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Climate oscillation impacts on water supply augmentation planning

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Abstract
Climate oscillations ranging from years to decades drive precipitation variability in many river basins globally. Current climate adaptation science estimates that the water sector will require new infrastructure investment of up to $100B per year[1,2]. However, these estimates focus on long-term trends, preparing for average climate conditions at mid- or end-of-century. The impact of climate oscillations, which bring prolonged and variable but temporary dry periods, on water supply augmentation needs is unknown. Current approaches for theory development in nature-society systems are limited in their ability to realistically capture the impacts of climate oscillations on water supply. Here we develop an approach to build middle-range theory on how common climate oscillations affect low-cost, reliable water supply augmentation strategies. We extract contrasting climate oscillation patterns across sub-Saharan Africa and study their impacts on a generic water supply system. Our approach integrates climate model projections, nonstationary signal processing, stochastic weather generation, and reinforcement learning-based advances in stochastic dynamic control. We find that longer climate oscillations often require greater water supply augmentation capacity but benefit more from dynamic approaches. Therefore, in settings with the adaptive capacity to revisit planning decisions frequently, longer climate oscillations do not require greater capacity. By building theory on the relationship between climate oscillations and least-cost reliable water supply augmentation, our findings can help planners target scarce

resources and guide water technology and policy innovation. This approach can be used to support climate adaptation planning across large spatial scales in sectors impacted by climate variability.

Significance Statement

Large-scale oscillations in the climate system create temporary dry spells lasting years to decades, necessitating costly infrastructure investment to maintain reliable water supply. Here, we develop methods to build theory on what approaches to water supply augmentation are reliable and cost-effective in addressing common climate oscillation patterns across sub-Saharan Africa. We find that long, decadal oscillations require the largest infrastructure investments if traditional planning methods are used. However, monitoring oscillations and responding with temporary solutions that match the period of the oscillation can mitigate the need for new infrastructure. This underscores the importance of adaptive capacity in addressing long-term climate variability and targeting infrastructure investments for climate adaptation.

Main Text

Introduction

Climate change impacts on precipitation will require new infrastructure in many regions to ensure reliable water supply for people, agriculture, and the economy[1]. Many studies use climate-model projections of long-term regional precipitation trends to assess future water infrastructure needs[3–5]. However, interannual and interdecadal variability in precipitation can have greater impacts on water supply than changes in long-term trends[6,7]. Globally, patterns of precipitation variability are linked to large-scale climate oscillations in sea surface temperatures (SST) such as the El-Niño Southern Oscillation (ENSO, 3-7 y period) and Pacific Decadal Oscillation (PDO, 10-30 y period)[8,9]. Climate oscillations have been found to impact essential water resource benefits, such as water supply[10], hydropower[11], flood control[12], and ecosystem services[13], as well as other sectors including agriculture[14] and electricity systems[15].

While there is a long literature on the impact of interannual variability on water supply[16], we do not know which types of water supply augmentation strategies, ranging from short-term management options like reducing irrigation use to long-term infrastructure development like reservoirs[17], are most cost effective in addressing different types of climate oscillation patterns. To address uncertain long-term precipitation trends, where monitoring gradual changes can indicate when adaptation measures are needed[18,19], permanent infrastructural approaches to augmenting supply, such as expanding reservoir storage capacity or installing desalination or wastewater recycling facilities, are often cost effective[20]. However, permanent infrastructure investments may be less cost effective in addressing climate oscillations, which lead to temporary dry periods, due to infrequent use. We hypothesize that dynamic planning approaches, in which water supply plans are revisited frequently, and shorter-term management solutions, like temporary water sourcing, inter-basin transfers, groundwater pumping, or demand management[21–24], may be more cost effective in addressing climate oscillations. The effectiveness of this approach likely depends on the length of the oscillation period relative to the length of the augmentation approach, as well as how quickly adaptive plans can be revisited and implemented.

Developing understanding of the impact of climate oscillation patterns on water supply planning requires new systems modeling approaches. Robust decision-making and other computational modeling methods develop high-fidelity but location-specific water supply strategies that are robust to a wide range of future climates[25–30]. Conversely, approaches that focus on developing location-independent theory on human-nature systems often require simplified system representation[31]. Balancing these goals, middle-range theory aims to understand the conditions under which a phenomenon of interest holds for a class of cases[32]. This approach has been applied in sustainability science domains including natural resource management[33], land use change[34], and energy transitions[35], but not integrated with computational decision-support modeling. Developing middle-range theory on the conditions under which different types of climate adaptation approaches can improve the reliability of infrastructure services at low cost can help water planners target scarce resources for climate adaptation across regions, enabling water, food, energy, and economic security for more communities.

Here we develop an approach to build middle-range theory on how climate oscillation patterns impact least-cost reliable water supply augmentation planning. We capture realistic representations of common climate oscillation patterns and develop theory on the planning approaches and augmentation techno-economics that ensure reliable water supply at the lowest cost. To do this, we integrate nonstationary signal processing, reinforcement learning-based stochastic optimization[36,37], and water resource systems simulation. We apply this approach to water supply planning in surface-water dominated river basins in sub-Saharan Africa (SSA), where a range of climate oscillations impact water systems[38] and new water supply is likely needed to meet growing demand and changing climates[39]. Our results show that dynamic planning approaches, where water supply is augmented in response to climate oscillations, can reduce the cost of water supply reliability for climates where long, decadal-scale oscillations dominate. However, this is only true when augmentation options with low capital costs are available, such as short-term drought management approaches, and planners have the capacity to respond quickly to changing oscillations. This approach can be used to support planners in targeting resources and innovating in technology and policy solutions across sectors impacted by climate variability.

Results

Developing middle-range theory on climate oscillation patterns and water supply planning

We apply our approach to theory development, illustrated in Figure 1. The overall approach is to identify the cost structure, lifetime, and capacity of water augmentation options that result in least-cost reliable water supply in each of five representative climates with contrasting oscillation patterns. First, we select the class of cases for which we aim to build theory. Hydrologically, we limit our cases to river basins in SSA where runoff is generated primarily by fast surface water processes and can be reasonably modeled using a lumped approach. Socially, we focus on cases where a centralized planner makes infrastructure investment decisions and has access to financing for large projects and where water demand is well characterized and must be reliably met. Additionally, given the focus on oscillations, we do not consider long-term trends in water availability or demand.

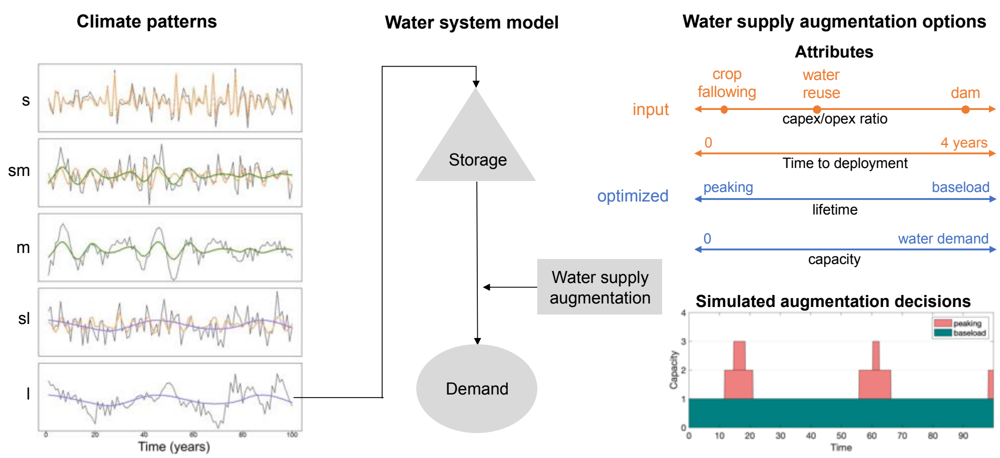

Figure 1. *Schematic illustrating approach to middle-range theory development*

After identifying the class of cases, we perform the modeling analysis. We start by using wavelet analysis to extract the dominant oscillations in subbasin-scale climate model projections of precipitation across SSA. We then select five climate oscillation patterns: short (s; 4-10 y period), medium (m; 10-30 y period), long (l; 30-60 y period), short + medium (sm), and short + long (sl). These ranges are chosen to represent common and contrasting oscillation ranges observed in the precipitation data that have meaningfully different impacts on planning. These are illustrated in the left panel where the black lines represent the precipitation time series, and the smooth colored lines represent the signal associated with each climate oscillation. For each climate oscillation pattern, we generate synthetic precipitation time series with comparable oscillations to capture stochastic variability in the oscillations. Next, the synthetic precipitation time series are used to force a generic water system model where demand is slightly higher than current runoff, necessitating water supply augmentation. In parallel, we characterize potential water supply augmentation options, defined broadly to include both infrastructural and management approaches to increasing water availability including water treatment, supply imports, and demand management. For generality, we characterize augmentation options using the following techno-economic parameters, rather than specific options: 1) ratio of capital costs to annual operating costs (capex/opex); 2) lifetime, the length of time the augmentation is available for use; 3) capacity, and 4) time to deployment (TTD), the length of time after the planner decides to augment supply before it is available for use. These parameters can represent a wide range of augmentation options. Annual management decisions like groundwater pumping[40] can be represented by a low capex/opex ratio with short lifetime and TTD. In contrast, a dam[39] has a high capex ratio with long lifetime and TTD, and water reuse[41] has intermediate values.

Finally, we apply reinforcement learning-based simulation-optimization methods to develop optimal control policies that use information about the climate oscillation signal and water storage to dynamically augment capacity. "Optimal" here means the least-cost approach that maintains 100% reliability, defined as supplying all demand across all simulations i.e. incurring no water supply deficits. We simulate the optimal policies to illustrate (bottom right) how the type, timing, and capacity of optimal water supply augmentation differs across climates oscillations. In this example, we see one unit of baseload capacity, defined as capacity deployed at the outset and stays online for the full 100-year planning period, and two units of peaking capacity, defined as capacity deployed dynamically in response to dry oscillation phases. See methods for details.

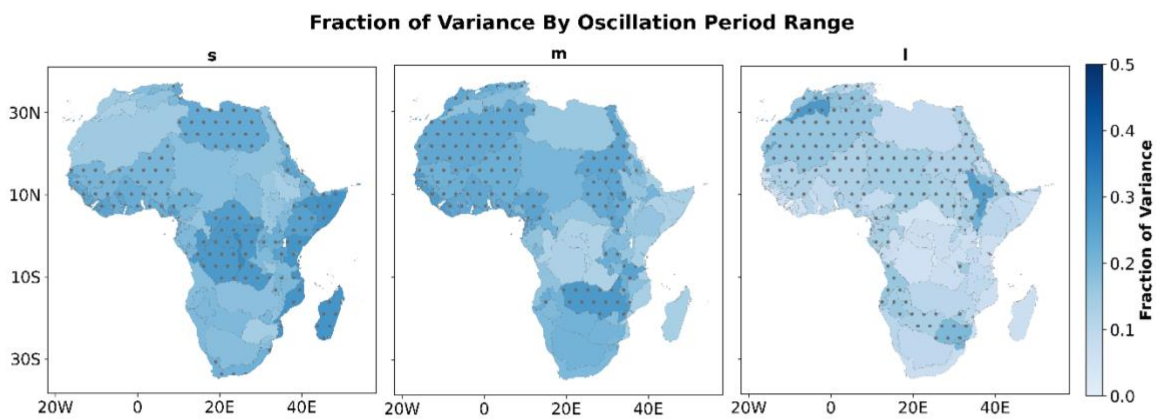

***Figure 2**: Fraction of total variance in 1950-2100 subbasin precipitation contributed by oscillation period range. Stippling indicates subbasins where the fraction of variance contributed by that period range is greater than the expected contribution from white noise. See methods for details.*

Wavelet analysis of climate oscillations across sub–Saharan Africa

Having introduced the approach, we now present results from the climate oscillation analysis in Figure 2, which illustrates the fraction of annual precipitation variability contributed by the different ranges of oscillation period: s, m, and l (see Methods). Looking across subbasins in SSA, we see large differences in which combinations of oscillations contribute above expected fractions of variance, leading to diverse climate oscillation patterns. Some regions (Southern Africa, equatorial Africa) with a large ENSO influence do not have substantial influence from m or l oscillations, while others (coastal West Africa; southern Nile; parts of equatorial East Africa) have elevated variance fractions from both s and m or l oscillations. This is consistent with previous work that found several large-scale, overlapping climate oscillations with wide ranging periods impact the variability of precipitation throughout Africa[38,42,43]. This finding highlights the importance of understanding how different climate oscillation patterns impact water supply planning.

Additionally, our results show alignment with previous studies of oscillation patterns in SSA. We find that s oscillations explain the highest proportion of annual precipitation variance throughout the continent. While high frequency oscillations typically comprise the greatest share of variance in any time series, many subbasins, indicated by stippling, show more variance than expected compared to white noise. These subbasins are focused in equatorial Africa, the region of the intertropical convergence zone (ITCZ), as well as Southern Africa. This is consistent with previous studies that identify the influence of ENSO in modulating advection of moisture into these regions[44–46]as well as its influence on the position of the ITCZ[42]. Longer period oscillations (m or l) contribute relatively greater variance outside of equatorial Africa. This could be due to the stronger PDO influence in these regions[38]. The alignment of our findings with previous studies demonstrates that the wavelet analysis is an appropriate method for capturing a wide range of climate oscillation patterns across SSA to use for middle-range theory development.

Impact of climate oscillation patterns on optimal water infrastructure augmentation

Next, we present results from the optimization analysis on the impacts of contrasting climate oscillation patterns on least cost reliable water supply augmentation approaches in Figure 3. First, results show that climates with longer oscillation periods often but not always require a greater average capacity of water supply augmentation. When storage capacity is low (panel a), maintaining reliable supply requires additional baseload capacity across all climate oscillation patterns. This is a static approach to addressing climate variability by adding capacity at the outset to be prepared for future uncertainty. The downside of the static approach, however, is that it risks stranding assets with long lifetimes that are used infrequently. Additionally, in climate oscillation patterns with longer periods, we see an increasing amount of peaking capacity, which is brought online dynamically in response to low storage levels and dry oscillation phases. See Figure S1 for an illustration of dynamic vs. static approaches.

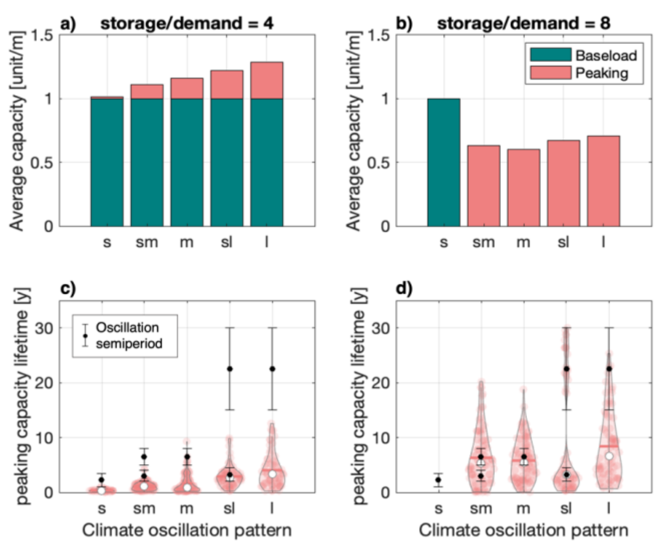

***Figure 3**: Capacity and lifetime of optimal infrastructure augmentation by climate oscillation pattern. Top row: Average capacity across simulations of baseload vs. peaking supply infrastructure. Bottom row: Distribution of lifetime of peaking capacity by climate, with red each point representing one capacity augmentation and surrounding violin plot representing density of lifetimes across simulations. Black points and bars show oscillation half-period average and range. Left column: Existing storage =4x monthly demand. Right column: Existing storage =8x monthly demand.*

Results are from baseline scenario where: no water supply deficit is incurred (i.e. 100% reliability), demand is 7% greater than mean annual runoff, and capex is 4x annual opex.

However, when more storage is available (panel b), the direct relationship between oscillation period and capacity disappears. The s climate oscillation pattern has higher, rather than lower, average capacity. This is driven by the limited value of peaking capacity for addressing short oscillations due to two reasons. First, responding dynamically to short oscillations with <10 year periods would require frequent augmentation and associated capex, which is four times of the cost of annual opex in our base case. Second, the short oscillation signal is noisier than longer oscillation signals, so the policy is not able to learn clear patterns in the signal and anticipate future oscillations as easily.

We also identify a striking relationship between the oscillation period length and the lifetime of the peaking augmentation capacity, shown in panels c) and d). Similar to the average capacity results, we see longer lifetimes for peaking capacity associated with longer climate oscillations. More specifically, when there is no baseload capacity (panel d), the distribution of lifetimes of the peaking capacity is centered around the oscillation half period. Compound climate oscillation patterns, like sl, have a bimodal distribution with high density of lifetimes centered about each oscillation half period. When lower storage leads to baseload capacity (panel c), lifetimes are shorter, centered around approximately the oscillation quarter-period. This result is driven by the dynamic behavior of peaking capacity, responding only to dry oscillation phases. When ample storage is available and oscillations are > 10 years, baseload capacity is not cost effective because it is used less frequently, and peaking capacity addresses the full dry phase of the oscillations. However, without storage, a greater volume of baseload capacity is cost effective, leading peaking capacity to address only the most severe part of dry oscillations. Figure S2 shows these results for additional storage/demand ratios, demonstrating that the relationship between oscillation period length and peaking capacity lifetime does not depend on the specific values of storage and demand shown in Figure 3. It does depend on the choice to focus on cases where reliability is always met. Figure S5 shows that minimal baseload capacity is used when substantially higher water supply deficit is allowed, a fundamental change from the peaking behavior discussed here.

Interactions between climate oscillation patterns and augmentation techno-economics

Next, we analyze the role of techno-economic parameters, which vary considerably across augmentation options, in mediating the effect of climate oscillation patterns on least cost augmentation approaches (Figure 4). For example, large-scale water reuse technologies may have high capex and require several years to deploy, while non-infrastructural augmentation options, such as repurposing irrigation water from fallowed agriculture fields, may require little capital but incur high annual costs. We find that increasing the capex/opex ratio of available water augmentation favors augmentation approaches with more capacity and longer lifetimes. This reflects a shift to a greater proportion of baseload, rather than peaking capacity. Instead of responding dynamically and incurring multiple large capital costs, it is more cost effective to build excess capacity early and keep it online for a long time. This is demonstrated in Figure 4a), where the average capacity across simulations increases and eventually plateaus at an integer increment corresponding to the amount of baseload capacity added. This finding holds when higher water supply deficit is allowed, though the differences across climate oscillation patterns diminish. See Figure S6. In contrast, lower capex/opex ratios favor optimal water supply augmentation strategies that respond dynamically, augmenting supplies in response to the dry phase of an oscillation.

Interestingly, the mid-range climate oscillation patterns (sm, m, sl) have longer average lifetimes at high capex/opex ratios compared to s and l (Figure 4c). This reflects that more dynamic peaking behavior occurs in both oscillation extremes when capex/opex ratios are high. Responding dynamically to long oscillations is cost effective because it requires the least number of new capital expenses, while responding dynamically to short oscillations is cost effective because it reduces the amount of capacity required, only adding peaking capacity in the most severe droughts. Figure S3 illustrates this process over time for a few simulations representing different climate oscillations.

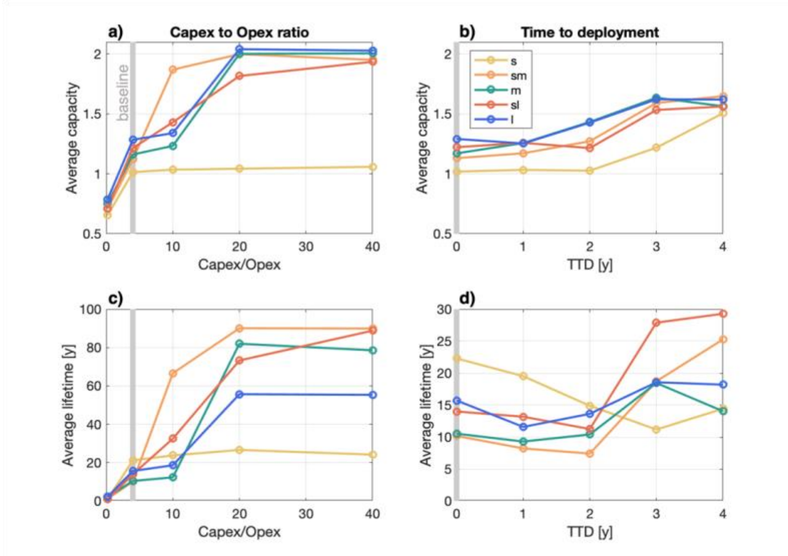

Figure 4*: Influence of capex/opex ratio and TTD on average capacity (top row) and lifetime (bottom row) of optimal water augmentation by climate oscillation pattern (colored lines). Baseline scenario values of capex/opex and TTD shown in grey bar. Results show the least-cost solution with 100% reliability (i.e. incurs no deficit), assuming existing storage of 4x demand*

Finally, we find that increasing TTD has only a modest effect on optimal augmentation strategy, leading to a slight increase in average capacity and no consistent trend in average lifetime (Figure 4 b,d). This contrasts our initial hypothesis that longer TTD makes it more difficult to respond in real time to dry conditions. This may be due to two factors. First, the length of the dry phase (oscillation half period) is long compared to the TTD range; an extra year may not affect the dynamics in a 20-year oscillation. Second, we assume that the planner knows the current phase of the climate oscillation signal, providing insight on whether precipitation is likely to increase or decrease in the future, which may offset the effect of greater TTD. Collectively, the results in Figure 4 highlight that the types of water augmentation options available in a basin have a large influence on the amount and timing of capacity that is needed for low-cost reliable water supply.

Decision frequency impacts on least-cost water augmentation

Our previous results demonstrate that a dynamic strategy that augments supply in response to dry oscillation phases can maintain reliable water supply at lower cost when oscillations are long and costs are dominated by operating, rather than capital, expenses. However, this finding assumes that water supply planners can revisit augmentation decisions monthly. In practice, water supply plans are often revisited only once every 10 years. Our final result, illustrated in Figure 5, assesses the impact of decision frequency on the cost of water supply augmentation required under different climate oscillation patterns.

Results illustrate three main findings. First, total costs increase as the time between decisions increases, and this cost increase is greater for climate oscillation patterns with a m or l component. The nonlinear shape of the curves suggest that, for regions currently making decisions every 10 years, a large increase in decision frequency, to ~2 years, is required to achieve substantial cost savings. This reflects the cost savings of revisiting decisions more often when a dynamic approach is used to augment supply. Indeed, much of the cost increase in m and l climate oscillation patterns results from a transition from a dynamic to a static water supply augmentation approach. Figure S4 illustrates this in a few simulations over time. Second, when augmentation decisions are revisited monthly, the total cost is about the same for all climate oscillation patterns except s. This highlights the challenge of planning for oscillations longer than 5 years: static approaches with enough capacity to weather long dry phases are prohibitively expensive, but dynamic approaches come with increased incurrence of capital costs. Third, the variance in costs is greater for climate oscillation patterns with an s component. Optimal control policies for s oscillations rely primarily on baseload capacity, with rare deployment of additional short-term (~1 year) peaking capacity to buffer emergency shortages. The occurrence of this "emergency peaking" behavior (illustrated in Figure S1), is highly variable across simulations, driving high variance in costs because emergency peaking is costly. These results demonstrate the benefit of building adaptive capacity in planning institutions to revisit decisions more frequently, especially in regions facing climate oscillation patterns with long periods.

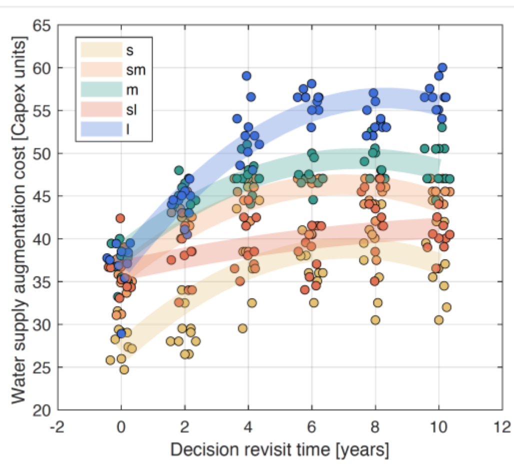

Figure 5*: Total cost of water supply augmentation alternatives over 100-year planning period by climate oscillation pattern and decision revisit time. Costs here refer to the total capital and operating costs over the 100 year planning period, quantified in capex units where 1 capex unit = the capex of 1 additional unit of augmentation. Scatter points correspond to 10 simulations from the optimal policy from each climate oscillation pattern and decision frequency. Colored bands present a second-order polynomial trend line to interpolate between decision frequencies. Results shown for baseline scenario where no water supply deficit is incurred (i.e. 100% reliability), capex/opex ratio = 4, and storage/demand = 4.*

Discussion

In this study we analyze the impact of climate oscillations with periods ranging from years to decades on water supply augmentation planning. Much of climate adaptation science has focused on long-term trends, preparing for average climate conditions at end-of century. However, our results highlight the large influence of interannual and interdecadal variability on precipitation and demonstrate that a wide range of contrasting climate oscillation patterns impact precipitation across SSA. This underscores the importance of understanding how oscillations with different periods impact planning in water supply and other precipitation-dependent sectors – impacts which are less obvious than long-term trends alone.

Our results identify opportunities to reduce the need for large, long-lived projects to manage climate variability. While climates with longer oscillation periods often require a greater average capacity of water supply augmentation with longer lifetimes, longer oscillations also make it easier to leverage dynamic peaking augmentation strategies, reducing the average capacity needed to maintain reliability. This is because dry spells occur less frequently and because monitoring longer oscillation signals provides more advance warning of dry spells. Conversely, dynamic peaking has limited usefulness in addressing short oscillations. Responding dynamically to short oscillations would require augmentation every 2-5 years and incur high capital costs each time, and the noisiness of the climate signal increases the frequency supply is augmented but not needed. The dynamic approach is more effective when augmentation strategies have lower capex/opex ratios, suggesting that either short-term management approaches technology innovation to reduce capital, rather than operating, costs may be especially useful in regions with long oscillations.

Additionally, a planner's ability to revisit augmentation decisions frequently reduces the cost of reliable water supply by making dynamic augmentation cheaper. Indeed, when decisions can be revisited annually, the cost of maintaining reliability is about the same across all climate oscillation patterns. When decisions can only be revisited every 10 years, the cost in l climate oscillations in nearly double the cost in s climate oscillations. This suggests an important interaction: adaptive capacity to respond nimbly to dry periods is more important in settings where low capex, non-infrastructural strategies such as inter-basin transfers, crop fallowing, and managed aquifer storage are available. In settings where institutions cannot revisit decisions frequently, large infrastructural augmentation options that leverage economies of scale are more cost effective. This has important equity implications, as large infrastructure projects frequently have negative environmental and social impacts on local communities. This suggests an opportunity for multilateral development agencies to focus on investing in adaptive capacity that enables dynamic augmentation approaches rather than large infrastructure investments like dams and pipelines, especially in regions where precipitation variability is driven by longer-term oscillations. Looking across domains, we hypothesize that while long-term climate oscillations challenge infrastructure service provision, building adaptive capacity to monitor oscillations and respond with temporary solutions that match the period of the oscillation can reduce the need for new infrastructure.

While basin-specific case studies guided by local expertise are essential, building theory on the conditions under which different adaptation solutions are effective can play an important role in planning as well. Understanding the broad classes of water supply augmentation approaches that are cost effective for different climate oscillation patterns prevalent across SSA can provide screening analysis to target resources. Additionally, by focusing on techno-economic characteristics of least-cost water augmentation rather than location- and technology-specific options, theory can guide innovation efforts in water technology and policy. Future work could scale our approach to all the climate oscillation patterns across SSA, coupled with more variation in hydrological system representation, to identify what classes of water supply approaches are likely to benefit a wide range of regions. Future work could also adapt the approach to support planning in other sectors affected by climate oscillations such as agriculture and electricity systems.

The benefit of middle-range theory lies in identifying general in solutions; however, the generalizability is limited to the specific class of cases that can be represented within the systems modeling approach used. For example, we identify a striking relationship between oscillation period length and augmentation lifetime, with the lifetimes of peaking capacity approximately equivalent to an oscillation half-period without baseload capacity available and an oscillation quarter-period with baseload. This relationship is general across storage volumes but only holds when reliability is 100%. Further, it is limited by simplifying assumptions made about the hydrology, demand, and planning context in our chosen class of cases. Future work can further explore the conditions under which our findings hold and increase the direct usefulness to planning. In particular, future work can more fully explore a multi-objective analysis, evaluating how least-cost planning strategies change when demand management is used and reliability is not constrained to 100%. Addressing demand uncertainty is an important area for future work, given that demand uncertainty is often greater than supply uncertainty[47] and that water demand is likely correlated with climate oscillations as well. In many river basins, augmentation decisions are made by multiple institutions, not all of which have ready access to infrastructure financing; future work can explore these different panning contexts. Finally, the current insights we develop are independent of specific locations, and future work can use case studies and leverage ensembles of climate models to validate theoretical findings against high fidelity regional analysis.

Materials and Methods

Data and Code

To analyze the climate oscillation patterns across subbasins in SSA, we obtain annual precipitation timeseries (1850-2100) from CMIP6 climate scenario SSP2-4.5 of FIO-ESM-2-0[48], which was chosen as it has been found to simulate observed Nino sea surface temperature patterns and precipitation teleconnections in Africa relatively well[49]. However, climate models have generally been demonstrated to poorly capture climate dynamics in SSA[50], and developing more reliable model projections in the region remains an active area of research. The use of one model is sufficient for our focus, which is to identify a range of oscillation patterns that reflect realistic and contrasting patterns of climate variability across SSA to use in location-independent theory development. We confirm this by comparing our findings to previous literature on oscillations in SSA. Assessing a larger number of GCMs would likely provide more robust spatial patterns for each oscillation period, which is outside the scope of the present study. We use a model projection rather than reanalysis data both to provide the longest possible time series for analyzing multidecadal oscillations and for consistent representation of the physical mechanisms underlying oscillations, which are likely to be less reliable in reanalysis due to limited data availability in SSA. First, we use spatial averaging to convert the precipitation timeseries to subbasin averages. We use subbasin definitions from WMO Basins and Sub-Basins (WMOBB) project of the Global Runoff Data Centre (GRDC)[51], chosen as a scale relevant for water supply planning. Second, we fit and remove a trend using local polynomial regression, allowing us to isolate the impact of oscillations on water supply. Third, we calculate standardized anomalies, facilitating comparison of power spectra across subbasins with different levels of precipitation. Computer code used in this study is available at: https://github.com/m-zaniolo/Climate-oscillation-impacts-on-water-supply-augmentation-planning

Wavelet Analysis

To identify dominant oscillations patterns of precipitation, we apply wavelet analysis following the methods described in[52] to each subbasin. Designed for spectral analysis of non-stationary, non-periodic signals, several studies have applied wavelet analysis to identify climate oscillations in precipitation time series e.g.[53–55]. We use a Morlet wavelet, a common choice in climate analysis for its high frequency resolution[56], a time step δt of 1 year, and vary the scale s from 1 to 80 years with a decomposition level ds of 1/100 to calculate the wavelet power spectrum for each subbasin. To compare the relative power, or contribution to overall variance, of oscillations of different periods, we divide the periods into: short (s; 4-10 years), medium (m; 10-30 years), and long (l; >30-60 years). We choose these ranges, first, because they are distinct enough to have meaningfully different planning implications and, second, because the data showed elevated variance in these regions in many river basins. We did not include periods <4 years because nearly all basins showed high variance contributions in the <4 year range, and the wavelet approach could not distinguish between typical annual variability and elevated variability from oscillations with <4 year periods. We calculate the area under the curve of the global wavelet power spectrum (GWP) across each period range, which reflects the fraction of total variance in the time series the period range contributes[57]. Finally, we calculate the statistical significance of the global wavelet power spectrum at each scale value by comparing it to the global wavelet power spectrum of white noise[52].

Identifying Representative Subbasins

We analyze the effects of five representative climate oscillation patterns: short only (s), short and medium (sm), medium only (m), short and long (sl), and long only (l), defined by having statistically significantly pronounced variance contributed by the corresponding period range relative to white noise. We develop these, first, by selecting three subbasins with s, sm, and sl oscillation patterns using spectral peaks in the GWP. For example, we consider a subbasin with two statistically significant spectral peaks, one 4-8 years in period and the 10-16 years in period, to represent a sm climate oscillation pattern. To facilitate the stochastic precipitation generation, we also select subbasins with clear, well-defined significant spectral peaks. Using these criteria, the subbasins we selected are shown in SI Figure S6 with plots of the GWP and locations. To develop the m and l climates, we remove the short oscillation component from the m and l climates respectively.

Stochastic Precipitation Generator

For the three selected subbasins, we apply stochastic weather generation methods to develop an ensemble of plausible precipitation timeseries with similar climate oscillations patterns. We use the wavelet-based block k-Nearest Neighbors (kNN) algorithm[58]. Wavelet component signals are reconstructed for each statistically significant period range using the wavelet transform, following[52]. This allows to decompose the original time series P_t into up to C =3 components $S_{c,t}$ with a frequency band in s, m, and/or l ranges. The frequency band is chosen to reflect the statistically significant spectral peaks from the GWP. Each component comprises an oscillation signal that explains a significant proportion of total variability. The decomposition also includes a residual series ε_t, with the full decomposition as follows: $P_t = \sum_{c=1}^{C} S_{c,t} + \varepsilon_t$. Unlike the traditional block kNN, we apply bootstrap resampling separately to each wavelet component signal $S_{c,t}$. We use parameter values of number of neighbors k=20 and block size B = 10, which were manually calibrated to produce time series with visually realistic synthetic component signals and apply smoothing spline regression to the joins between the blocks. We produce one hundred 100-year time series for each climate oscillation pattern. SI Figure S7 presents a sample of synthetic time series. Finally, we use a novel validation approach to confirm the synthetic precipitation time series have similar wavelet spectra to the historical time series they were based on: we compare the fraction of variance contributed by short, medium, and long period ranges to that of the historical time series. Validation results are shown in SI Figure S8. The output of the generator yields synthetic precipitation time series that maintain similar oscillation patterns to the original time series but captures stochastic variability in both the specified climate oscillation signal and other frequencies. This output is used to force the simulation model for the optimization, detailed below.

Water Resource Simulation Model

We use a lumped, conceptual water resource system model with a monthly time scale to explore the effect of climate oscillations on oscillation water supply infrastructure planning. The model was originally developed for the Mwache River, a surface water system with one major reservoir and optional supply augmentation which together supply agricultural and urban demand. Water supply augmentation capacity is installed in incremental units per month, where demand totals 90 units per year. Mean annual precipitation and runoff are 846 mm and 113 MCM/year respectively. We rescale the standardized anomalies of the synthetic precipitation time series using the mean and variance of precipitation in Mwache, and we disaggregate to monthly values using the historical monthly seasonality of precipitation. The rainfall-runoff process is modeled using CLIRUN II[59,60]. Because the rainfall-runoff process is dominated by surface water with approximately annual residence times and our climate oscillation analysis focuses on interannual variability, our analysis is insensitive to the specific rainfall-runoff processes and seasonality in Mwache, making it generalizable to other subbasins dominated by fast surface water processes. Additionally, we make the analysis insensitive to the specific precipitation and runoff characteristics in Mwache by representing all precipitation, runoff, and demand quantities in relative, rather than absolute terms. We assume that demand is 7% greater than mean annual runoff. Demand is fixed and not considered as an uncertainty in the model. The simulation model computes two objectives: J^{Cost}, the sum of installation costs and annual operating costs of water supply augmentation, and $J^{Deficit}$ the squared volume of water supply deficit over 100-years.

Techno-Economic Parameters

To develop theory on the relationship between climate oscillations and water infrastructure techno-economics, we model new capacity using an abstracted representation of technologies with adjustable techno-economic parameters, rather than specific technologies themselves. We model water supply augmentation as a technology which provides constant, precipitation-independent capacity. This could represent a range of specific technologies, including water reuse, production, imported supply, groundwater banking, or demand management such as crop fallowing. Water supply augmentation is characterized by the parameters in Table 1; each parameter is either pre-specified (S) and varied using sensitivity analysis or optimized (O) by solving the optimization problem described in the next section. Table S1 in the SI details all baseline assumptions as well as the sensitivity analysis performed on techno-economic parameters. We model total undiscounted costs so that insights about the utilization of dynamic, small-scale augmentation strategies can be clearly attributed to hedging against supply uncertainty and not to discounting incentives to delay capital costs. We do not model cash flow limitations, which is aligned with focus of our class of cases being limited to systems with ample access to infrastructure financing.

Lifetime	Capex/Opex ratio	Capacity
Continuous O: 0-100 years	S: 4 in baseline scenario; sensitivity between ¼ and 40	Integer O: 0-6 units of annual demand

Table 1. *Representation of water supply augmentation techno-economics*

Optimization

We formulate our analysis as a multi-objective stochastic dynamic control problem representing the decision policy π of a planner to augment water supply while minimizing water supply deficit $J^{deficit}$ and water augmentation costs J^{Cost} . We assume that the planner knows the current phase of the underlying climate oscillation signal and how the climate oscillation signal has changed in the past 6 months. The future phase of the oscillation cycle is related to the recent evolution of the oscillation; therefore, including recent evolution of the oscillation gives the planner partial information about the future. However, the planner does not have explicit foresight into future oscillations or future precipitation; thus, precipitation is an unknown, stochastic forcing in the optimization model represented by the synthetic precipitation time series. This reflects current climate science, in which, for example, the current state of the ENSO cycle is well known and used to make predictions about future phase changes. We also assumed that demand is fixed and known by the planner focusing the scope of our analysis on supply-side rather than demand-side uncertainty.

The control problem is formulated as follows. The current state of the system x_t is a vector comprising indicator variables x_t= {S_t, I_t, O_t^i, D_t^i}. S_t is the reservoir storage volume in time t and I_t is the capacity of installed water augmentation in time t. O_t^i is the amplitude of oscillation signal component i in time t where $i \in \{s, m, l\}$. D_t^i is the difference between the signal at times t and $t-6$ months for the relevant climate signal(s) for the basin. Including these signal components as indicator variables reflects that the planner knows the current oscillation phase, and how it compares to the phase 6 months ago. The state transition equation is $x_{t+1} = f(x_t, \varepsilon_t, \pi)$ where ε_t is the disturbance forcing from the synthetic precipitation time series in time t, π is the planning policy, and f is the system dynamics of the water resource simulation model. The planning policy π links the state of the system with the planning decisions u_t which specify the decision to augment capacity: $u_t = \pi(x_t)$. We search for the optimal control policy using direct policy search, which specifies π within a class of functions $\pi = \pi(\theta)$ and searches for its optimal parameter set θ^*. We select a single layer gaussian radial basis function as the functional class given their flexibility[39]. We search for θ^*using a heuristic simulation-optimization approach in which a genetic algorithm identifies a set of policies approaching the Pareto frontier. All the results presented in the main text have 100% reliability i.e. the part of the Pareto frontier where J^{defict} = 0. This is equivalent to a single-objective formulation to minimize J^{Cost} subject to a 100% reliability constraint. Figure S5 and S6 in the SI illustrates the tradeoffs between J^{Cost} and J^{defict} in the multi-objective formulation. However, the main results, and therefore general relationships identified, apply to the 100% reliability case only.

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