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YSSP Report

Young Scientist Summer Program

Robust African Hydropower Development under Socio-Economic Uncertainties

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September 30, 2021

This report represents the work completed by the author during the IIASA Young Scientists Summer Program (YSSP) with approval from the YSSP supervisor.

It was finished by ____________________ and has not been altered or revised since.

Supervisor signature:

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ABSTRACT

Population growth and improved energy access are worldwide triggering investments in power capacity expansion. Meanwhile, hydropower is experiencing a boom in many energy portfolios, especially in developing regions where most of the untapped hydropower potential lies. Strategic planning of hydropower development is crucial to reduce environmental and social impacts, and provide good performance in multiple sectors with competing objectives considering water, energy, economy and climate.

Nevertheless, due to the deep uncertainty involved in socio-economic projections, often overlooked in strategic dam planning, policy makers are required to take planning decisions with an unclear vision of the future. This is especially true for Africa, where projections for population and energy demand are highly uncertain, and where more than 300 new hydropower projects are under consideration, mostly in the least developed and most uncertain areas. The development of these power plants is contingent on meeting future energy demands and therefore strongly tied to the associated uncertainty.

Here, we examine energy portfolios considering each hydropower project reported in the African Hydropower Atlas, using a continental power system model driven by uncertain final energy demands based on the shared socioeconomic pathways (SSPs). We derive the most important hydropower plants under consideration and study how planning changes over the different future scenarios. We finally produce a two-stage plan which is adjusted as soon as uncertainty is revealed: this ensures robustness in the short term while reducing its price in the long term.

ACKNOWLEDGMENTS

I first want to acknowledge the IIASA as a whole. The institution provides a motivating and active environment for interdisciplinary and exploratory research across the many domains that are relevant to explore sustainable solutions for some of the crucial social and environmental issues of the next decades. It has been a privilege to experience the benefits of this vibrant atmosphere, even just for a short time and virtually. I also acknowledge the whole institution for the financial support during the three months of research.

I want to thank Matthias Wildemeersch (IIASA), my YSSP supervisor, for taking the time to discuss regularly and for helping me through the difficulties encountered in this work. His constant support kept me motivated while its methodological curiosity pushed me towards directions that improved the work and that I wouldn't have considered before.

I want to thank Sebastian Sterl (Vrije Universiteit Brussel) for his timely support and availability to explain and discuss the data reported the African Hydropower Atlas.

I also thank Will Usher (KTH Royal Institute of Technology) and Ioannis Pappis (KTH Royal Institute of Technology) for their help and suggestions on the usage and modification of the OSeMOSYS-TEMBA model.

I also want to thank Piotr Zebrowski (IIASA) and Brian Fath (IIASA) and all ASA scientists: their organization, their attention to the presentations of each YSSP participant during progress workshops, and their availability for the 'Ask ASA scientist' initiative made me feel part of a group and provided me also clear directions for research.

I want to thank all the YSSP staff for their availability and efficient communication, as well as all the other YSSPers for organizing events to facilitate interaction.

Finally, I want to thank my supervisors at my home institution Andrea Castelletti (Politecnico di Milano) and Matteo Giuliani (Politecnico di Milano), for guiding and supporting the conceptualization of this research project.

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List of Abbreviations and Acronyms

Below is the list description of all abbreviations or acronyms used in the following text.

Abbreviations/Acronym	Description
OSeMOSYS	Open-Source Energy MOdelling SYStem
TEMBA	The Electricity Model Base for Africa
AHA	African Hydropower Atlas
SSP	Shared Socio-economic Pathway
SPA	Shared Policy Assumptions
GDP	Gross Domestic Product

List of Nomenclature

Below is the list description of all nomeclature used in the following text.

Symbol	Set
r	REGION
t	TECHNOLOGY
f	FUEL
m	MODEOFOPERATION
y	YEAR
l	TIMESLICE
e	EMISSION

Symbol	Variable
AFC	AnnualFixedCost
AVC	AnnualVariableCost
ACC	AnnualCapitalCost
DSV	DiscountedSalvageValue
DTEP	DiscountedTechnologyEmissionsPenalty
NC	NewCapacity
ROA	RateOfActivity
SV	SalvageValue

Symbol	Parameter
ρ	DiscountRate
FC	FixedCost
OL	OperationalLife
RC	ResidualCapacity
VC	VariableCost
YS	YearSplit
CC	CapitalCost
CF	CapacityFactor
CTAU	CapacityToActivityunit
AF	AvailabilityFactor
OAR	OutputActivityRatio
SAD	SpecifiedAnnualDemand
SDP	SpecifiedDemandProfile
IAR	InputActivityRatio
AAD	AccumulatedAnnualDemand
TAMaC	TotalAnnualMaxCapacity
TAMiC	TotalAnnualMinCapacity
TTAAUL	TotalTechnologyAnnualActivityUpperLimit
TTAALL	TotalTechnologyAnnualActivityLowerLimit
TTMPAUL	TotalTechnologyModelPeriodActivityUpperLimit
TTMPALL	TotalTechnologyModelPeriodActivityLowerLimit
EAR	EmissionActivityRatio
EP	EmissionsPenalty
AEE	AnnualExogenousEmission
AEL	AnnualEmissionLimit
MPEL	ModelPeriodEmissionLimit

Here is reported a list of the optional variables and parameters used to include the African Hydropower Atlas in the OSeMOSYS-TEMBA model, and for the robust scenario analysis.

Symbol	Description
sc	SCENARIO (set)
COTU	CapacityOfOneTechnologyUnit (parameter)
NNTU	NumberOfNewTechnologyUnits (integer variable)

1 Introduction

The required development of the energy system in Africa depends crucially on three main sources of uncertainty. First, Africa's economy is projected to experience a large expansion during this century but population growth projections still remain uncertain: an increase is projected but its magnitude remains largely unresolved (Gerland et al., 2014; Samir and Lutz, 2017) propagating uncertainty to a variety of socio-economic development scenarios affecting prominently energy projections. Second, the African energy system is already undergoing major changes reflecting the improving energy access: large gaps are still present and it remains an issue to be solved in the next decades. Energy access is expected to continue growing in the short term, and final energy demands will be affected by that, even though the magnitude of the increase is still debated (Jones and Warner, 2016; Panos et al., 2016; Falchetta et al., 2020; Dalla Longa and van der Zwaan, 2021). A third major driver of uncertainty and change in the African energy system is climate policy and the consequent transition to clean energy sources. While it has been shown that renewable energies can represent a large share of new capacity with economic and environmental benefit (Sterl et al., 2020) - whose cost is also rapidly going down (Lucas et al., 2015; Hafner et al., 2018; Schwerhoff and Sy, 2019) - the development of a clean energy system is undermined by a diversity of challenges ranging from trade-offs with other sustainable objectives (Mutanga et al., 2018) to the historical dependency on coal of some regions (Steckel et al., 2020).

Hydroelectricity provides the lowest cost option for generation of large scale electricity in Africa (Hafner et al., 2018), and is a central component of building a solution to the intricate problems affecting the development of the African energy system. Indeed, African hydropower is expected to boom in response to future demand (Cole et al., 2014; Zarfl et al., 2015; Zhang et al., 2018) along with the development of some of the largest hydroelectric schemes in the world (Taliotis et al., 2014; Sridharan et al., 2019). Nonetheless, hydropower comes with a variety of impacts (Zarfl et al., 2015), from threatening biodiversity (Winemiller et al., 2016), to compromising ecosystem services providing wide social and economic benefits (Grill et al., 2019), and increasing GHG emissions (Deemer et al., 2016). In addition, large cost overruns and projects delays are also frequently observed in hydropower projects (Ansar et al., 2014; Sovacool et al., 2014). In order to tackle some of these issues, strategic dam planning links hydropower development to associated consequences and aims to satisfy power demand at the lowest cost for the environment (Schmitt et al., 2018; Almeida et al., 2019; Siala et al., 2021).

Strategic dam planning can reveal strong interactions between the water and the energy system. This water-energy nexus (Bazilian et al., 2011) requires more detailed energy system modelling techniques beyond the improved integration methodologies (Khan et al., 2017). The recent decade has seen an increasing number of open source energy system modelling projects (Howells et al., 2011; Pfenninger and Pickering, 2018; Chowdhury et al., 2020). Among the models available, OSeMOSYS -TEMBA is the implementation of one of these modelling frameworks for the whole African energy system (Taliotis et al., 2016). These new energy system models aim to answer policy-relevant questions, but have importance limitations regarding the treatment of uncertainty (Pfenninger et al., 2014) and the representation of hydropower (Ibanez et al., 2014). Indeed, most of these energy system models are run over deterministic scenarios under the assumption of perfect foresight. Using the scenario analysis approach (Swart et al., 2004; Guivarch et al., 2017), energy policies can be studied and evaluated over exogenous uncertainty. Although insightful on itself, scenario analysis does not provide useful guidelines for planning under an uncertain future. In the face of uncertainty, decision makers are instead focused on finding efficient energy solutions that have acceptable performance independent of the socioeconomic development and future climate policy. Regarding the representation of hydropower, most models are unable to capture the power-plant specific hydrological variability, since aggregated power output is typically reported using capacity factors or gross hydropower potential. This approach might blur potential benefits deriving from reservoir hydropower flexibility (Ibanez et al., 2014) and potential climate change impacts (Van Vliet et al., 2016; Turner et al., 2017).

Bearing in mind the discussed limitations of current energy system models, the contribution of this work to the body of literature is twofold:

i The introduction of power system model refinements: Expanding on an existing energy system model of the African continent, OSeMOSYS-TEMBA, we update information on hydropower projects derived from the African Hydropower Atlas (Sterl et al., 2021) to improve spatial and hydrological detail. Furthermore, we build different final energy demands combining socio-economic and climate policy uncertainty based on the SSP scenario database (Riahi et al., 2017).

ii The integration of uncertainty in the analysis of power systems: To account for uncertainty in the final energy demands projections, we introduce multiple approaches for capacity expansion planning. We adopt the standard scenario analysis technique (Alcamo, 2008; Guivarch et al., 2017), and in addition we propose a two-stage approach that ensures robustness in the short term (via robust optimization) while allowing for adaptation as soon as the uncertainty is revealed to reduce the price of robustness.

The developed model allows us to address the following three research questions. First, does power and, in particular, hydropower capacity expansion change significantly over different socio-economic and climate policy scenarios? Second, what are the most robust hydropower projects and what is their optimal timing? Third, can we reduce the price of robustness by simulating the process of learning and adapting after the realization of uncertainty?

2 Methods

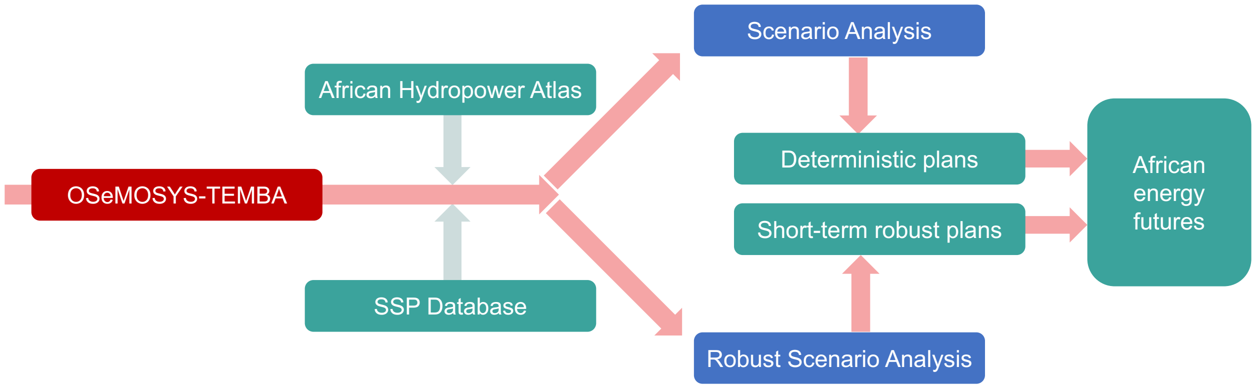


Figure 1: Overview of the methodology: the OSeMOSYS-TEMBA model (Taliotis et al., 2016) is updated with information based on the SSP databse (Riahi et al., 2017) and the African Hydropower Atlas (Sterl et al., 2021). Subsequently, scenario analysis provides deterministic energy plans, while robust scenario analysis provides short-term robust energy plans that are adapted in the long term as uncertainty is revealed. Both the results obtained are examined as potential African energy futures with a focus on hydropower development in the continent.

In this work, we leverage on the OSeMOSYS modelling framework (Open Source Energy MOdelling SYStem) (Howells et al., 2011) and its implementation for the African continent, the TEMBA model (The Electricity Model Base for Africa) (Taliotis et al., 2016; Pappis et al., 2019). This energy system model is used to analyze the evolution of the energy sector in the African continent and its structure is described in Section 6.2.1. It minimizes the total discounted costs of energy system planning and operations to meet the predefined final energy demands. The solution provides as output the new capacity to be installed and the activity (which includes the generation) from each technology over a multi-year horizon divided into seasonal time-steps. We use the energy system model to analyze hydropower development plans under future socioeconomic and climate policy scenarios.

The modeling framework improves upon the existing OSeMOSYS-TEMBA model in multiple ways: two improvements related to model realism and two methodological improvements regarding decision making under uncertainty. First, we improve the representation of hydropower in the energy system model including information from the African Hydropower Atlas. Each hydropower plant (existing, planned, committed or candidate) is considered individually as a single technology and its power generation is now described over the different seasons based on hydrological models' output. This improved representation of hydrological processes allows for more detailed representation of hydropower generation in space and time. Details on the integration of this data into the OSeMOSYS-TEMBA model are provided in Section 6.2.2.

Second, we build new final energy demand projections combining the existing ones from OSeMOSYS-TEMBA model, which we trust more in the short term, and the ones obtained via downscaling from the SSP database, which we trust more in the long term. These are used to describe long-term socio-economic and climate policy scenarios and are useful to represent the range of potential socio-economic evolution in each country considered. The procedure adopted is described in detail in Section 6.2.3.

Third, in the face of scenarios described above, we study the energy planning problem using the scenario analysis approach to derive power, and in particular hydropower, capacity expansion under all the scenarios. This step is further examined and described in Section 6.2.4.

Fourth, to explicitly account for the uncertainty in socio-economic and climate policy scenario and to better represent the conditions under which the policy makers need to take their decisions, we remove the perfect foresight assumption. We do so by leveraging robust optimization to build a capacity expansion plan which is robust in the short term. Furthermore, we simulate the policy maker's learning process over time as we allow for adaptation of decisions in the long term when uncertainty about the socio-economic and climate policy scenario is revealed. We refer to this two-step methodology as robust scenario analysis and we explain it extensively in Section 6.2.5.

The model outputs provide insights into the most relevant hydropower projects for the African energy system, and demonstrates how hydropower development is affected by socio-economic and climate policy uncertainty. Relaxing the assumption of perfect foresight, the model provides us with a hydropower capacity expansion plan which is robust in the short term and considers adaptation for the long term when uncertainty is revealed.

The data used in this work is composed of three main datasets: the African Hydropower Atlas, the OSeMOSYS-TEMBA model data, and the SSP database. The African Hydropower Atlas (AHA) (Sterl et al., 2021) collects information on 633 existing, committed, planned, and candidate hydropower projects in Africa. Its main purpose is to provide information and data to improve the representation of hydroelectric generation in power and energy system models in order to better assess the role of hydropower in the energy transition. The OSeMOSYS-TEMBA model (Taliotis et al., 2016; Pappis et al., 2019) is an energy system model for long-term planning in the African continent and combines different sources to describe the techno-economic parameters (e.g., costs, installed capacities, final energy demands) required as inputs. The model finds the least cost plan to satisfy prespecified final energy demands for electricity, coal, oil, natural gas, biofuel and waste for 47 African countries. The Shared Socio-economic Pathways (Riahi et al., 2017) are plausible socio-economic narratives used to project into the future - up to 2500 (Meinshausen et al., 2020) - population, economic, social and energy trends in the different regions of the world. In this work, we use energy consumption derived from the integrated assessment models run under the different scenarios to build final energy demands and describe their uncertainty.
Detailed information on the data used in this work is available in Section 6.1.

3 Results

In this section we examine and discuss the results obtained to discover the impact of uncertainty and its propagating effects to hydropower capacity planning. After briefly discussing the energy demands, we consider the results obtained under the standard scenario analysis to quantify the variability of hydropower development resulting from socioeconomic and climate policy uncertainty. These are modeled based on the same scenarios used in IPCC AR6 and describe the spectrum of potential evolution from a sustainable to a fossil-fuel driven world: SSP1-19, SSP1-26, SSP2-45, SSP3-Baseline, SSP5-Baseline. Second, we employ robust optimization to develop a robust capacity expansion plan to highlight the most important hydropower projects in the short-term, i.e., from 2020 to 2035, half of the full horizon. Last, we study the value of information, i.e. how much the price of robustness can be reduced, by learning and adapting power system and hydropower capacity expansion plans in the second part of the horizon after the realization of uncertainty.

3.1 Final energy demands

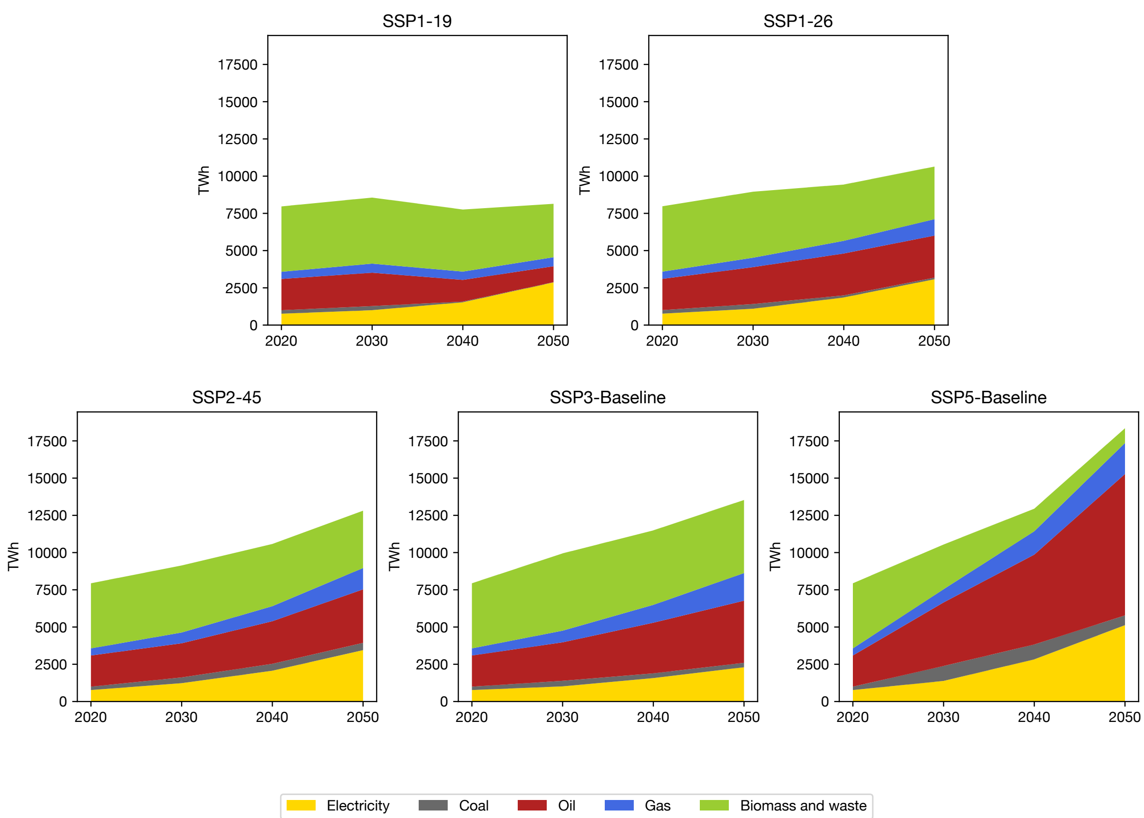


Figure 2: Final energy demands under the five scenarios examined

The final energy demands for electricity, coal, oil, gas, and biomass are reported in Figure 2. SSP5 represents the scenario with the highest total final energy demand followed by SSP3, SSP2-45, and finally by SSP1-26 and SSP1-19, which remains almost stable over the thirty year period. Even though the scenarios differ for their total demand, more differences are visible looking at the different components of the demand. In SSP1-19 we have a strong reduction of coal and oil over time, and we have a strong reduction in coal also in SSP1-26, but oil demand grows most of the scenarios. Biomass, remains one the main components except for SSP5 where it is replaced by oil and electricity. As for electricity, which drives demand in the power sector that we will analyze more in detail, the most significant growth is observed under SSP5. SSP2-45, SSP1-26 and SSP1-19 follow with similar values over the horizon. Last we have SSP3 where elecitricity demand remains small describing a system projecting business as usual demand share among the different energy types.

3.2 Different power and hydropower capacity expansions under climate policy and socio-economic uncertainty

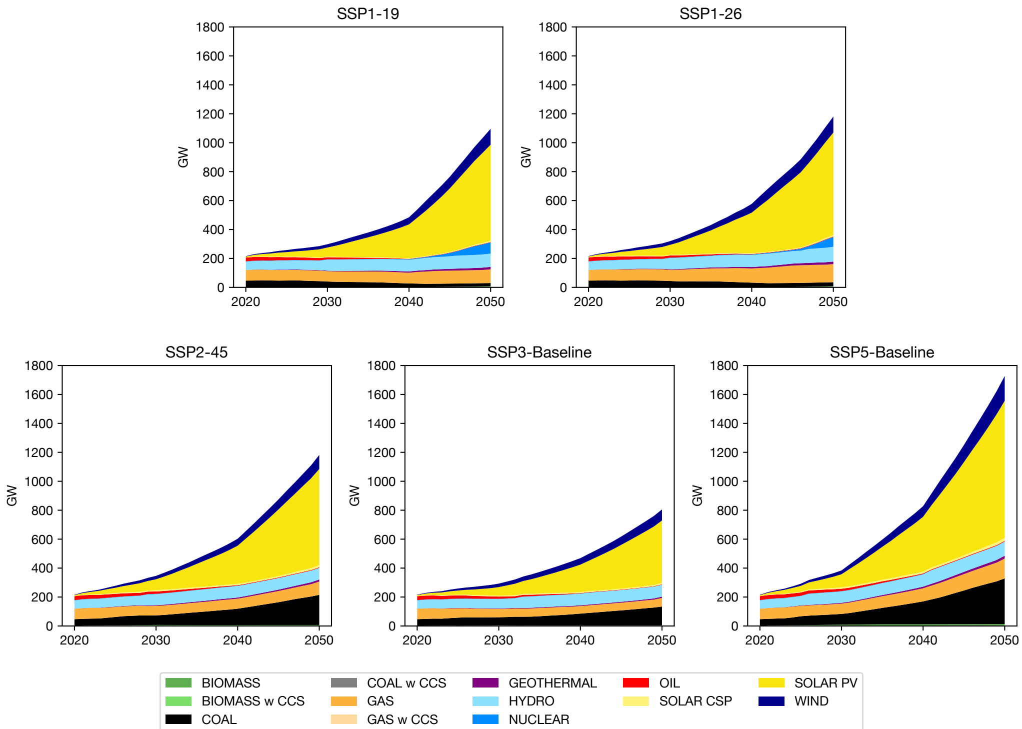
Using scenario analysis, energy plans, consisting of power capacity expansion and activity of technologies, are deterministically built to satisfy the final energy demands of each scenario considered. As a consequence, the main driver of results in this section is the final energy demand with SSP5-Baseline requiring the largest total costs and power capacity expansion among all the scenarios examined, as reported in Table 1 and Figure 3a. Among the other scenarios, the second highest cost is associated with the 'middle of the road' scenario, i.e. SSP2-45, what is usually adopted as the most plausible scenario. Lower costs are associated with SSP3-Baseline scenario, where regional rivalry prevents full development of the African economy and most of the energy demand is still satisfied using thermal energy. Finally, the lowest costs are associated with climate policy scenarios, where most of final energy demand is electrified, allowing for a reduction of total costs.

Scenario	Total Discounted Cost $[10^{12} USD]$
SSP1-19	2.6
SSP1-26	3.0
SSP2-45	2.7
SSP3-Baseline	2.6
SSP5-Baseline	4.2

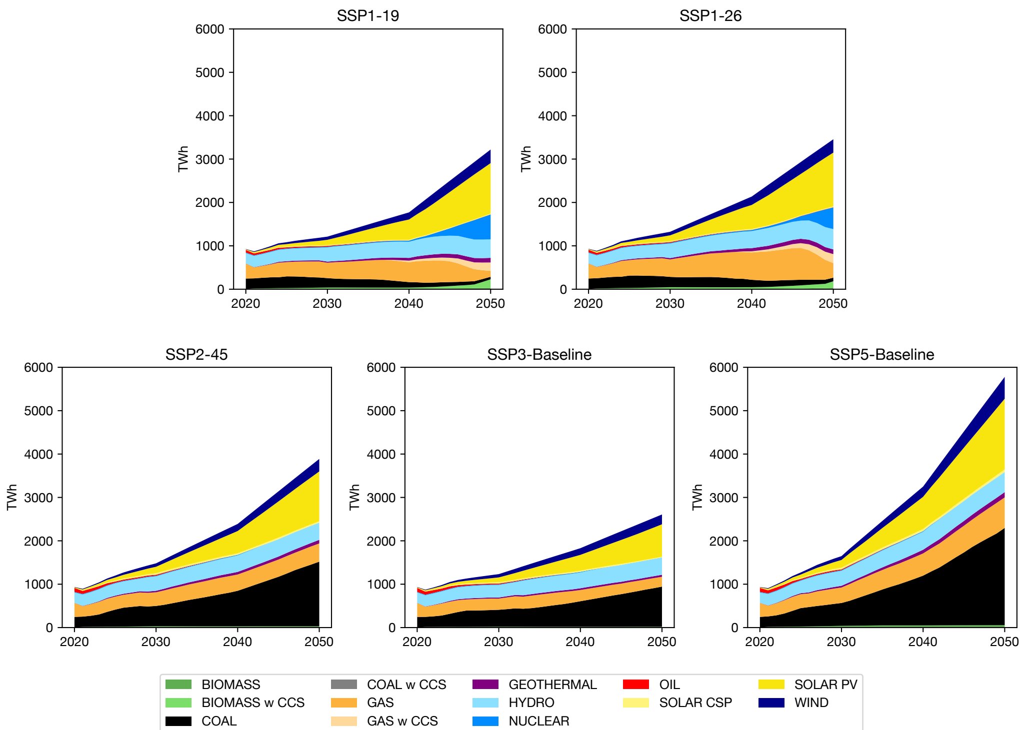
Table 1: Total discounted costs for the 5 SSP scenarios examined

The new power capacity installed under all scenarios is reported in Figure 3a. All the scenarios substantially expand solar PV capacity, from 500 GW in SSP3-Baseline up to around 1 TW for SSP5-Baseline. While coal is abandoned under climate policy scenarios, it is expanding under all other scenarios. Importantly, hydropower is expanding and almost doubling current capacity under all scenarios. Finally natural gas capacity increases in climate policy scenarios and SSP5-Baseline, while it is reduced under other scenarios. As climate policy scenarios must deal with a hard constraint on GHG emissions, they also need to install a significant amount of nuclear power capacity, especially in the last years of the horizon when emissions constraints become more stringent.

Power generation is instead reported in Figure 3b. Final electricity demand drives the magnitude of generation with SSP5-Baseline generating the most electricity, followed by

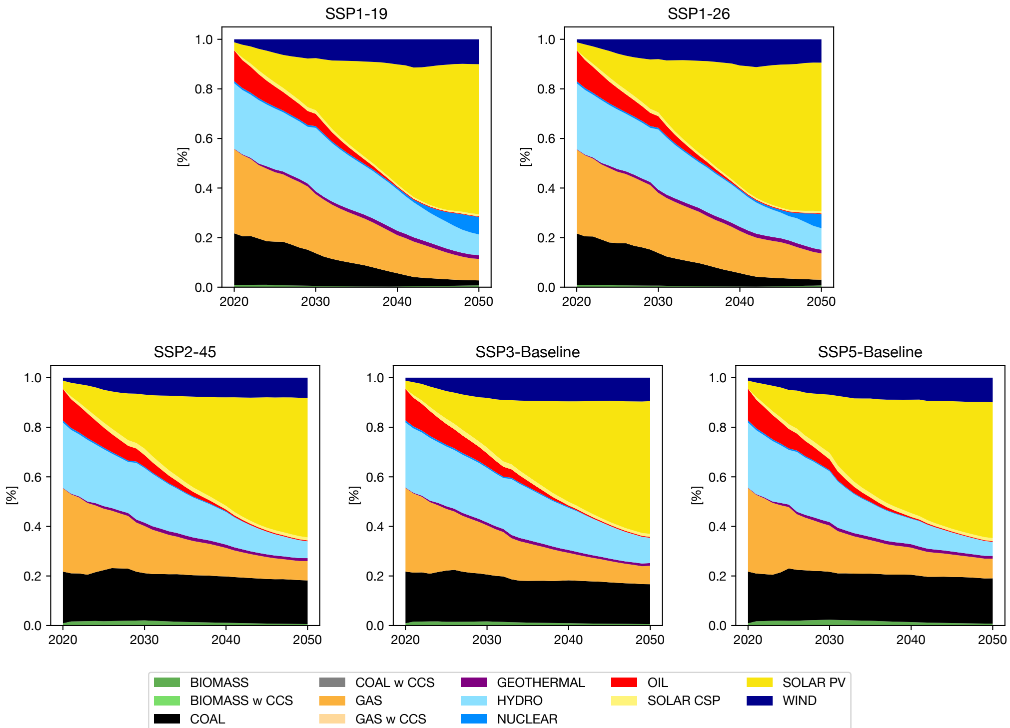


(a)

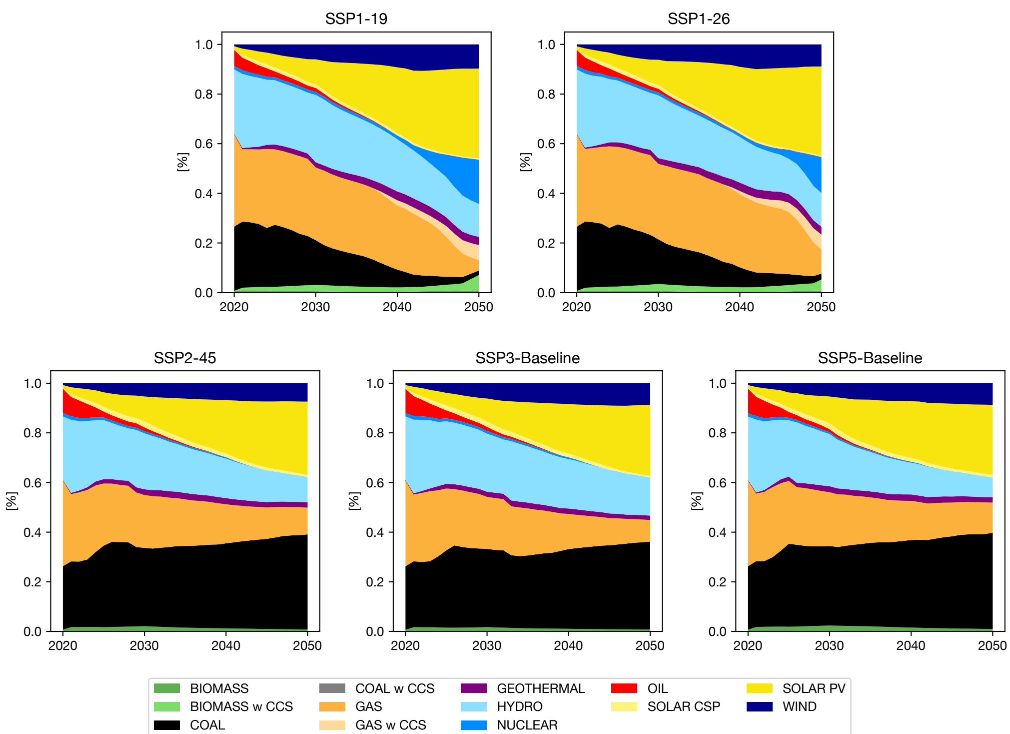


(b)

Figure 3: (a) Installed power capacity, and (b) power generation in Africa obtained under the 5 SSP scenarios examined using scenario analysis



(a)



(b)

Figure 4: (a) Share of power capacity and (b) power generation in Africa obtained under the 5 SSP scenarios examined using scenario analysis

SSP2-45, SSP1-26, SSP1-19 and SSP3-Baseline. Another major driver of differences is the presence of emissions constraints. SSP1-19 and SSP1-26 are reducing their coal consumption throughout the horizon and almost reach zero coal usage in 2050. For the same reason, they rely on nuclear power and also on natural gas with CCS. These two scenarios are also the ones most heavily relying on hydropower generation.

Shares of capacity and generation are reported in Figure 4a and Figure 4b. These plot are interesting to better understand the large transformation that the African power system will undergo moving from a system where capacity and generation are currently dominated by coal, gas and hydro to a system mostly dominated by solar and coal if stringent climate policy is not implemented. It is also interesting to notice that hydropower is a major component of capacity and generation mix, and it will be crucial during the transition to the new system with shares around 20% of both generation and capacity in all scenarios. Yet, at the end of the horizon its role will be diminished by the large development of solar, and coal under scenarios not considering climate policy.

As far as hydropower capacity expansion is concerned, maps with optimal timing and location of projects are reported in the appendix in figs. 10 to 14. It is evident that there is a cluster of hydropower projects that are developed under most of scenarios early in the horizon and geographically encompasses mostly West Africa and Sudan. Similarly, it can be seen that new large hydropower and development in specific regions seem to be dependent on the scenario, with climate policy being a crucial driver of more intensive expansion of capacity, especially in the longer term.
Most importantly, the high variability of hydropower development plan can be observed by looking at the number new projects and corresponding new capacity installed for each scenario reported in Table 2 and Table 3. As can be seen, uncertainty can results in 77 additional hydropower plants and the maximum difference in installed hydro capacity is more than 20 GW over the whole horizon.

Scenario	Number of new hydropower projects
SSP1-19	215
SSP1-26	224
SSP2-45	151
SSP3-Baseline	147
SSP5-Baseline	173

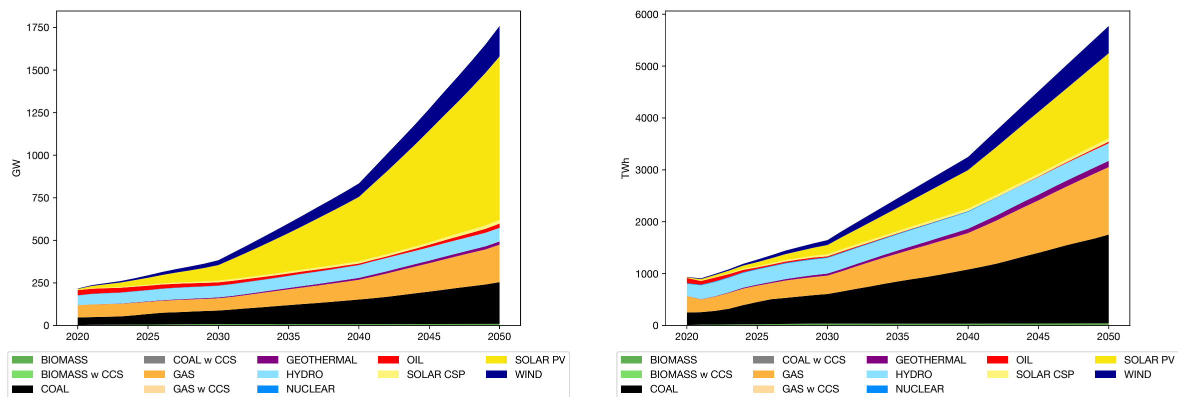
Table 2: Number of new dams built for the 5 SSP scenarios examined

3.3 Optimal timing and location of new hydropower projects to robustly meet future demand

We now examine the problem from the perspective of the decision maker that needs to take decisions under uncertainty. Given the large variability of final energy demands, and consequent variability in power system capacity expansion and hydropower development, we employ robust optimization to design a capacity expansion plan to meet final energy demands under all scenarios. We employ robust optimization and derive this plan by solving

Scenario	New hydropower capacity [GW]
SSP1-19	49.1
SSP1-26	60.2
SSP2-45	38.2
SSP3-Baseline	39.9
SSP5-Baseline	55.4

Table 3: New hydropower capacity in the 5 SSP scenarios examined



(a) **(b)**

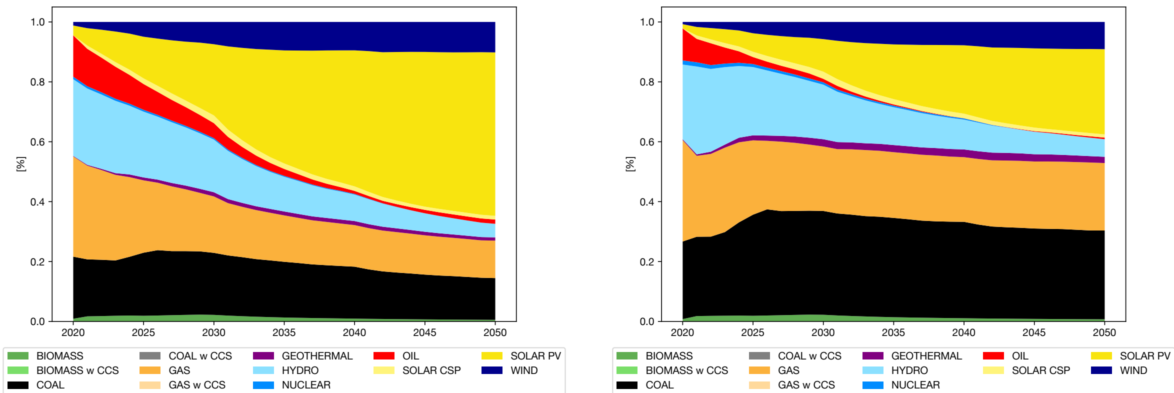
Figure 5: (a) Installed power capacity, and (b) power generation in Africa obtained by solving the robust counterpart

the robust counterpart (see Section 6.2.5), to examine the future power system configuration as well as the timing and location of new hydropower projects.

As we focus on the worst case, the solution of the robust counterpart is unequivocally driven by the largest final energy demands, as emissions constraints are removed to allow the problem to remain feasible. In fact, when emissions constraints are enforced final energy demands of scenarios without any climate policy cannot be met. Indeed, total costs of the robust counterpart solution are equal to the ones of the SSP5-Baseline scenario. Furthermore, also the installed power capacity and power generation is also in line with the one of SSP5-Baseline in the deterministic scenario analysis, as reported in Figure 5a and Figure 5b.

We report shares of capacity and generation in Figure 6a and Figure 6b and examine how the large development of solar capacity and the usage of coal, which is not constrained to any limit, result in a strong reduction of hydropower capacity and generation, in percentage terms. Yet, as we are considering the worst case scenario, hydropower is developing at a fast pace with almost 28 GW of added capacity in the short term, i.e., in the first 15 years of the horizon.

In particular, for what concerns hydropower, the capacity is expanded by around 28 GW until 2035. The location and optimal timing of such new projects is reported in Figure 7. Among the selected power plants, many power plants are built in West Africa and Tanzania as soon as possible in the horizon, i.e. 2020. Other hotspots of hydropower development are



(a) **(b)**

Figure 6: (a) Share of power capacity and (b) power generation in Africa obtained by solving the robust counterpart

located in Sudan and Ethiopia, with hydropower development within the first five years of the horizon. It is interesting to highlight that larger dams, such as the Inga dams are not built early by this plan and more in general the robust short term plan takes advantage of small hydropower projects as it builds 149 projects for a total of 28 GW. This aspect requires further investigation but we suppose that adding smaller capacity makes it easier to meet demand over many different sets of constraints representing the different scenarios.

3.4 Adjustment of decisions and the value of information

We finally simulate the process of learning over uncertainty by studying the adaptation of the energy system supposing the uncertainty over the scenario is revealed in 2035. We do so by solving the deterministic linear program over the whole horizon for each scenario imposing that the new capacity equals the robust solution capacity expansion in the first fifteen years, from 2020 to 2035. These non-anticipativity constraints allow us to enforce the robust capacity expansion in the short term while optimizing the operations and long-term capacity decisions based on each scenario eventually realizing.

The solutions to these optimization problems and their associated costs can be used to estimate the value of information, or conversely, the reduction in the price of robustness that can be achieved by learning and adapting. The total discounted costs of each solution adopting this approach are reported in Table 4. The cost of the robust solution is equal to the cost of SSP5-Baseline showing that this is the one constraining the most the robust solution. All the other scenarios result in lower cost after adaptation as capacity expansion and generation can be adjusted to meet the demand of each specific scenario. The difference between the total discounted costs in SSP5-Baseline and each scenario represents the reduction in the price of robustness and quantifies the value of information on the realization of uncertainty in year 2035. Conversely, most of scenarios incur in higher cost than under the perfect foresight assumption adopted in scenario analysis, as expected. In addition to that, we observe that ranking is changed with respect to scenario analysis as the value of cost for SSP1-26 is higher

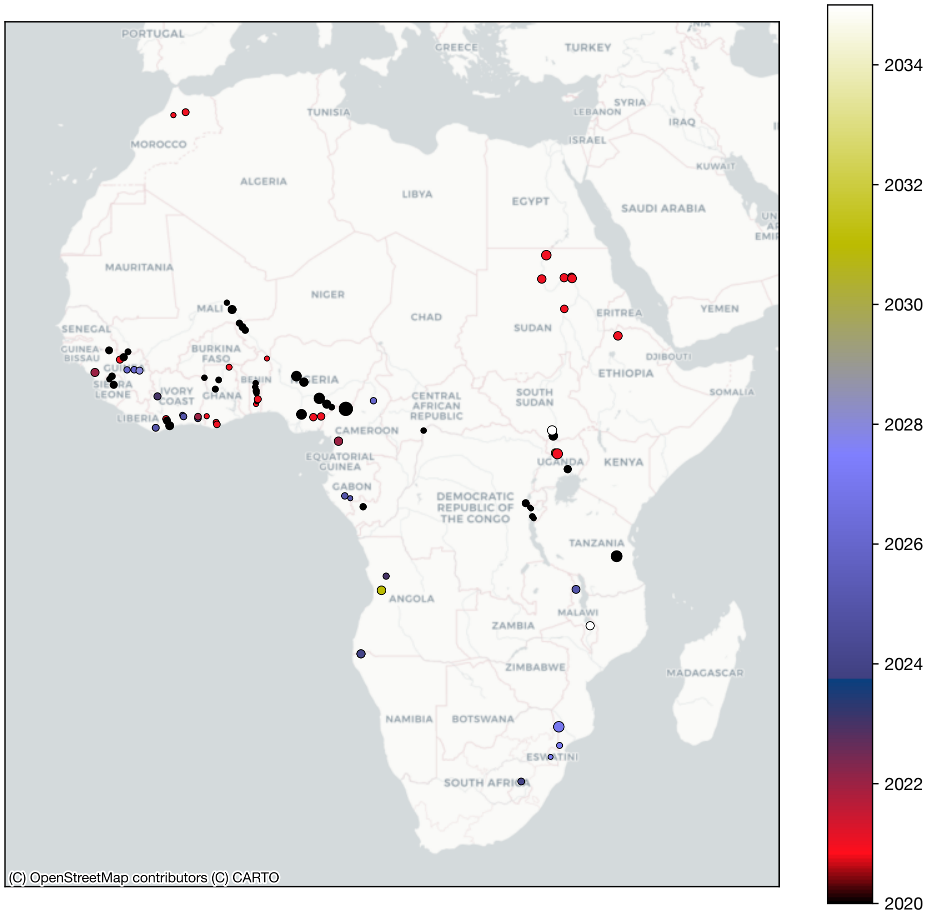


Figure 7: Location and optimal timing of dams for the short-term robust plan

than SSP3-Baseline. Indeed, the climate policy scenarios incur in higher costs as they are forced by the short term robust plan to build new capacity which would not have been considered under perfect foresight and that remains unused (e.g., coal and gas).

Power generation capacity and power generation are reported in Figure 8a and Figure 8b.The overbuilding of capacity is evident in all the scenarios, except for SSP5-Baseline, as all the remaining scenario slow or even stop capacity expansion for some time after 2035, especially SSP3-Baseline, SSP1-19 and SSP2-45. Climate policy scenarios' fossil fuel capacity shrinks after 2035 while hydropower and solar increase substantially, especially towards the end of the horizon. It is interesting to notice that coal is also overbuilt for SSP3-Baseline, a notoriously fossil-fuel intensive scenario, where a small decline in capacity between 2035 and 2045 can be observed.

The above comments can be further appreciated considering the shares of capacity and generation reported in Figure 9a and Figure 9b. It is evident how the different plan react after 2035 to realization of uncertainty: climate policy scenarios move towards hydropower more decidedly right after, as they also realize that their emissions will be constrained. As a result, hydropower gains of importance also in the generation mix until the last decade,

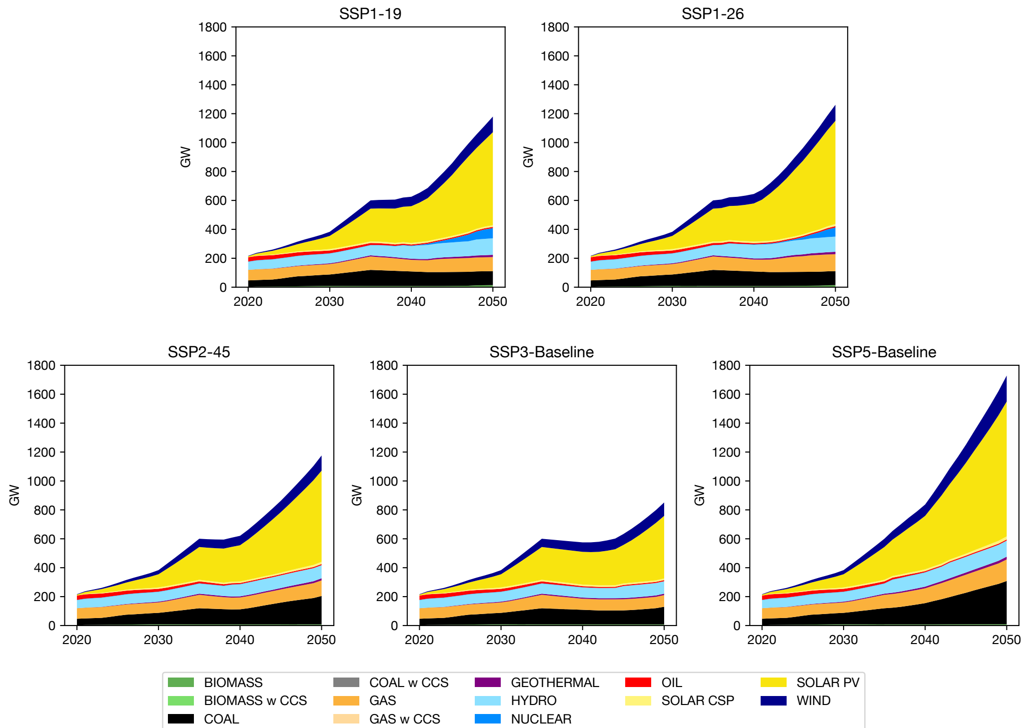
Scenario	Total Discounted Cost $[10^{12} USD]$
Robust	4.2
SSP1-19	3.0
SSP1-26	3.3
SSP2-45	2.8
SSP3-Baseline	2.9
SSP5-Baseline	4.2

Table 4: Total discounted costs for the 5 SSP scenarios under robust optimization and after the realization of the uncertainty

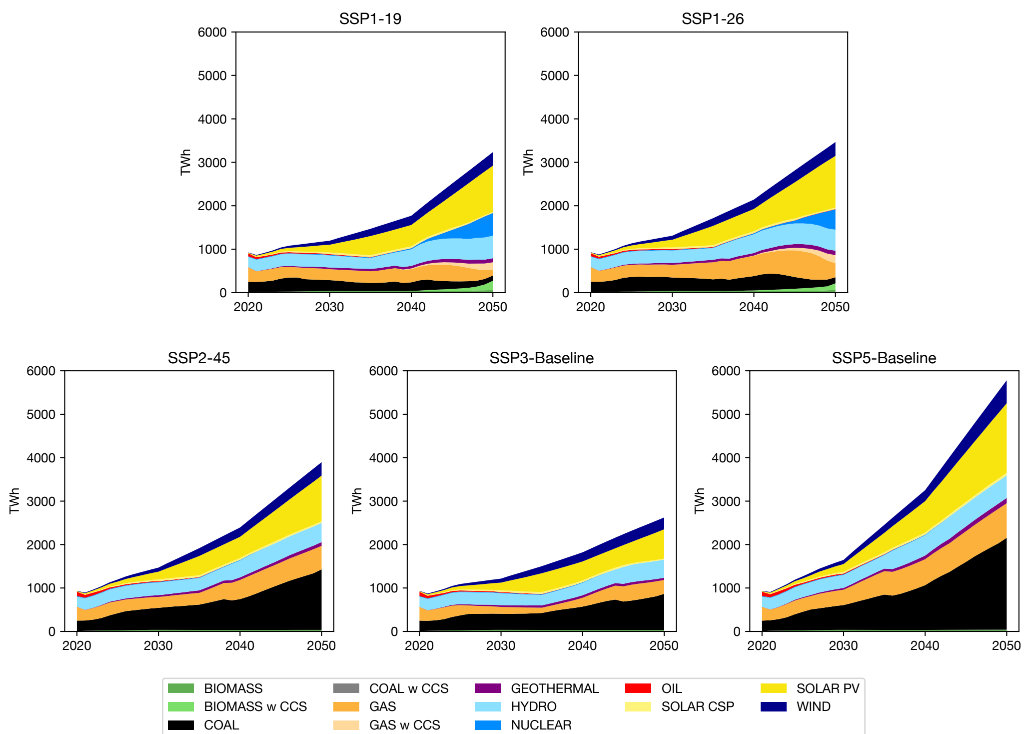
where the high demand results in more nuclear and solar, reducing the importance of hydro in percentage terms. On the other hand, scenarios without climate policy, exploit carbon and gas, and even reduce solar share of generation, until the end when solar is again needed to satisfy the growing demand.

As far as power generation is concerned, we can clearly understand how the coal capacity built in the first fifteen years remains mostly unused by climate policy scenarios. They are significantly more reliant on solar and hydropower, and this difference in even more pronounced in the long term, when also nuclear provides a substantial share of the generation mix. As for the other scenarios, the pattern does not change significantly from what can be seen in the scenario analysis as they are not subject to hard emissions constraints. Indeed, the adaptability of short term operational decisions is crucial to reach the ambitious emission reductions target and a more complex approach leveraging decision rules should be adopted to take this decision under uncertainty based on observations as time progresses. Indeed, the generation mixes for the climate policy scenarios starts to change and diverges substantially from other scenarios in 2024 when coal stops increasing to start declining by 2025.

Hydropower development in the period 2035-2050 is reported for each SSP examined in the appendix in figs. 15 to 19. By looking at these figures, we can appreciate how strongly climate policy scenarios and SSP5-Baseline insist on new hydropower development also after 2035. On the other hand, SSP2-45 and SSP3-Baseline have already built the hydropower that would have been planned in the standard scenario analysis and add only a few projects. Interestingly, in all the plans consider the Grand Inga dam in Congo, the largest by capacity in the African Hydropower Atlas with a nominal power output of 11050 GW, is built in this second stage of the problem, depending on the demand for electricity and on stringency of emissions constraints.

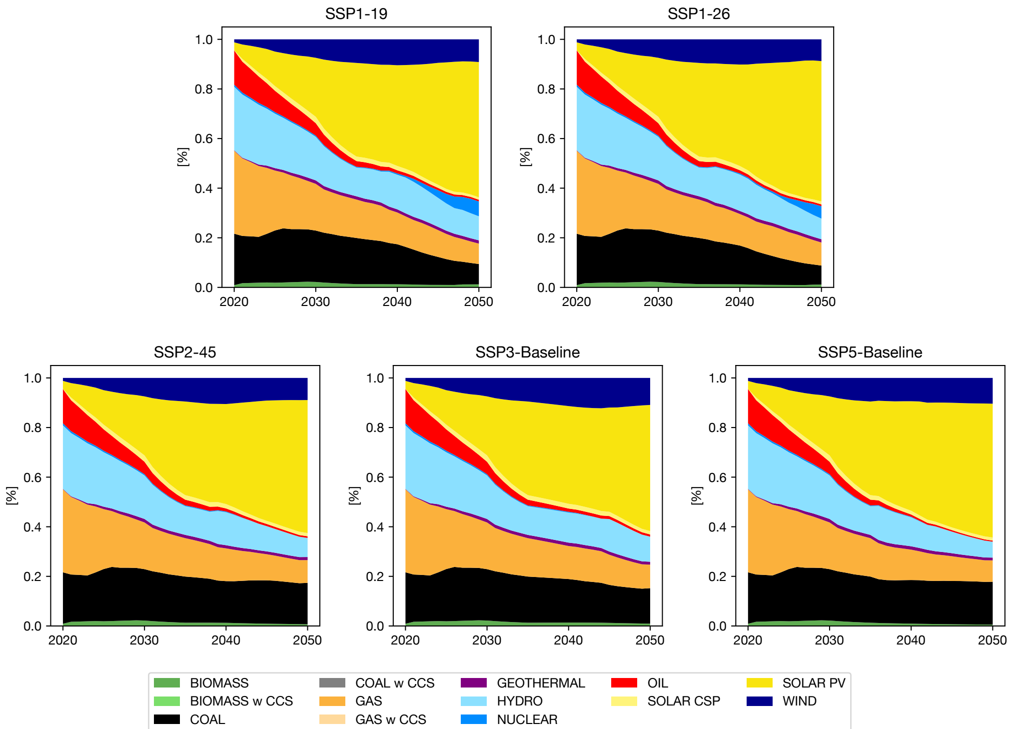


(a)

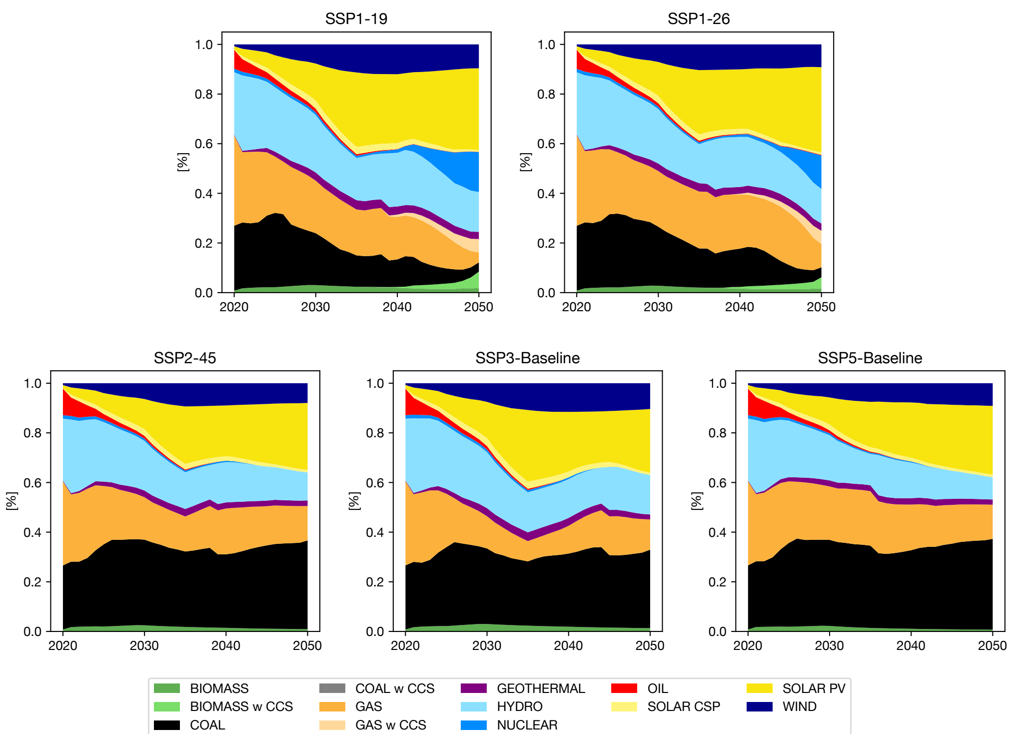


(b)

Figure 8: (a) Installed power capacity, and (b) power generation in Africa under robust scenario analysis for the 5 SSP scenarios examined



(a)



(b)

Figure 9: (a) Share of power capacity, and (b) power generation in Africa under robust scenario analysis for the 5 SSP scenarios examined

4 Discussion

The main results of this analysis of hydropower capacity expansion using an energy system model whose final energy demands are affected by socio-economic and climate policy uncertainty are reported in terms of total costs, number of new hydropower projects and additional hydroelectric capacity in tables 5 to 7. With respect to costs, the robust solution is hedging against the worst case scenario, represented by SSP5-Baseline. As a consequence, the robust solution result in the highest costs. Yet, by adapting decision after half of the horizon, the price of robustness, i.e. the additional cost to ensure meeting demand, can be strongly reduced, up to 93% for scenarios without climate policy and up by 75% for climate policy scenarios. The latter incur in higher costs due to fossil fuel capacity overbuilding as emissions constraints cannot be enforced when solving the robust counterpart. Indeed, this capacity remains unused as the operations of the system are designed after realization of the uncertainty and taking into account emissions constraints, when present. Therefore, while new capacity can be planned under uncertainty, operations cannot: the price of planning capacity under uncertainty is capacity overbuilding, which has an effect also in the short term. Additionally, we believe the two-step methodology to be also more realistic with respect to the true unfolding of energy futures: some impact on decision will be paid in the short term, but significant long-term impacts of robust choices can be reduced by adjusting choice when more information is available.

In terms of number of new hydropower projects and their capacity, climate policy scenarios are the ones developing the most projects under both scenario analysis and robust scenario analysis. As a consequence, we believe that climate policy is the main driver behind hydropower expansion, even though this should be further analyzed in further research. Yet, as far as their capacity is concerned, SSP5-Baseline is always very close to the largest hydropower expansion, meaning that socio-economic scenario plays an important role too. Furthermore, climate policy scenarios seem to develop more small hydropower while SSP5 seems focused on large dams. A preference for small hydropower is instead evident in the short-term robust plan which builds a large number of dams (149) in 15 years. While this is almost comparable to the number of dams built over the whole horizon by SSP3-Baseline in scenario analysis, it results in 28 GW of additional capacity, as opposed to the 40 GW of SSP3-Baseline in scenario analysis. This highlights the relevance that small hydropower projects play in the short-term robust plan.

-	Total Discounted Costs [10^{12} USD]	
Scenario	Scenario analysis	Robust scenario analysis
SSP1-19	2.6	3.0
SSP1-26	3.0	3.3
SSP2-45	2.7	2.8
SSP3-Baseline	2.6	2.9
SSP5-Baseline	4.2	4.2
Robust	-	4.2

Table 5: Total discounted costs for the 5 SSP scenarios under the different solution methods

-	Number of new hydropower projects	
Scenario	Scenario analysis	Robust scenario analysis
SSP1-19	215	211
SSP1-26	224	210
SSP2-45	151	154
SSP3-Baseline	147	154
SSP5-Baseline	173	174
Robust	-	149

Table 6: Number of new dams built for the 5 SSP scenarios under the different solution methods

-	New hydropower capacity [GW]	
Scenario	Scenario analysis	Robust scenario analysis
SSP1-19	49.1	58.8
SSP1-26	60.2	49.3
SSP2-45	38.2	40.6
SSP3-Baseline	39.9	40.4
SSP5-Baseline	55.4	56.3
Robust	-	27.7

Table 7: New hydropower capacity in the 5 SSP scenarios under the different solution methods

5 Conclusions and future research

In this work, we expand an existing energy model, OSeMOSYS-TEMBA, with data from the African Hydropower Atlas and the SSP database, to examine alternative energy development pathways in the African continent with a strong focus on hydropower and uncertainty. We determine the energy and hydropower development plans in term of location and timing under perfect foresight using scenario analysis. Due to the strong variability in hydropower development, we adopt robust optimization to derive a plan to ensure the demand is met under all the scenarios. Furthermore, we explore the potential to reduce the price of robustness by adapting operational and long-term decisions after the realization of uncertainty, an approach we called robust scenario analysis. Following this approach and focusing on the first 15 years, hydropower projects located especially in West Africa and mostly of small size are part of the robust capacity expansion plan ensuring that demand deficit is minimized under all scenarios. The impacts of uncertainty and learning are examined on total energy system costs, number of dams built and hydropower expansion capacity. Allowing for learning over time can reduce costs between 75% and up to 93% for all scenarios with respect to the non-anticipatory approach. We also observe that climate policy and, to a lesser extent, socio-economic uncertainty, drive hydropower expansion both in terms of timing and preference for small or large dams: small dams are preferred in the short term and strong climate action requires sustained hydropower capacity expansion also after 2035. Without climate policy, we find that no robust solution is feasible and that the capacity of coal is always augmented, stressing the relevance of climate policy in the immediate future and its impact on capacity expansion plans.

We recognize nonetheless that several assumptions are affecting capacity expansion and generation outcomes and should be carefully considered in future research:

- the idealized cooperative setting that allows for free exchange of energy and electricity among regions;
- the omitted representation of other conflicting water uses, especially agriculture and ecosystem conservation that could be negatively impacted by these hydropower expansion projects;
- the absence of climate change impacts on hydrology and their consequent impact on hydropower generation;
- the assumption of perfect knowledge over uncertainty realization after half of the horizon;
- the assumption of perfect foresight for optimizing the rate of activity of the different technologies considered;
- the conservative approach of robust optimization;
- the absence of emissions linked to new impoundments.

As for the first, constraints could be imposed to force countries to produce a set percentage of their final energy consumption that would make the model more realistic to current energy exchange conditions in the countries of Africa. The second is probably the strongest limitation of the work: as population grows, not only final energy demand, but also food demand increases with associated agricultural water demand. This could actually result in less water available for hydroelectricity with significant changes in the results of the analysis. While this aspect would add realism to the analysis, it was not included due to the additional computational requirements needed. Similarly, the third point would result in improved temporal and spatial representation of hydrological processes underlying hydropower generation and strengthen the validity of the results obtained. These model limitations merit further development in future research. For the three following points, more complex methodologies allow for a more nuanced representation of the problem of dealing when uncertainty, especially for what concerns adaptability of solutions and pessimistic approaches. We refer in this case to adjustable robust optimization and distributionally robust optimization, whose application could add realism to the decision-making process. Finally, for what concerns emissions from reservoirs, data were not directly available to perform a computation of emissions due to new reservoirs but we think this would also unveil new interesting conflicts and trade-offs especially under strong climate policy scenarios.

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6 Appendix

6.1 Data

6.1.1 African Hydropower Atlas

The African Hydropower Atlas (AHA) (Sterl et al., 2021) is a dataset collecting information on existing and future hydropower projects in Africa. Its main purpose is to provide information and data to improve hydropower representation in power and energy system models in order to better assess the role of hydropower in the energy transition. Additionally, it should also support the quantification of the ability of hydropower to balance variable renewable energy sources by providing the operational flexibility needed by future power and energy systems. Indeed, the African Hydropower Atlas is the largest publicly available dataset collecting information on the hydropower sector in Africa and it describes both storage and run of the river power plants: 266 existing, 60 committed, 44 planned and 263 candidate projects for a total of 633 hydropower plants.

It combines technical information such as the power plant nominal capacity, the reservoir volume, the geographical location, as well as some crucial information such as inflow to the reservoirs, and an estimation of the monthly capacity factor. The capacity factor is a parameter often used in power and energy system modelling to describe the power output of hydroelectric power plants as a ratio of their nominal capacity. In the African Hydropower Atlas this parameter is estimated for every month of the year using an hydrological model (SWAT+) simulated with meteorological data over the time period 1980-2016.

The data is freely available on Hydroshare and the code for reproducing figures and capacity factors is available on GitHub.

6.1.2 OSeMOSYS-TEMBA model data

The OSeMOSYS-TEMBA model (Taliotis et al., 2016; Pappis et al., 2019) is an energy system model for long-term planning in the African continent. It describes the least cost plan to satisfy prespecified final energy demands for electricity, coal, oil, natural gas, biofuel and waste for 47 African countries. The plan determines the investment in new capacity, new transmission lines and the activity for each technology considered. It also includes information on water consumption and withdrawal using water factors for each technology considered.

The data needed to run the model are provided together with it and the model is available on GitHub. The data include:

- final energy demands for each country based on population data (United Nations, 2017), energy balances (United Nations, 2018; International Energy Agency, 2017a) and Gross Domestic Product (GDP) projections (Keramidas et al., 2018);
- data on primary energy such as fossil fuel reserves and renewable energy potential, combined from different sources (Hermann et al., 2014; Ndhlukula et al., 2015; United Nations, 2016; IRENA, 2018; EIA, 2019; World Bank, 2019);

- the installed capacity and cooling system technology in place in each country derived from the Global Platts database (S&P Global Platts, 2018);
- techno-economic parameters (such as variable, fixed and capital costs) of the power generation and conversion technologies, based on different sources (E3MLab / ICCS at National Technical University of Athens, 2014; International Energy Agency, 2017b; IRENA, 2018; IEA-ETSAP, 2019);
- water factors for the different technologies and fuel processes (Medarac et al., 2018)

The OSeMOSYS-TEMBA model is run under three climate policy scenarios: the first, TEMBA_Refer, is a reference scenario where no emissions limit is imposed (but emissions penalty related to carbon taxes already in place are anyway considered). The second scenario, TEMBA_2.0, is a scenario compatible with a 2°C temperature increase and the third one, TEMBA_1.5, is in line with the objective of remaining within 1.5°C of atmospheric temperature warming. These scenarios are obtained by constraining the annual emissions of the African energy system to a cap obtained using the MAGICC 6 model (Van Vuuren et al., 2011) and information from the JRC GECO report (Keramidas et al., 2018). For these two climate policy scenario, also final energy demands are reduced in the OSeMOSYS-TEMBA model, with electricity consumption reduced by 11% and 27% and fossil fuel consumption reduced by 39% and 71% in TEMBA_2.0 and TEMBA_1.5 respectively (Pappis et al., 2019).

6.1.3 SSP database

The Shared Socio-economic Pathways (Riahi et al., 2017) are plausible socio-economic narratives used to project into the future - up to 2500 (Meinshausen et al., 2020) - population, economic, social and energy trends in the different regions of the world. These are key inputs needed to run integrated assessment models and derive emission pathways to be used in climate change assessment by the United Nation's Intergovernmental Panel on Climate Change (IPCC), as well as for a variety of different purposes such as climate policy design, and energy and agricultural policy evaluation among others (Rogelj et al., 2015; Cai et al., 2017; Hasegawa et al., 2018; Rogelj et al., 2018; Van Meijl et al., 2018).
At the core of these, there are 5 socio-economic scenarios: SSP1, SSP2, SSP3, SSP4 and SSP5. Each of these is associated to specific assumptions on technological growth and relationships among the country and regions. Indeed, each scenario can be shortly described by keywords that hint at their overall behavior, as well as to corresponding challenges to climate mitigation and adaptation: 'Sustainability' is used to refer to SSP1, 'Middle of the road' for SSP2, 'Regional rivalry' for SSP3, 'Inequality' for SSP4 and 'Fossil-fueled development' for SSP5.
Additionally, to each of the SSP scenarios, different level of climate policy strength can be associated based on the Shared Policy Assumptions (SPA) (Kriegler et al., 2014) in order to develop the SSP-SPA scenario matrix (Van Vuuren et al., 2014) where those two dimensions are combined. Those scenarios are identified by adding to the SSP scenarios the end of century radiative forcing resulting out of greenhouse gases emissions: as an example, SSP1-1.9 would indicate the scenarios SSP1, 'Sustainability', run under an ambitious climate policy scenario aiming for a end of century radiative forcing of 1.9 $[W/m^2]$. The radiative forcing levels covered by the Shared Policy Assumptions enlarge the ones adopted for the RCP

scenarios (Moss et al., 2010) and are the following: 1.9, 2.6, 3.0, 3.4, 4.5, 6.0, 7.0, 8.5. Some of these socio-economic and climate policy combinations now appear less likely than others but these scenarios, especially the ones deemed as the most plausible and representative, i.e., SSP1-19, SSP1-26, SSP2-45, SSP3-Baseline (7.0), SSP5-Baseline (8.5) (O'Neill et al., 2016), are still at the core of climate change impacts assessment across the uncertain dimensions of socio-economic and climate policy futures (O'Neill et al., 2020).
The SSP database combines information about the different integrated assessment model simulations used to quantify and examine these narratives. It is publicly available online and it consists of several components:

- projections of basic components such as GDP and population at the country level;
- projections for energy, technology, economy, population, land cover, emission and agriculture from integrated assessment modelling scenarios at the regional level (five regions are considered: OECD, Reforming Economies, Middle East and Africa, Asia and Latin America);
- emissions for the different pollutants considered for the CMIP6 project.

In this work, we are interested in the energy consumption derived from the integrated assessment models run under the different scenarios as they will be used to describe uncertainty in future final energy demands. Specifically, we rely on the "Tier 1" scenarios proposed after the Scenario Modelling Intercomparison Project (ScenarioMIP) (O'Neill et al., 2016) and used in the IPCC AR6 report; we map them coherently with existing OSeMOSYS-TEMBA model configurations as reported in Table 8.

Table 8: SSP scenarios considered and their mapping to OSeMOSYS-TEMBA model configurations

SSP scenario	TEMBA Energy Demand	TEMBA Emission Limit	Temperature Target
SSP1-19	TEMBA_1.5	TEMBA_1.5	1.5 °C
SSP1-26	TEMBA_2.0	TEMBA_2.0	2.0 °C
SSP2-45	TEMBA_Refer	TEMBA_Refer	-
SSP3-Baseline	TEMBA_Refer	TEMBA_Refer	-
SSP2-Baseline	TEMBA_Refer	TEMBA_Refer	-

6.2 Model

6.2.1 OSeMOSYS-TEMBA

OSeMOSYS (Open Source Energy MOdelling SYStem) (Howells et al., 2011) is a modelling framework used to describe energy systems and since its development has found many applications in the scientific literature (Moksnes et al., 2017; Burandt et al., 2019; Sridharan et al., 2019; Jayadev et al., 2020; Sridharan et al., 2020). It is modular and it can be easily adapted to the necessities of the case study examined. In its simplest term, OSeMOSYS determines the the least cost planning and operations of the energy system in order to meet specified final energy demands, such as electricity, residential heating, industry, transport and others. It can describe various features of modern energy systems such as storage components, renewable energy targets, emissions reductions targets, different sectors and types of energy and it can be easily connected to a variety of modelling tools to analyze climate-land-energy-water interactions (Beltramo et al., 2021). Mathematically, OSeMOSYS formulates a linear programming problem where the decision variables are the annual additional capacity to be built and the rate of activity of different technologies over each time step considered. These technologies represent also extraction and usage of energy carriers and therefore do not necessarily correspond to a power plant. The full formulation of the optimization problem is reported in Section 6.2.6.

In this work, we adopt the implementation of OSeMOSYS for the African continent, the TEMBA model (The Electricity Model Base for Africa) (Taliotis et al., 2016), that has also been used for many studies available in the literature both at the continental and regional level (Taliotis et al., 2014; Rocco et al., 2021). We adopt the most recent version of the model, which is available on GitHub and whose results are publicly available and published in a technical report (Pappis et al., 2019).

6.2.2 African Hydropower Atlas in OSeMOSYS-TEMBA

In our case, we improve the representation and granularity of information about hydropower in the OSeMOSYS -TEMBA model by describing each of the projects reported in the African Hydropower Atlas: to do so we need to know their nominal capacity and their capacity factors, i.e., the ratio of their actual power output to their nominal capacity, which is influenced by the hydrological variability of each specific hydropower plant.

In the OSeMOSYS-TEMBA model hydropower is described by aggregating all hydropower plants into a single technology, with a common capacity factor. To improve the level of detail, we first add new hydropower technologies corresponding to each of the hydropower projects reported in the African Hydropower Atlas in the countries where these are present and update the installed capacity of aggregate hydropower in such countries, in order to account for hydropower plants not described in the Afrian Hydropower Atlas. We also ensure that no new hydropower can be built, except for the candidate, planned and committed power plants in the African Hydropower Atlas. We employ an optional OSeMOSYS parameter to enforce that if an hydropower project is built, this is built according to its nominal capacity which results in formulating a mixed integer linear programming problem. Further explanation is given in Section 6.2.7.

Capacity factors from the African Hydropower Atlas are used for the hydropower plants that are described individually while for aggregate hydropower OSeMOSYS-TEMBA capacity factors are left unchanged. It is important to highlight that we are taking into account hydrological variability with higher detail with respect to the OSeMOSYS-TEMBA model but we are not considering the impacts of climate change on the hydrological cycle as the capacity factors are computed over the horizon 1980-2016.

For what concerns the capital and variable costs, since no specific information is available in the African Hydropower Atlas, hydropower projects capital and variable costs are based on cost data (IRENA, 2021). This step is important in order to reduce the symmetry of the resulting mixed integer linear programming problem to be solved and speed up computational time. This step if further explained in Section 6.2.8

Most of the remaining hydropower parameters are left unchanged with respect to traditional hydropower in OSeMOSYS-TEMBA as no other information is available.

6.2.3 Building SSP-driven final energy demand projections

In its original formulation, the OSeMOSYS-TEMBA model is solving a deterministic linear program with hard constraints on demand satisfaction. In this work, we introduce uncertainty in final energy demands as we build five demand projections based on 5 SSP scenarios encompassing socio-economic and climate policy uncertainty. The SSP-driven final energy demands are computed by combining the OSeMOSYS-TEMBA projections, more reliable in the short term, and the SSP scenarios, to which is given more importance in the long term. This is represented as follows:

$$D_{r,t}^{SSP,ene} = \alpha_t D_{r,t}^{TEMBA,ene} \frac{D_{MAF,t}^{SSP,ene}}{M_{SSP}[D_{MAF,t}^{SSP,ene}]} + (1-\alpha_t) D_{MAF,t}^{SSP,ene} \frac{GDP_{r,t}^{SSP}}{GDP_{MAF,t}^{SSP}} \tag{1}$$

$$\alpha_t = \alpha_{2020} - (t-2020)/80 \tag{2}$$

$$\alpha_{2020} = 1 \tag{3}$$

$$\alpha_{2100} = 0 \tag{4}$$

where $M_{SSP}[\cdot]$ represents the median over SSP, $D_{r,t}^{SSP,ene}$ is the demand for energy type ene, in scenario SSP, for region r, at time t. The demand is computed as a convex combination of the OSeMOSYS-TEMBA original demand ($D_{r,t}^{TEMBA,ene}$) and the SSP projection at the regional level ($D_{MAF,t}^{SSP,ene}$, MAF stays for Middle East and Africa) downscaled using the GDP of the country as a proxy variable. The downscaling of SSP scenarios is carried out using the pyam package (Gidden and Huppmann, 2019). In contrast to what would have been a more intuitive formulation for building the final energy demands, reported below:

$$D_{r,t}^{SSP,ene} = \alpha_t D_{r,t}^{TEMBA,ene} + (1-\alpha_t) D_{MAF,t}^{SSP,ene} \frac{GDP_{r,t}^{SSP}}{GDP_{MAF,t}^{SSP}} \tag{5}$$

$$\alpha_t = \alpha_{2020} - (t-2020)/80 \tag{6}$$

$$\alpha_{2020} = 1 \tag{7}$$

$$\alpha_{2100} = 0 \tag{8}$$

we are shifting the original energy demand depending on the SSP scenario considered, by considering OSeMOSYS-TEMBA final energy demands as a reference central projection. For this reason, we multiply the OSeMOSYS-TEMBA projections by the total final energy demand in that SSP scenario over the median final energy demand under exam for the SSP scenarios considered. Therefore, if we're in a high demand scenario, also the projection in the short term will be influenced by that and will moderately increase with respect to the original TEMBA projection smoothly moving towards the SSP downscaling level pprojection. This allows for a representation of uncertainty in the short term which is also aligned with the original projections.

6.2.4 Scenario Analysis

Environmental systems planning and management usually has to deal with substantial uncertainties, especially when long-term horizons are considered (Swart et al., 2004). One of the most standard ways of dealing with such uncertainties, especially when they are not easily reducible to a small set and hard to define, is the scenario analysis approach. It is also called the scenario planning approach or just scenario approach and it was first used to aid decision-making under social and political uncertainty (Kahn and Jones, 1960; Kahn, 1962; Kahn et al., 1967). In recent decades, it also became more common practice in the field of environmental systems decision-making. In brief, in the scenario approach future storylines are built and used to develop possible future states of the system under exam upon which decisions can be based (Swart et al., 2004; Alcamo, 2008). This methodology is still very much used in many environmental decision-making problems regarding energy, climate, water and other sectors (Guivarch et al., 2017).

In our case, we start our analysis by employing this method over the scenarios examined. This means that we run the optimization model assuming perfect foresight over the socio-economic and climate policy scenario under exam. From the decision-making point of view, this is by no means different from current usage of the OSeMOSYS-TEMBA model. The difference with respect to the standard OSeMOSYS-TEMBA model lies in the information from the African Hydropower Atlas and in the SSP-driven final energy demands.

6.2.5 Robust Scenario Analysis

In the real decision-making process, we do not have information about which one of the SSP scenarios will realize; actually, we don't even have information on which one of them is more probable, unless we rely on expert judgement (Ho et al., 2019). Our decisions today must deal with this deep uncertainty and many methods have been developed and used in socio-environmental system modelling (Lempert, 2002; Hall et al., 2012; Kasprzyk et al., 2013; Haasnoot et al., 2013; Moallemi et al., 2020; van der Pol et al., 2021). Their tractability is usually limited to fast simulation models and their application is not straightforward in energy systems analysis as most of the models are self-optimizing models that solve for the least cost option adopting mathematical programming techniques. On the other hand, when large-scale optimization models are considered, robust optimization is a methodology often used. It is indeed the only approach coherent with the absence of probabilities on SSP scenarios and for this reason it has been usually applied in this context (Cai et al., 2017; Lincke and Hinkel, 2018).

Robust optimization is a field of mathematical optimization focusing on preventing that stochastic, parametric and model uncertainty put at risk the optimality of a solution: indeed, the field aims at finding solutions to problems which perform well even under the worst realization of multiple uncertainties (Ben-Tal et al., 2009). It is indeed often used in energy system for decision-making under uncertainty (Dehghan et al., 2013; Gacitua et al., 2018).

Additionally, in our work, we want to describe how energy system's decisions will adapt to the scenario realization after some time, when additional information on uncertainty will be gained. This adaptation and learning modelling effort is an emergent trend in environmental system decision-making models and it has been implemented for flood protection (Haasnoot

et al., 2013), but it's also used in energy systems modelling (Mejia-Giraldo and McCalley, 2014), in this case based on adjustable robust optimization (Ben-Tal et al., 2004; Caunhye and Cardin, 2018).
To do so, we adopt a simplified two stage approach assuming that we have full realization of the uncertainty at the beginning of the second stage. In the first stage (from 2020 to 2035), as we don't know what scenario will realize we solve a robust optimization problem, i.e. we hedge against the worst case outcome, by solving the robust counterpart (Ben-Tal and Nemirovski, 1999) for the whole horizon, i.e. finding the solution that minimizes the costs while satisfying constraints under all the scenarios. The solution of the robust counterpart produces a trajectory of decisions regarding new capacity to be installed and rate of activity of each technology. In the second stage, we suppose to know the realization of the scenario and we optimize again over the whole horizon but we suppose the new capacity of the first 15 years to be set equal to the one obtained by solving the robust counterpart. Therefore, in the second stage, we are optimizing rate of activity for all the model horizon (from 2020 to 2050) and new capacity for the long term (from 2035 to 2050). Mathematically, we solve a robust optimization problem over the whole model horizon fomulated as follows:

$$\min_{[NC^{robust}_{r,t,y}, ROA^{robust}_{r,t,y}]} \max_{s \in SSP} \quad TotalDiscountedCost \tag{9}$$

$$s.t. \quad A * \; NC^{robust}_{r,t,y} + B * \; ROA^{robust}_{r,l,t,m,y} \geq D_{s,t} \qquad y \in [2020, 2050], \; s \in SSP \tag{10}$$

$$other\ constraints \tag{11}$$

and then use the solution obtained to solve the following problem exhaustively for each SSP scenario considered:

$$\min_{[NC_{r,t,y}, ROA_{r,t,y}]} TotalDiscountedCost \tag{12}$$

$$s.t. \quad A * \; NC_{r,t,y} + B * \; ROA_{r,l,t,m,y} \geq D_{\bar{s},t} \qquad y \in [2020, 2050] \tag{13}$$

$$NC_{r,t,y} = NC^{robust}_{r,t,y} \qquad y \in [2020, 2035] \tag{14}$$

$$other\ constraints \tag{15}$$

There are multiple reasons behind the choice of solving the robust optimization problem over the full horizon, even if we then only use the first 15 years of the solution. First, we want to avoid the optimization being affected by border effects. Additionally, we also want the plan to be designing capacity expansion in light of what could be the worst case over the following 15 years from 2035 to 2050.
The robust scenario analysis methodology allows us to study potential energy plans that allow to reach a satisfactory performance under all SSP scenarios, and to examine how they adapt under each scenario after their realization. Furthermore this methodology can also provide an idea of the information that is lost because of the uncertainty in each scenario, but also how much can be gained by using adaptation.
It is important to note here that in order for the robust optimization problem to be feasible, emissions constraints are removed. They are reintroduced in the deterministic problem describing adaptation to the realization of uncertainty. Similarly, the constraints on annual maximum technology activity are relaxed in the robust optimization problem so that the

maximum value between TEMBA_Refer, TEMBA_2.0 and TEMBA_1.5 was used for each technology to allow the solver to find a feasible solution. All the constraints which are modified for the robust optimization problem are then enforced correctly in the second stage of the approach, also for the first fifteen years in the upper level problem. The steps used to solve the two stages are discussed more in detail in Section 6.2.9.

6.2.6 OSeMOSYS-TEMBA model equations

The full name of the sets, variables and parameters used in the model is reported in the nomenclature.

$$\min_{u} \sum_{r,t,y} \left[\frac{AFC_{r,t,y} + AVC_{r,t,y}}{(1+\rho)^{(y-y^0+0.5)}} + \frac{ACC_{r,t,y}}{(1+\rho)^{(y-y^0)}} - DSV_{r,t,y} - DTEP_{r,t,y} \right] \tag{16}$$

$$s.t. \qquad AFC_{r,t,y} = FC_{r,t,y} * \sum_{yy:\ y-yy<OL_{r,t}\ \&\&\ y-yy\geq 0} \left[NC_{r,t,y}\right] + RC_{r,t,y} \tag{17}$$

$$AVC_{r,t,y} = \sum_{m} \sum_{l} VC_{r,t,m,y} * ROA_{r,l,t,m,y} * YS_{l,y} \tag{18}$$

$$ACC_{r,t,y} = CC_{r,t,y} * NC_{r,t,y} \tag{19}$$

$$DSV_{r,t,y} = \frac{SV_{r,t,y}}{(1+\rho)^{y^{end}-y^0}} \tag{20}$$

$$SV_{r,t,y} = \begin{cases} 0, & y + OL_{r,t} - 1 \leq y^{end} \\ CC_{r,t,y} * NC_{r,t,y} * \frac{(1+\rho)^{(y^{end}-y)}}{(1+\rho)^{(OL_{r,t}-1)}}, & else \end{cases} \tag{21}$$

$$u = \begin{bmatrix} NC_{r,t,y}, & ROA_{r,l,t,m,y} \end{bmatrix} \tag{22}$$

OSeMOSYS-TEMBA model formulates a linear programming problem whose objective function to minimize is the sum of various annual components of cost summed over the years, the technologies and the regions considered. As reported in (16), the total costs are composed by: annual fixed costs, described in (17), and annual variable costs, described in (18), discounted at mid-year as these costs occur during all over the year; additionally we have also annual capital costs, discounted at the beginning of each year and described in (19), discounted salvage value, described by (20) and (21), and discounted emissions penalty by technology, whose computation is described later in the text in (35).
Finally, in (22), the decision variables with respect to which the total costs are minimized are reported. These are the new capacity to be installed in year y for technology t in region r ($NC_{r,t,y}$) and the rate of activity in time-slice l (i.e. time step associated with season and day night conditions) during year y for technology t in region r with mode of operation m (for technologies that operate in multiple directions such as transmission lines, pumped-storage hydro) ($ROA_{r,l,t,m,y}$).
Additional constraints are imposed so that generation from each technology is constrained

by the installed capacity of the technology in a specific year, its capacity factor and its availability factor, that take into account for planned maintenance of technologies. This is described in (23) and (24).

$$\sum_{m} ROA_{r,l,t,m,y} \leq \left\{ \sum_{yy:\ y-yy<OL_{r,t}\ \&\&\ y-yy\geq 0} \left[NC_{r,t,y}\right] + RC_{r,t,y} \right\} * CF_{r,t,l,y} * CTAU_{r,t} \tag{23}$$

$$\sum_{m}\sum_{l} ROA_{r,l,t,m,y} * YS_{l,y} \leq \sum_{l} \left\{ \sum_{yy:\ y-yy<OL_{r,t}\ \&\&\ y-yy\geq 0} \left[NC_{r,t,y}\right] + RC_{r,t,y} \right\} * CF_{r,t,l,y} * AF_{r,t,y} * CTAU_{r,t} \tag{24}$$

Energy balances are formulated at the time-slice level in (25) and at the annual level (26). In their simplest terms, these equations ensure that enough energy is generated to meet demand from other technologies and pre-specified final energy demands, defined at the annual or time-slice level.

$$\sum_{m}\sum_{t} ROA_{r,l,t,m,y} * OAR_{r,t,f,m,y} * YS_{l,y} \geq SAD_{r,f,y} * SDP_{r,f,l,y} + \sum_{m}\sum_{t} ROA_{r,l,t,m,y} * IAR_{r,t,f,m,y} * YS_{l,y} \tag{25}$$

$$\sum_{m}\sum_{t}\sum_{l} ROA_{r,l,t,m,y} * OAR_{r,t,f,m,y} * YS_{l,y} \geq \sum_{m}\sum_{t}\sum_{l} ROA_{r,l,t,m,y} * IAR_{r,t,f,m,y} * YS_{l,y} + AAD_{r,f,y} \tag{26}$$

The following constraints, eqs. (27) to (30), ensure that the capacity and the new capacity installed remains between predefined maximum and minimum capacity and capacity investment.

$$\sum_{yy:\ y-yy<OL_{r,t}\ \&\&\ y-yy\geq 0} \left[NC_{r,t,y}\right] + RC_{r,t,y} \leq TAMaC_{r,t,y} \tag{27}$$

$$\sum_{yy:\ y-yy<OL_{r,t}\ \&\&\ y-yy\geq 0} \left[NC_{r,t,y}\right] + RC_{r,t,y} \geq TAMiC_{r,t,y} \tag{28}$$

$$NC_{r,t,y} \leq TAMaCI_{r,t,y} \tag{29}$$

$$NC_{r,t,y} \geq TAMiCI_{r,t,y} \tag{30}$$

Annual and whole horizon (or model period) activity limits are enforced for each technology using eqs. (31) to (34).

$$\sum_{l} ROA_{r,l,t,m,y} * YS_{l,y} \leq TTAAUL_{r,t,y} \tag{31}$$

$$\sum_{l} ROA_{r,l,t,m,y} * YS_{l,y} \geq TTAALL_{r,t,y} \tag{32}$$

$$\sum_{y} \sum_{l} ROA_{r,l,t,m,y} * YS_{l,y} \leq TTMPAUL_{r,t,y} \tag{33}$$

$$\sum_{y} \sum_{l} ROA_{r,l,t,m,y} * YS_{l,y} \geq TTMPALL_{r,t,y} \tag{34}$$

The discounted emissions penalty for each technology are computed in (35), while annual and model period emission limits are constrained using (36) and (37).

$$\sum_{e} \sum_{l} \sum_{m} EAR_{r,t,e,m,y} * ROA_{r,l,t,m,y} * YS_{l,y} * EP_{r,e,y} * \frac{1}{(1+\rho)^{(y-y^0+0.5)}} = DTEP_{r,t,y} \tag{35}$$

$$\sum_{l} \sum_{m} \sum_{t} EAR_{r,t,e,m,y} * ROA_{r,l,t,m,y} * YS_{l,y} + AEE_{r,e,y} \leq AEL_{r,e,y} \tag{36}$$

$$\sum_{l} \sum_{m} \sum_{t} \sum_{y} EAR_{r,t,e,m,y} * ROA_{r,l,t,m,y} * YS_{l,y} + AEE_{r,e,y} \leq MPEL_{r,e,y} \tag{37}$$

6.2.7 Additional constraints for including the African Hydropower Atlas in OSeMOSYS-TEMBA

To enforce that the new capacity built for a specific hydropower project is aligned to the nominal capacity reported in the African Hydropower Atlas, we adopt a set of built-in variables, parameters and constraints available in the standard OSeMOSYS model framework. We use the optional variable $NNTU_{r,t,y}$, defining how many new units of technology t are built in year y in region r, the optional parameter $COTU_{r,t,y}$, describing the minimum amount of capacity that has to be added when building technology t in year y in region r, and we add the additional constraint that relates these to the decision variable $NC_{r,t,y}$ using (38).

$$COTU_{r,t,y} * NNTU_{r,t,y} = NC_{r,t,y} \tag{38}$$

It should be noted that the variable $NNTU_{r,t,y}$ is defined as an integer variable and constrained to be 0 or 1, as building one technology unit for the hydropower project examined would result in its realization. Furthermore, the parameter $TAMaC$, set equal to the hydropower plant nominal capacity for each hydropower project, ensures that the project is built only once during the model period considered. As a result, we are now formulating a mixed-integer linear programming problem, whose computational complexity is notoriously higher than the one of a linear program.

6.2.8 Capital and variable costs for African Hydropower Atlas projects in OSeMOSYS-TEMBA

As information is not available on capital and variable costs from the African Hydropower Atlas, we derive two simple relationships to estimate the capital and variable costs of hydropower, rather than simply using values for the aggregate hydropower in each country available from OSeMOSYS-TEMBA.
With respect to capital costs we take the average capital cost for small (i.e. ¡10 MW) and large (i.e. ¿10 MW) hydropower projects in Africa from IRENA (2021). We then assign:

- the average capital cost between small and large hydropower projects to the capacity of 10 MW (i.e. 2836.5 USD/kW)
- the average capital cost for small hydropower projects to the capacity of 1 MW (i.e. 3256 USD/kW)
- the average capital cost for large hydropower projects to the capacity of 500 MW (i.e. 2446 USD/kW)
- we set an further higher point for capital cost by multiplying the average cost of small hydropower by 1.15 to capacity of 0.1 MW (3744.4 USD/kW)
- we set a lower point for capital cost by multiplying the average cost of average hydropower by 0.85 and we assing it to a capacity of 11 GW (2054.5 USD/kW)

Between the point defined above we adopt linear interpolation. Out of these point we adopt the same linear function used in the preceding interval. It should also be noted that hydropower projects in the African Hydropower Atlas have a capacity in the range between 0.09 MW and 11050 MW.
As far as variable costs are concerned, we stick to the value used in OSeMOSYS-TEMBA, but we introduce some variation based on the fact that observed cost are higher for smaller hydropower projects (IRENA, 2021). We adopt here a much simpler approach as data is not available: the variable costs of hydropower in OSeMOSYS-TEMBA (which is very low with respect to other technologies, 10^{-6} MUSD/PJ) is multiplied by a factor by a factor linearly dependent on the nominal capacity of the power plant. This factor is decreasing from 1.1, in the case of the smallest hydropower projects, to 0.9, in the case of the largest power plant.
These slight cost modifications are not only useful to represent more realistic information on the hydropower. They also ensure a reduction of symmetry in the mixed integer linear problem formulated. Symmetry in mixed integer linear program is a result of many similar alternative decisions slowing the ability of the solver to find a gradient among the possible decisions available using their corresponding total final cost. As an example, let's imagine the case where we would need to build 200 MW of hydropower in a country and we were given two options: building two dams of 100 MW each or a single one of 200 MW. If the costs were equal in the two options, both the options would produce the same result and the optimization would progress very slowly. On the other hand, if we give more information on true costs of the two options, the optimization proceeds faster towards the minimum cost option. If the example is scaled to more than 300 hydropower projects located in many

neighboring countries, it can be easily seen that symmetry problem can arise and preclude a fast convergence to the optimal solution (Alemany et al., 2014).

6.2.9 Robust scenario analysis - technical issues

For the robust optimization problem, an additional set has to be defined, SCENARIO, which is now indexing also the final energy demands, represented by $AAC_{r,f,y,sc}$ and $SAD_{r,f,y,sc}$. The energy balance constraints now must hold also over all the set of scenarios considered, and that is how the robust counterpart of the robust optimization problem is formulated.
For the second stage of the robust scenario analysis, the deterministic linear program used to describe adaptation to the scenario realization, $NC_{r,t,y}$ is not enforced directly, but rather the minimum annual capacity to be installed is constrained using the parameter $TTAMiCI_{r,t,y}$ and $TTAMaCI_{r,t,y}$ and setting them equal to the new capacity variable of the solution of the lower level problem for the first 15 years of the horizon, i.e. from 2020 to 2035. The variable $ROA_{r,l,t,m,y}$ is left free to vary also in the first over the 30 year span, i.e. also in the first 15 years of the horizon, in order to allow for finding a feasible solution. Indeed, if the rate of activity would have been set equal to the robust counterpart solution the annual emission limits for 1.5°C and 2°C temperature target would have made the mixed integer linear program infeasible.

6.3 Hydropower development maps

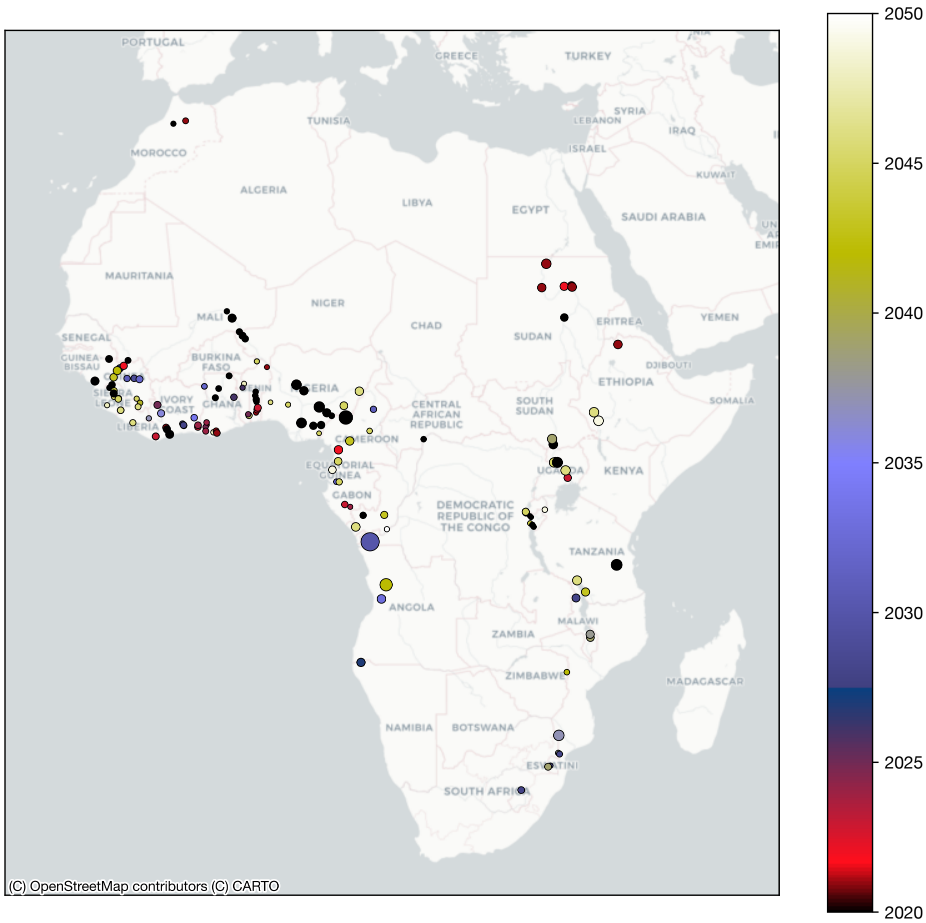

Figure 10: Location and optimal timing of dams for SSP1-19

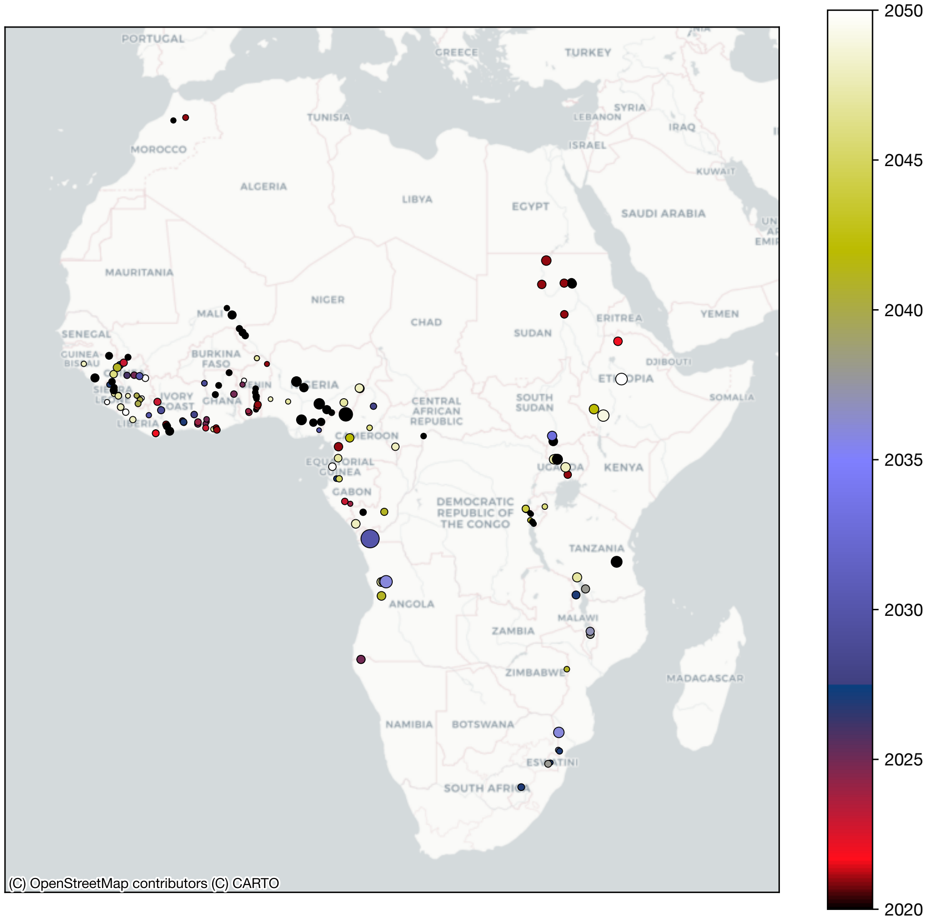

Figure 11: Location and optimal timing of dams for SSP1-26

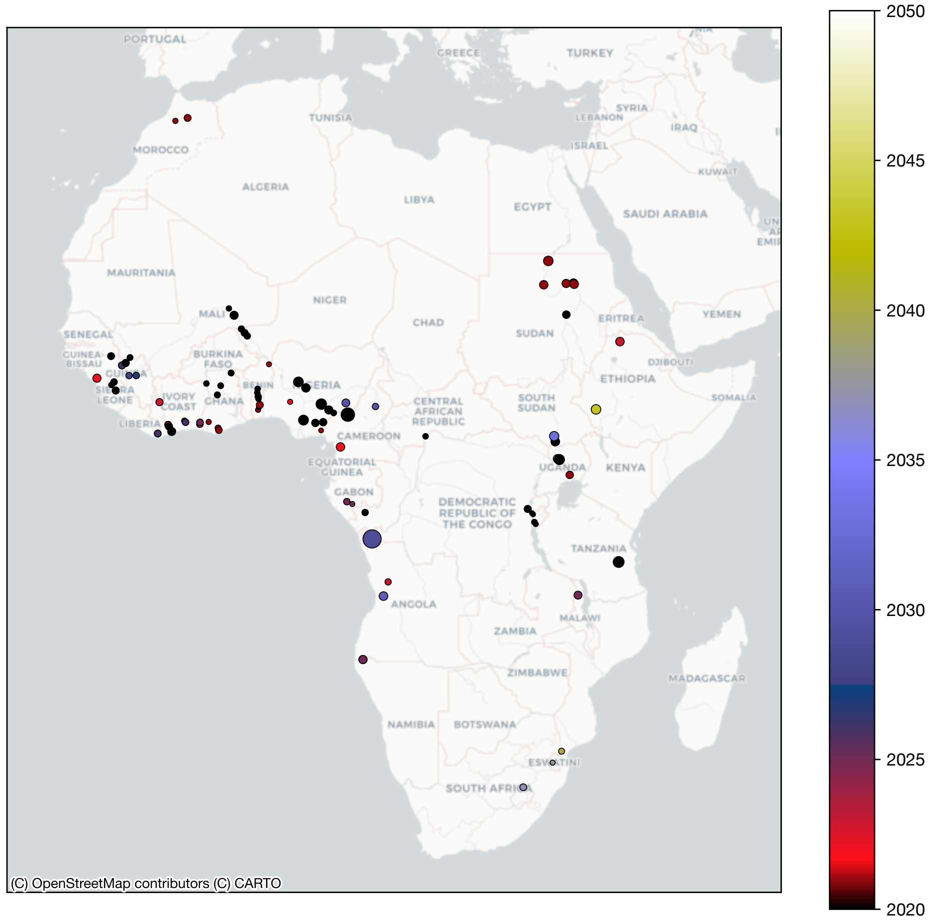

Figure 12: Location and optimal timing of dams for SSP2-45

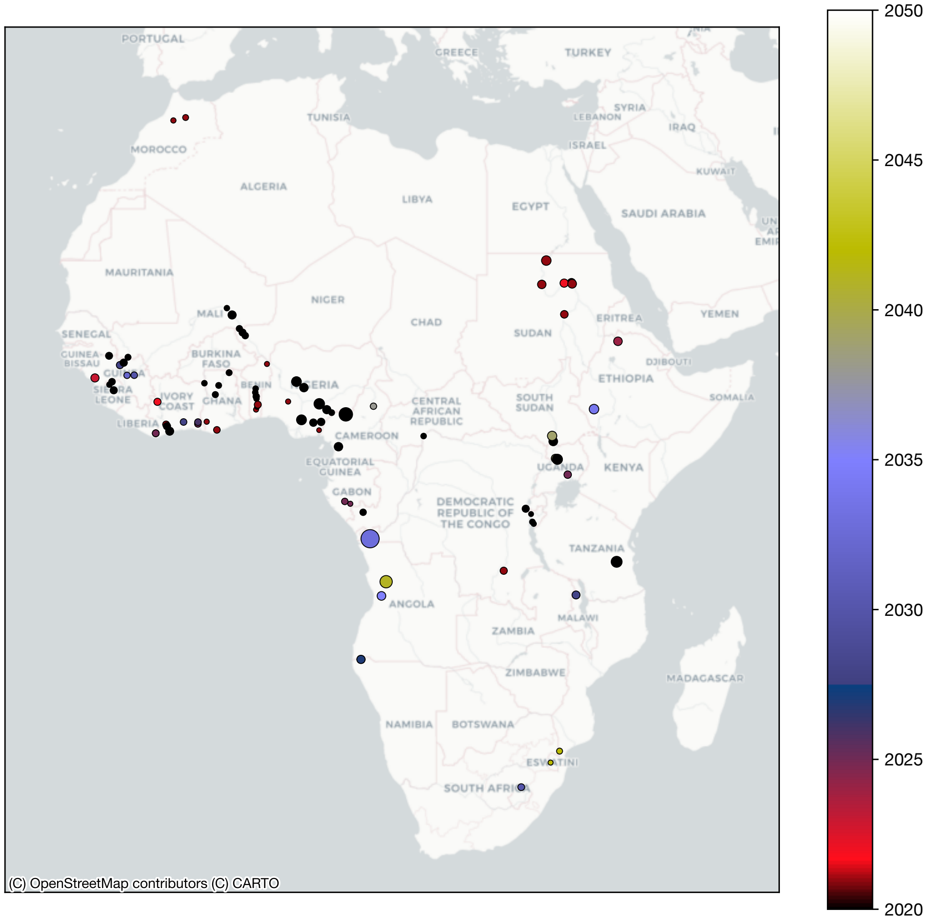

Figure 13: Location and optimal timing of dams for SSP3-Baseline

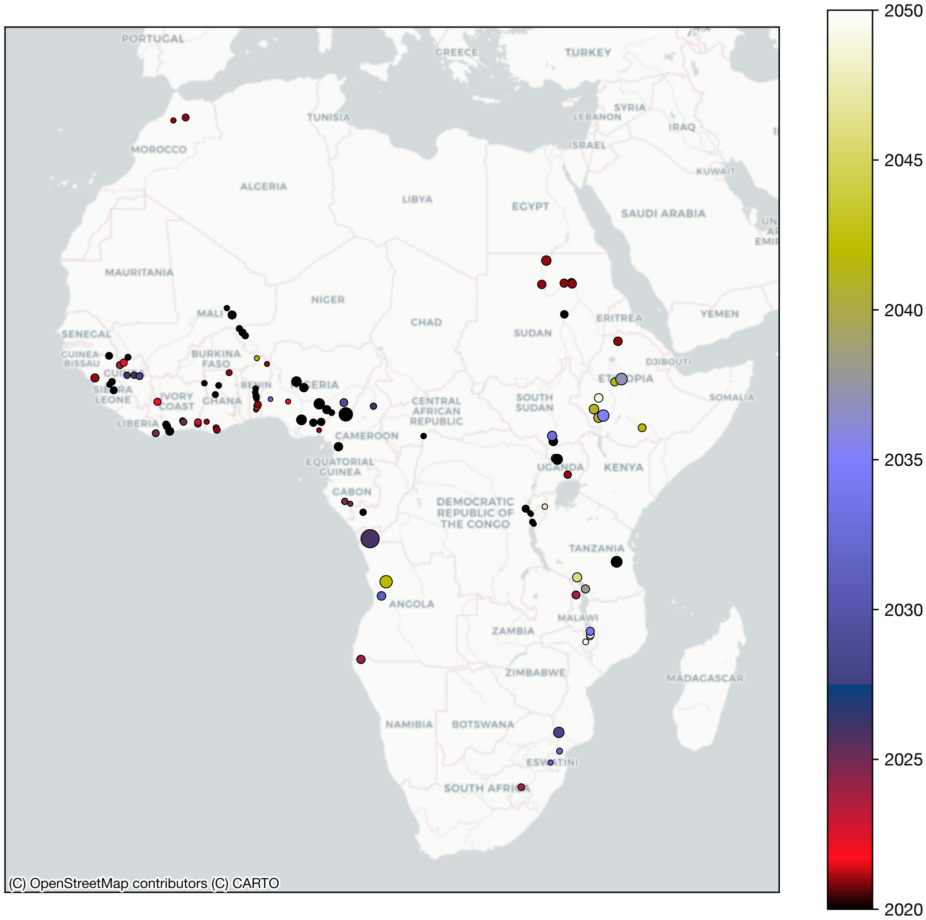

Figure 14: Location and optimal timing of dams for SSP5-Baseline

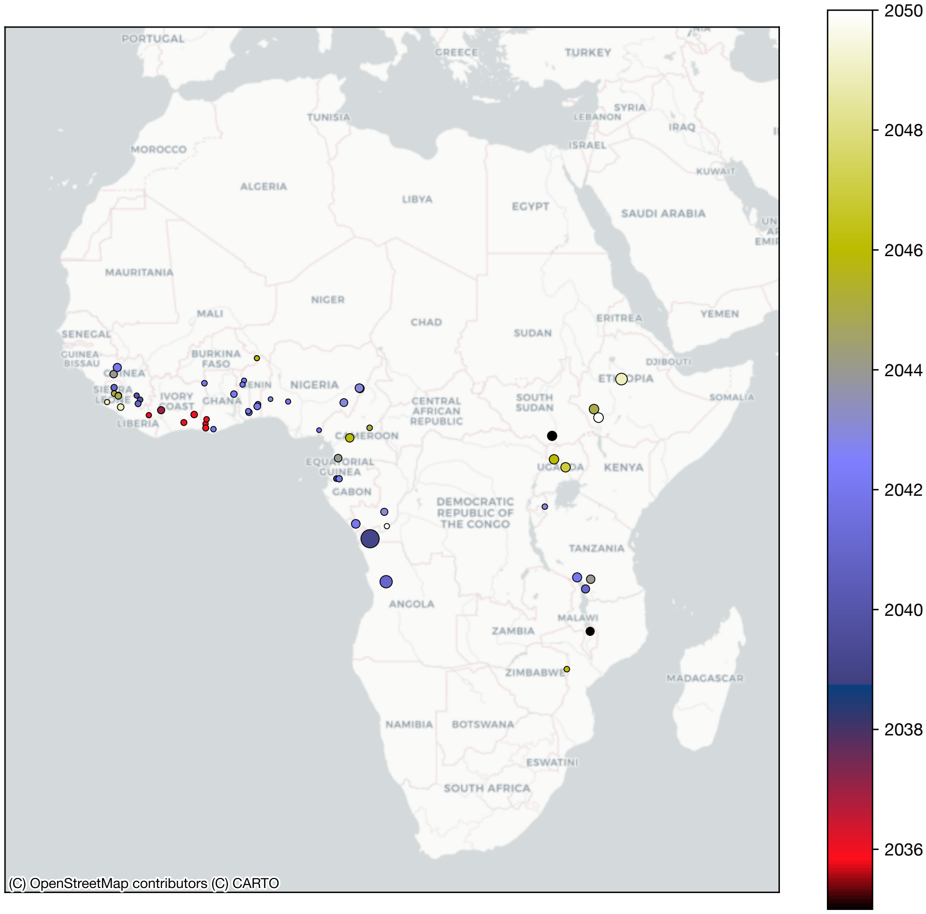

Figure 15: Location and optimal timing of dams for SSP1-19 under robust scenario analysis

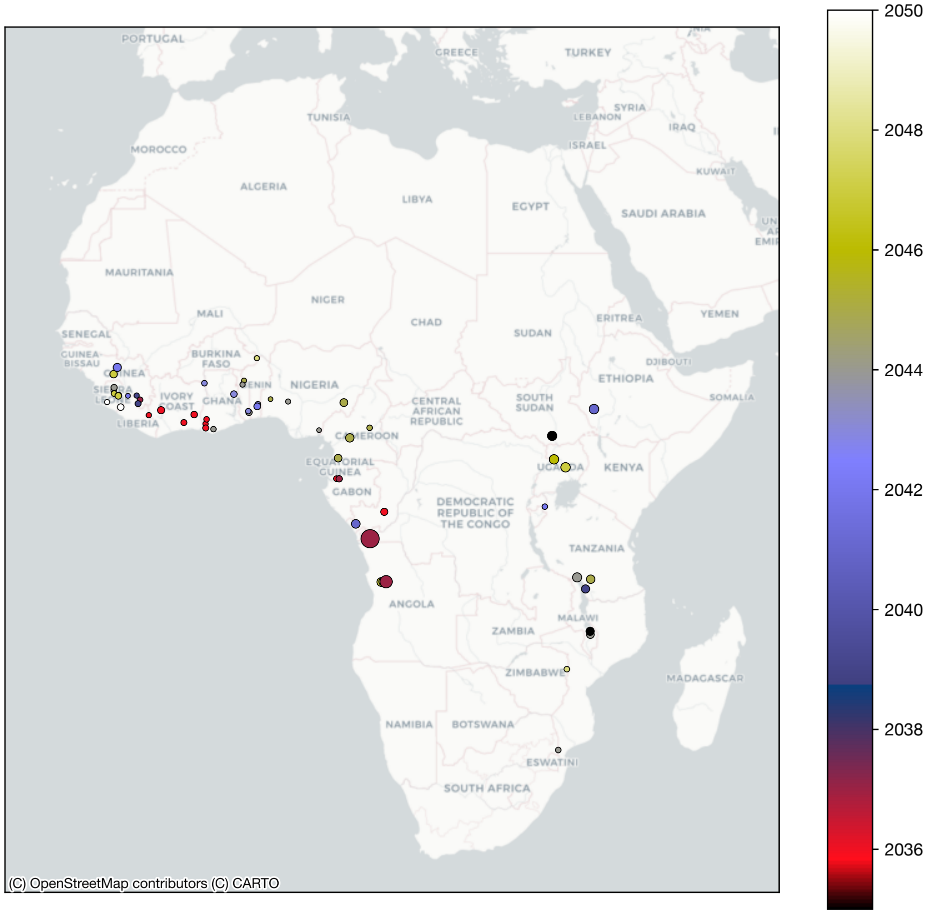

Figure 16: Location and optimal timing of dams for SSP1-26 under robust scenario analysis

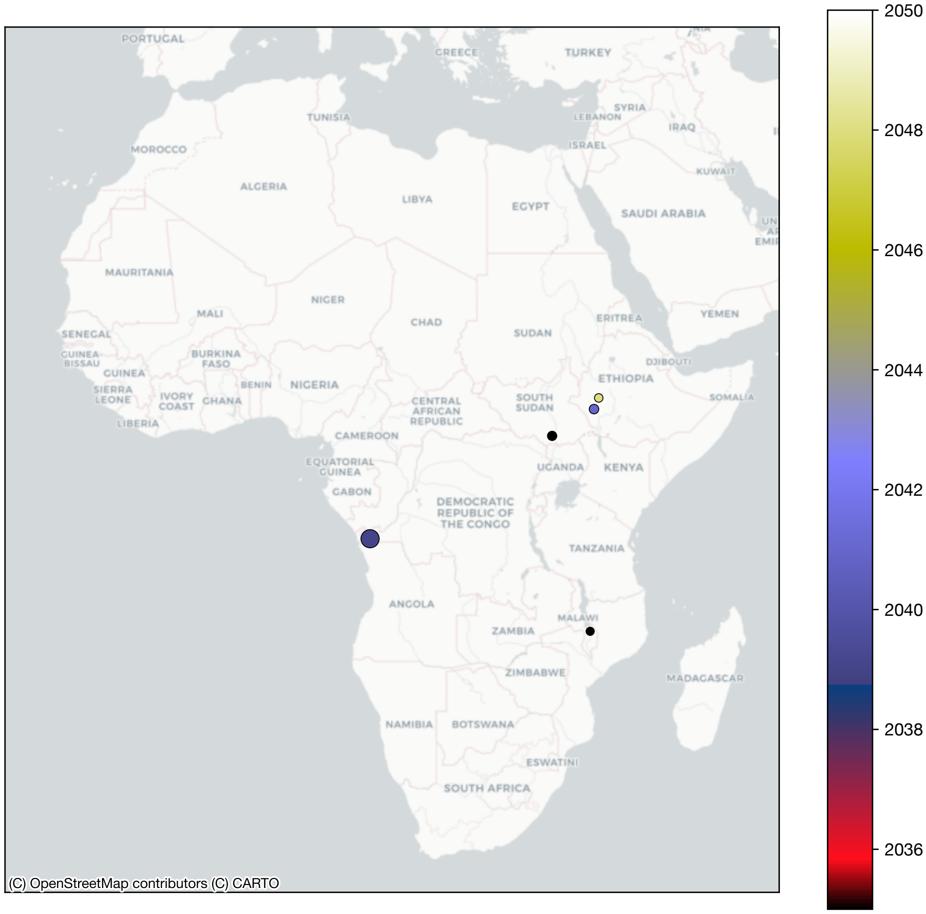

Figure 17: Location and optimal timing of dams for under SSP2-45 robust scenario analysis

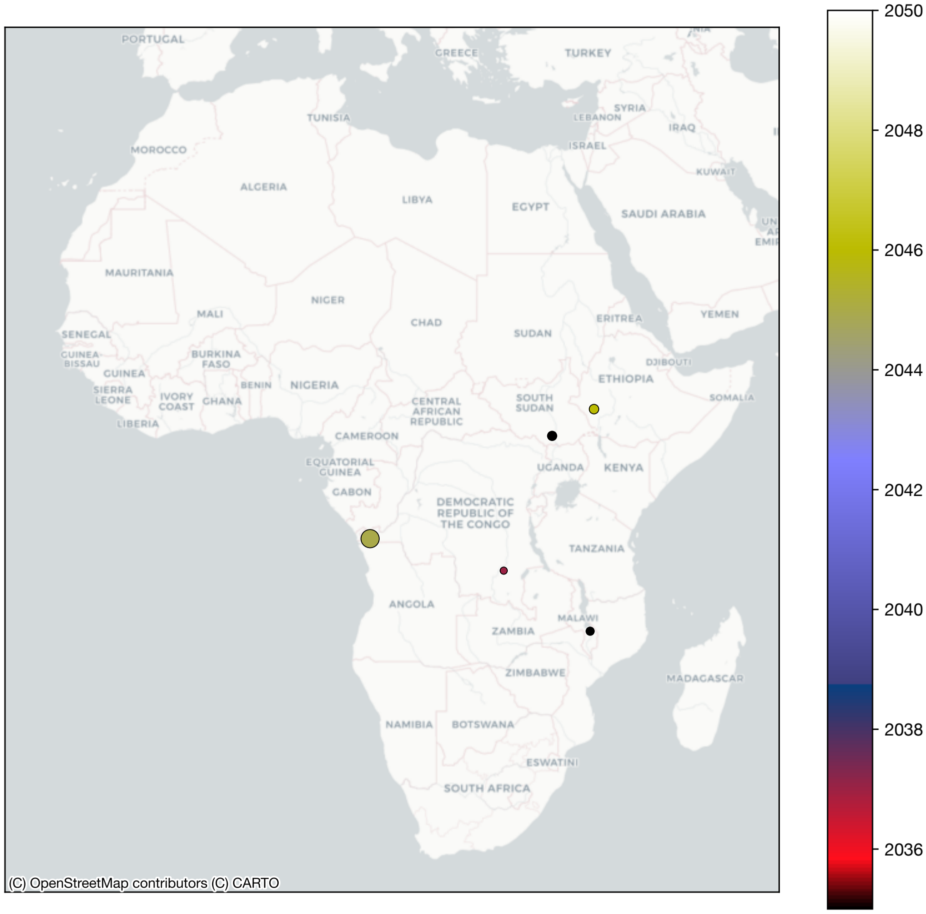

Figure 18: Location and optimal timing of dams for under SSP3-Baseline robust scenario analysis

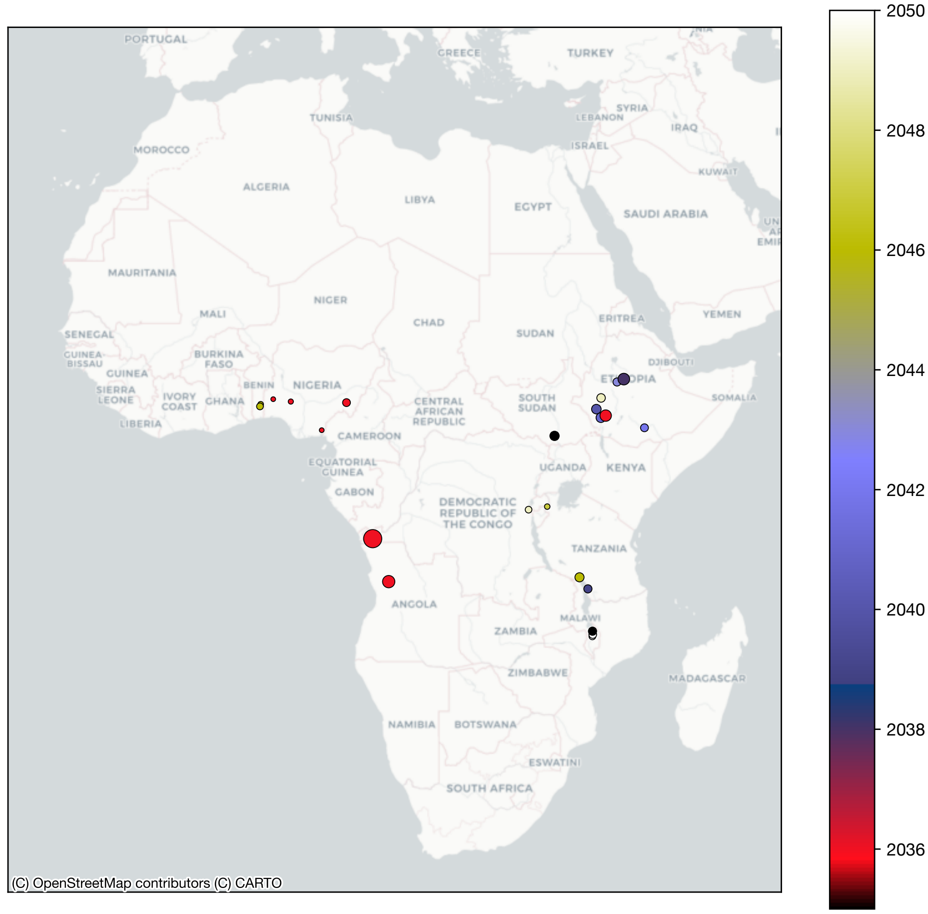

Figure 19: Location and optimal timing of dams for under SSP5-Baseline robust scenario analysis