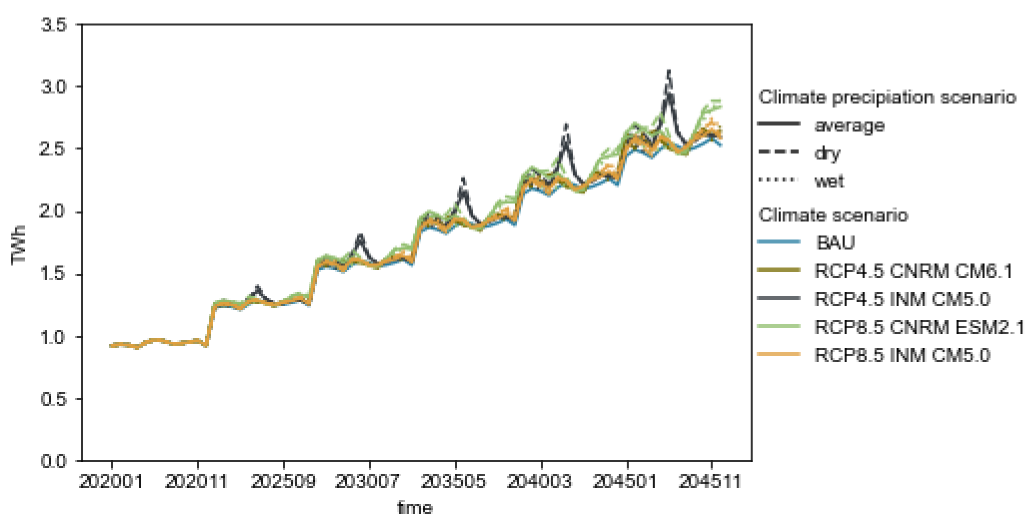

Figure 10. The daily electricity demand (TWh) from January 2020 to December 2045 under different climate change scenarios.

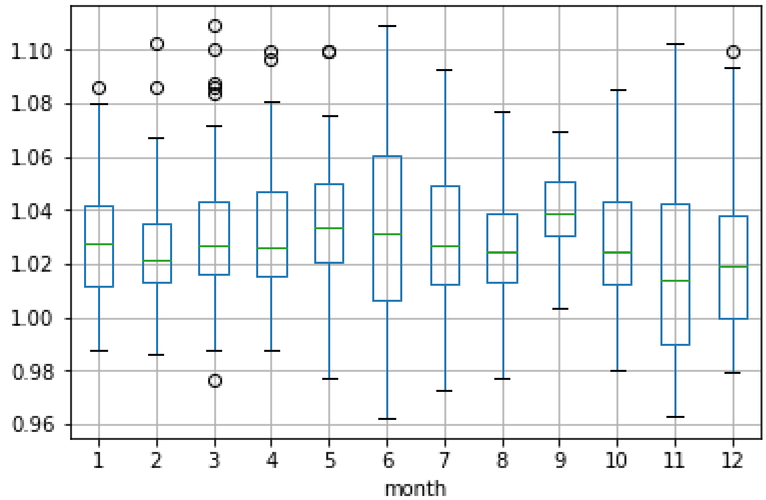

Figure 11. Distribution of the ratio of electricity demand under four climate scenarios for 2036-2055 compared to BAU.

3.3. Hydropower energy

We generated energy availability data for each existing and planned hydropower project using a spatially-distributed hydrological-water management model. We modeled eight river basins---Zambezi, Congo, Kwanza, Cunene, Rufiji, Orange, Limpopo, and Buzi---which encompass more than 90% of SAPP's total installed (13 GW) and projected (59 GW) hydropower capacity.

For each basin, we first used the Variable Infiltration Capacity (VIC) hydrological model to simulate daily runoff, evaporation, and baseflow. The gridded runoff simulated by VIC was then routed through the river network by VIC-Res, a water management model that simulates daily river discharge as well as the storage and release dynamics of each hydropower project’s reservoir (Dang, Chowdhury, and Galelli 2020). The water release for each reservoir was determined by dam-specific rule curves accounting for the reservoir water level, inflow, storage capacity, and downstream water requirements (for irrigation and other purposes). The design specifications of existing and planned reservoirs were retrieved from global reservoir and dam databases (Lehner et al. 2011; Zarfl et al. 2015), and complemented by basin-specific studies on Zambezi (Spalding-Fecher et al. 2014), Congo (Deng, Song, and Chen 2020), Cunene (Moor et al. 2000), Kwanza (Hamududu and Killingtveit 2016), Rufiji (Geressu et al. 2020), and Orange (Vonkeman, Bosman, and Basson 2019). For more details on methodology and validation, see (Chowdhury et al. 2022).

We used the temperature and precipitation data for the climate scenarios to drive the VIC-Res model and generated energy availability for each existing and proposed hydropower project. The list of hydropower projects and their associated energy availability were then fed into the power system planning model. For each climate scenario, we first estimated the monthly capacity factors of each hydropower project for the 20-year average and selected dry and wet years (as noted in Table 1). Then, we assume the monthly capacity factors will linearly change from historical average in 2020 to the corresponding capacity factors of average, dry, or wet condition in 2045.

Our results for all climate scenarios indicate that climate change is likely to reduce future streamflow (Figure 12), and thus hydropower production (Figure 13), particularly during wet season, in almost all river basins. The annual hydropower production for entire Southern Africa is likely to be less than the historical production in almost each of the future years between 2036-2055 across all climate scenarios (Figure 14). This suggests a strong likelihood of drying impact of climate change on Southern African hydropower systems, which was also reported in several previous studies (van Vliet et al. 2016, Conway et al. 2017).

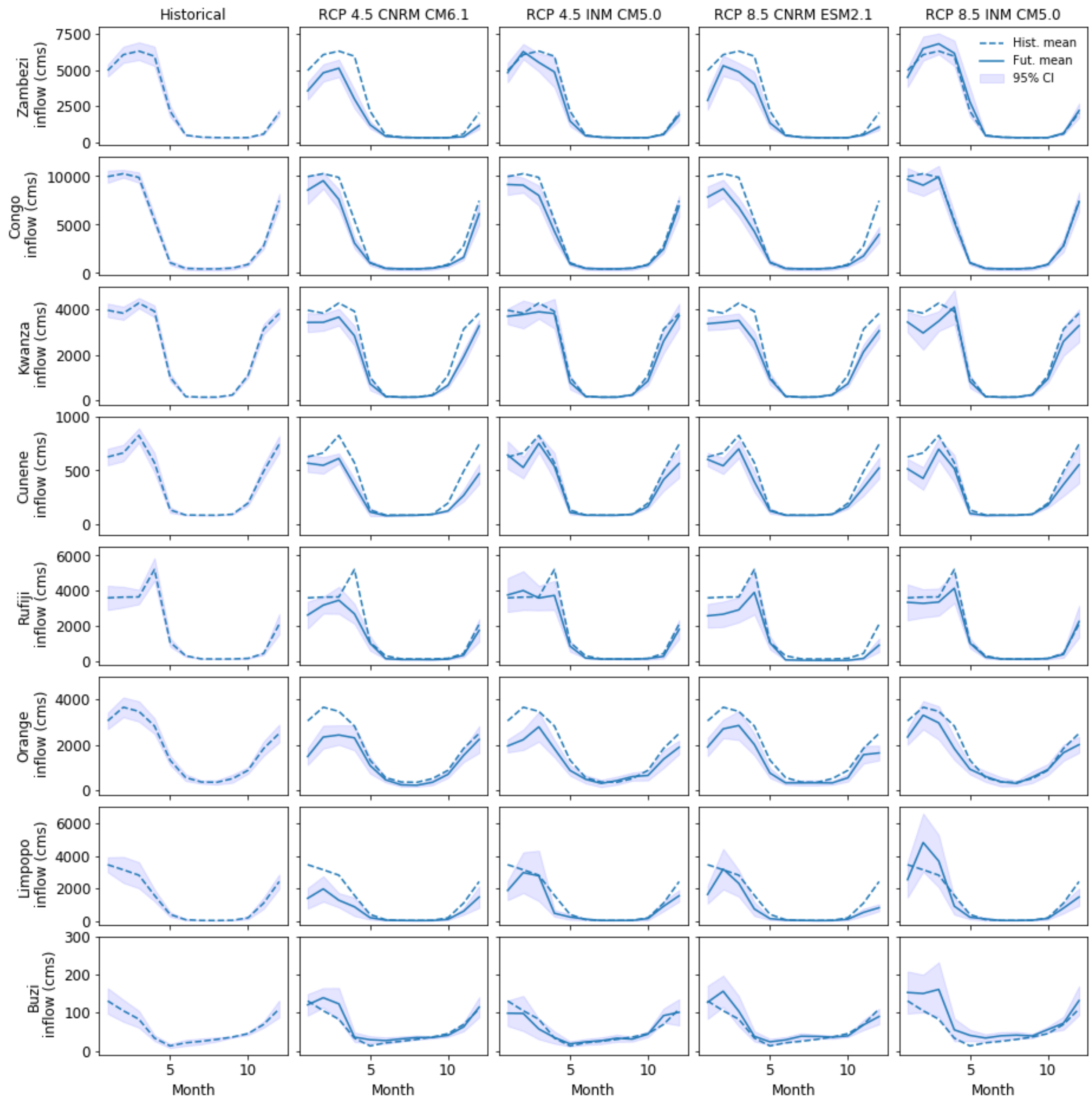

Figure 12: Basin-wise monthly average inflow (cms) with 95% confidence intervals for the historical (1996-2016) and future (2036-2055) periods for four climate change scenarios.

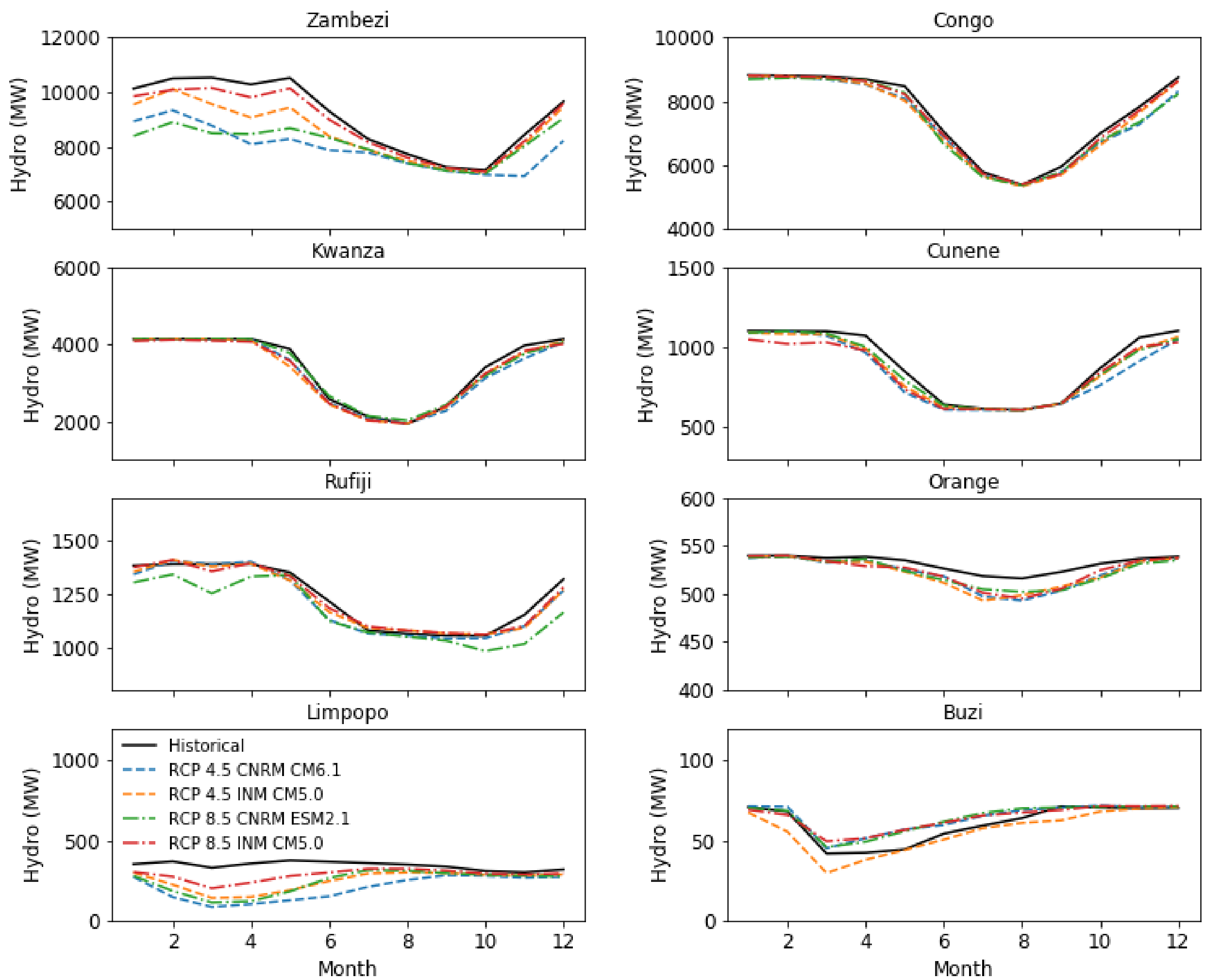

Figure 13: Basin-wise monthly average hydropower budgets (MW) for the historical (1996-2016) period and the future (2036-2055) period for four climate change scenarios.

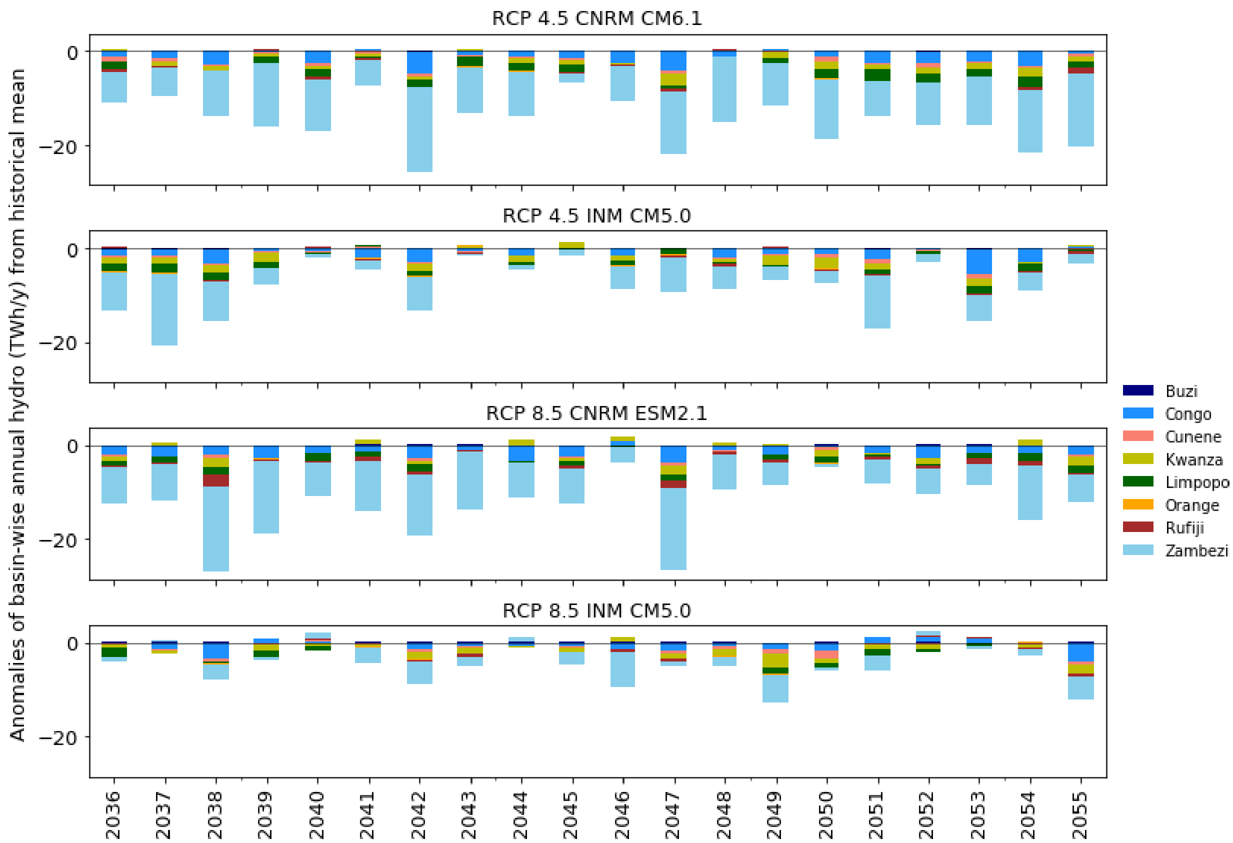

Figure 14: Anomalies in basin-wise annual hydropower (TWh/y) from historical mean for four climate change scenarios.

3.4. Thermal power plant availability

We derived the availability factors for thermal power plants under different climate scenarios using the function established by (Loew et al. 2020).

$$AF^{thermal}_{p,m,y} = \beta_T T_{p,m,y} + \beta_{RH} RH_{p,m,y} + \beta_{T:RH}(T_{p,m,y} \bullet RH_{p,m,y}) + \alpha$$

$$T_{p,m,y} = (T^{max}_{p,m,y} + T^{min}_{p,m,y})/2$$

Where $AF^{thermal}_{p,m,y}$ is the availability factor (% of installed capacity) in month *m*, year *y* for the existing thermal power plant *p*; $AF^{new}_{c,m,y}$ is the availability factor (% of installed capacity) in month *m*, year *y* for a new power plant in country *c;* $T^{max}_{p,m,y}$ is the monthly average of the daily maximum temperature for thermal power plant *p* in month *m*, year *y*; $T^{min}_{p,m,y}$ is the monthly average of the daily minimum temperature for thermal power plant p in month m, year y; β_T is the coefficient and $T_{p,m,y}$ is the value for the average air temperature (°C) in month m, year y for the thermal power plant p; β_{RH} is the coefficient and $RH_{p,m,y}$ is the relative humidity in month m, year y for thermal power plant p (%); $\beta_{T:RH}$ is the interaction term for air temperature and relative humidity; and α is the intercept.

The availability factor in the year t is calculated as

$$AF^{cc,thermal}_{p,m,y} = 0.75 \cdot \frac{AF^{thermal}_{p,m,y}}{AF^{thermal}_{p,m,2020}}$$

$$AF^{cc,thermal,new}_{c,m,y} = \sum_{p \in c} AF^{cc,thermal}_{p,m,y} \bullet CP_{p,m,y}) / \sum_{p \in c} CP_{p,m,y}$$

Where $AF^{cc,thermal}_{p,m,y}$ is the availability factor in month m, year y for thermal power plant p under climate change impacts; $AF^{cc,thermal,new}_{c,m,y}$ is the availability factor in month m, year y for a new thermal power plant in country c under climate change impacts; $CP_{p,m,y}$ is the installed capacity (MW) for the existing power plant p in month m, year y; $AF^{thermal}_{p,m,2020}$ is the estimated availability capacity in the month m in year 2020 for thermal power plant p; 0.75 is the assumed availability factor in the year 2020.

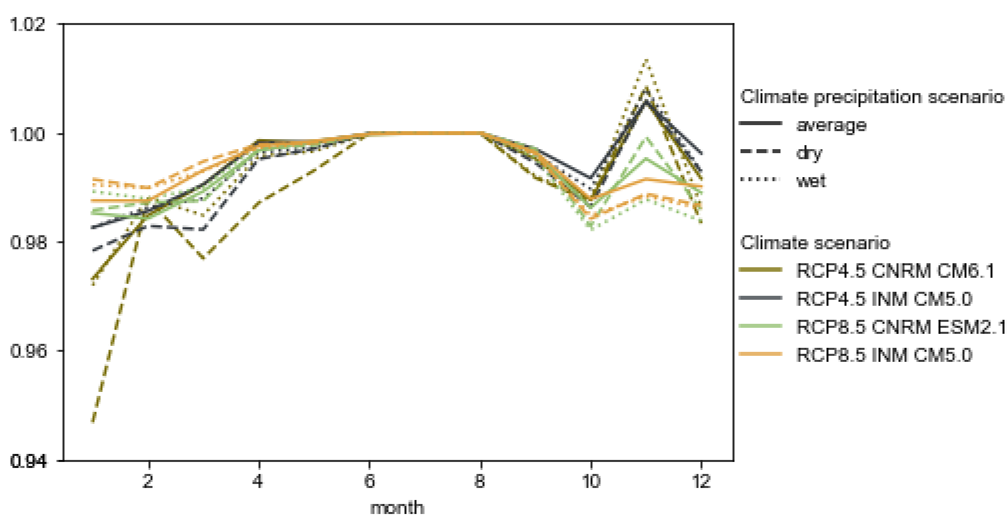

Figure 17. Ratio of the capacity-weighted annual average derating factors of thermal power plants in 2045 and 2020 for average precipitation and dry and wet precipitation years for four climate scenarios.

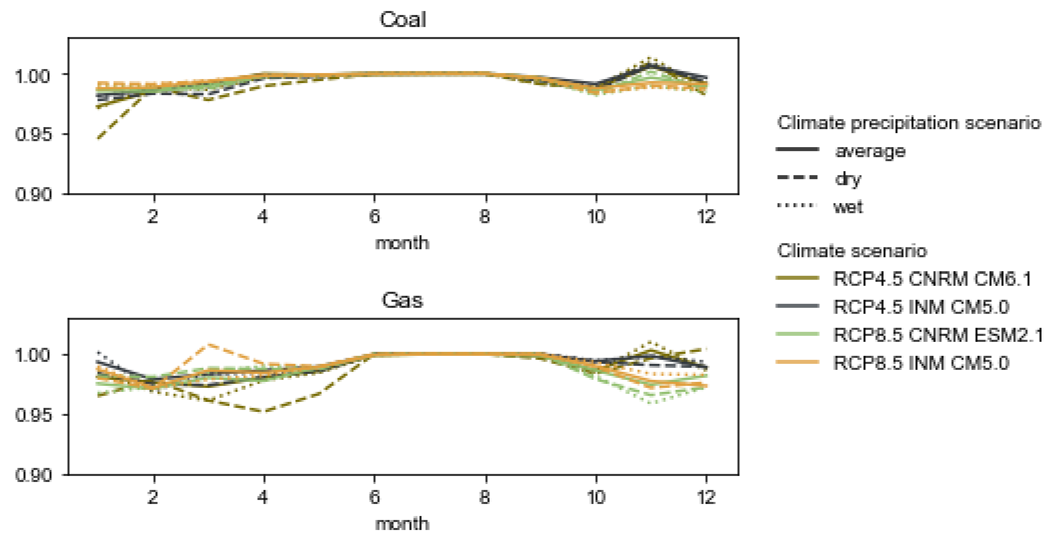

Figure 18. Ratio of the capacity-weighted annual average derating factors of coal and gas power plants in 2045 and 2020 for average precipitation and dry and wet precipitation years for four climate scenarios.

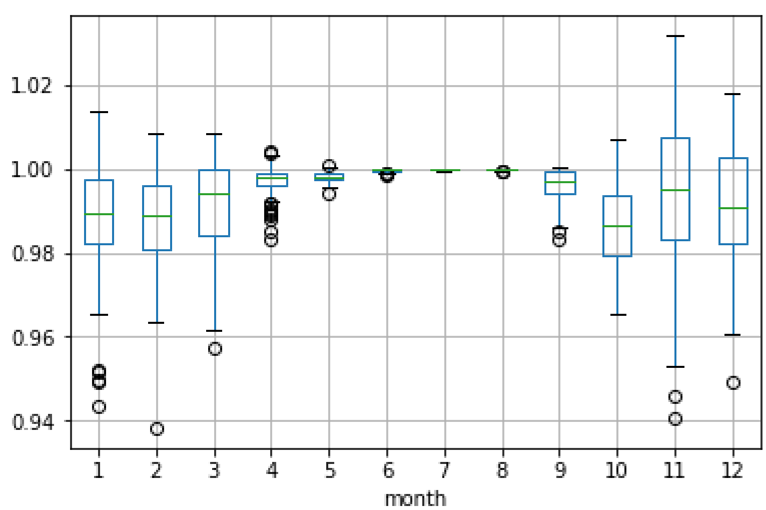

Figure 19. Distribution of ratios of capacity-weighted monthly average derating factors of thermal power plants across 4 climate scenarios (2036-2055).

3.5. Renewable energy generation and climate change impacts on solar PV

We simulated the air temperature effects on the availability factors for solar PV using the temperature coefficients of solar PV (Friesen, Pavanello, and Virtuani 2010).

$$AF^{PV}_{m,y} = 1 + (\overline{T_{c,m,y}} - 25) \bullet TC$$

$$\overline{T_{c,m,y}} = (\overline{T_{max,c,m,y}} + \overline{T_{min,c,m,y}})/2$$

$$AF^{cc,PV}_{p,m,y} = 1 \cdot \frac{AF^{PV}_{m,y}}{AF^{PV}_{m,2020}}$$

Where $AF^{PV}_{m,y}$ is availability factor (% of installed capacity) in month *m*, year *y* for solar PV in country *c*; $\overline{T_{c,m,y}}$ is the population-weighted average temperature of country *i* in month *m*, year *y*; *TC* is temperature coefficient (-0.46%/°C); $AF^{cc,PV}_{p,m,y}$ is the availability factor in month *m*, year *y* for solar PV in country *c* under climate change.

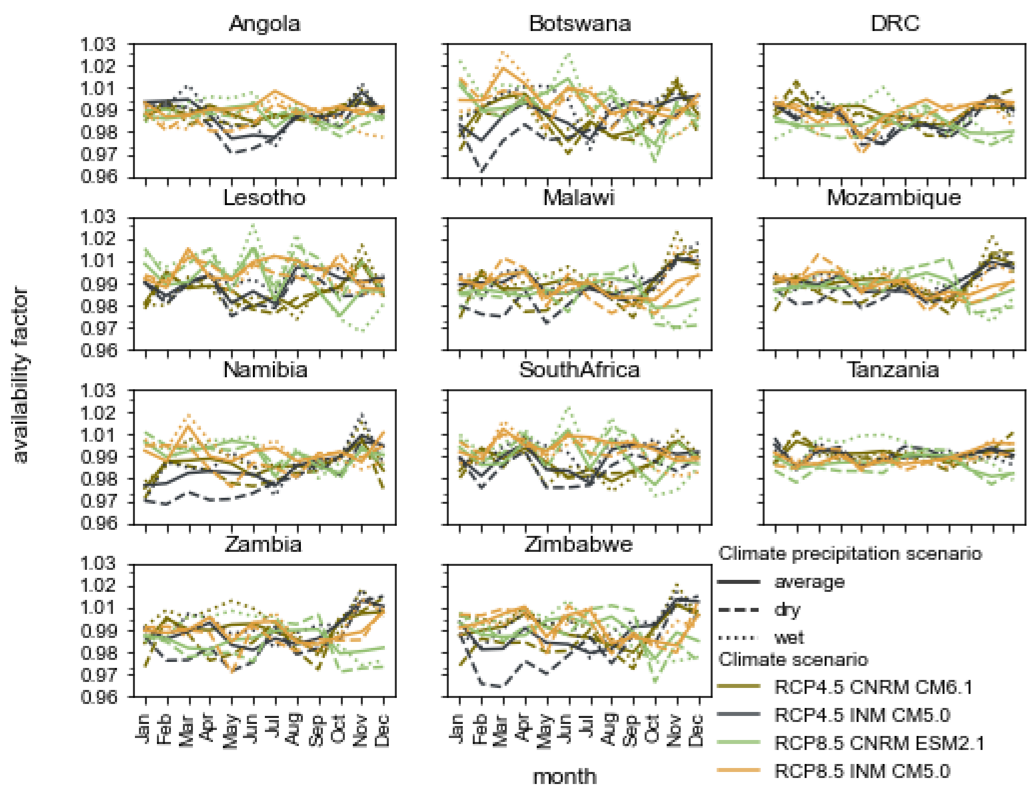

Figure 20. Ratio of the capacity-weighted annual average derating factors of solar PV power plants in 2045 and 2020 for average precipitation and dry and wet precipitation years for four climate scenarios.

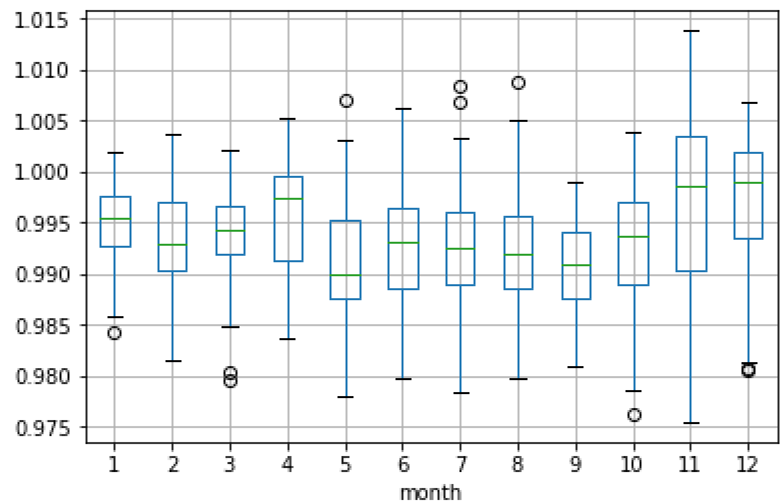

Figure 21. Distribution of ratios of capacity-weighted monthly average derating factors of solar PV power plants across 4 climate scenarios (2036-2055).

3.6. Electricity system planning and operation modeling

To identify cost-optimal electricity infrastructure investments in the SAPP for each of the scenarios, we used GridPath-SAPP model (Chowdhury et al. 2022), built on the open-source power system modeling platform (Mileva, De Moor, and Deshmukh 2021). Utilizing temporal and spatially-explicit demand, wind, solar, and hydro resource data along with various economic and technical constraints, GridPath's capacity-expansion functionality identifies cost-effective deployment of conventional and renewable generators, storage, and transmission lines by co-optimizing power system operations and infrastructure investments.

The GridPath-SAPP model has 12 load zones, each representing a SAPP member country. These load zones are joined by transmission corridors that have existing, planned, and candidate transmission capacities. We modeled six investment periods---2020, 2025, 2030, 2035, 2040, and 2045---each representing 5 years. The model can build new infrastructure or retire existing infrastructure during an investment period. We assumed a common 7% discount rate for each investment period to calculate the net present value of costs incurred during that period.

Within each investment period, grid infrastructure is dispatched to meet load and other constraints over 24 hours during 12 days, each representing a month, and weighted appropriately to represent a full year. Energy demand and supply is balanced in each modeled hour for each load zone. Hydropower and battery storage energy availability is constrained over each day.

The model co-optimizes investments (over each 5-year period) in new system infrastructure including generation, storage, and transmission, and hourly operating costs, while meeting country-wise hourly electricity demand, technical constraints on generators, storage, and transmission lines, and other policy constraints (e.g., clean energy targets). New generation capacities are selected linearly except for hydropower projects, which are discretely selected (binary decision). GridPath is written in Python and uses the Pyomo optimization language (Hart, Paul, and David 2011). The Gurobi solver was used for all simulations (Gurobi Optimization, LLC 2021).

Key inputs to GridPath include projected hourly electricity demand for each investment period, installed and candidate generation capacities, hourly capacity factors of wind and solar generators, monthly energy availability of hydropower projects, and existing capacities and unit investment costs of transmission infrastructure. Existing generation capacities---mostly composed of hydropower, coal, and natural gas, with small shares of nuclear, oil, diesel, biomass, wind and solar PV ---are adopted from the SAPP Plan (SAPP 2017). Installed coal plants are assumed to retire at an age of 55 years.

Candidate coal and gas plants are assumed only in countries with existing capacities of those technologies. Candidate wind and solar capacities and discrete hydro power plants are varied based on scenarios described earlier. Wind, solar, and battery storage costs are from the SAPP Plan (SAPP 2017) and their trajectories are adopted from the National Renewable Energy Laboratory's Annual Technology Baseline projections (NREL 2019). Coal and natural gas fuel cost projections are from the SAPP Plan. Emission factors for fuels are from the Energy Information Administration (EIA 2019).

Other techno-economic parameters of the generators including fixed operating and maintenance (O&M) costs, variable O&M costs, heat rates, fuel costs, start-up costs, ramp rates, minimum operating levels, minimum up and down times, capital costs, plant lifetimes, emission per unit generation, storage charging and discharging efficiencies, and transmission losses are adopted from the SAPP Plan (SAPP 2017), South Africa’s Integrated Resource Plan (DOE 2019), and other sources. Primary reserve margin (PRM) of 15% over peak demand is imposed as a constraint for new capacity investments. Only dispatchable generation and storage technologies and only 10% of wind capacity can contribute to PRM.

We assumed full coordination among the SAPP countries, with only transmission losses and transfer capacities as constraints to electricity trade. Existing interconnection transfer capacities are adopted from the SAPP (SAPP 2020b; 2020a). GridPath optimally builds new transmission capacities along existing and planned transmission corridors. Lengths of the interconnectors are estimated using the centroids of countries. Investment costs for new transmission lines and substations are from the Western Electricity Coordinating Council (Black & Veatch 2019). We assume bulk transmission losses of 1% per 100 miles (Eurek et al. 2016).

Major outputs are new-built capacities of generation, storage, and transmission, hourly electricity dispatch, curtailment, and transmission losses, exports and imports among the countries, operating and investment costs, and carbon emissions.

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