Anticipating water distribution service outages from increasing temperatures

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Abstract

With projected temperature increases and extreme events due to climate change for many regions of the world, characterizing the impacts of these emerging hazards on water distribution systems is necessary to identify and prioritize adaptation strategies for ensuring reliability. To aid decision-making, new insights are needed into how water distribution system reliability to climate-driven heat will change, and the proactive maintenance strategies available to combat failures. To this end, we present the model Perseus, a framework that joins a water distribution network hydraulic solver with reliability models of physical assets or components to estimate temperature increase-driven failures and resulting service outages in the long term. A theoretical case study is developed using Phoenix, Arizona temperature profiles, a city with extreme temperatures and a rapidly expanding infrastructure. By end-of-century under hotter futures there are projected to be 1%–5% more pump failures, 2%–5% more PVC pipe failures, and 3%–7% more iron pipe failures (RCP 4.5–8.5) than a baseline historical temperature profile. Service outages, which constitute inadequate pressure for domestic and commercial use are projected to increase by 16%–26% above the baseline under maximum temperature conditions. The exceedance of baseline failures, when compounded across a large metro region, reveals potential challenges for budgeting, management, and maintenance. An exploration of the mitigation potential of adaptation strategies shows that expedited repair times are capable of offsetting the additional outages from climate change, but will come with a cost.

1. Introduction

With increasing evidence of rapid changes in climate and resulting extreme events, infrastructure—the physical systems and managing institutions that deliver critical resources and protect us from hazards—must continue to perform reliably. Yet the designs of infrastructure are often made assuming that past climatic and hydrological conditions will persist into the long term (Chester and Allenby 2018), and the rules and codes by which they are designed do not change quickly (Olsen 2015, Chester et al. 2020). The confluence of a rapidly changing climate and slow-changing infrastructure, designed assuming stationarity of variability, results in a potential crisis (Chester and Allenby 2018, Milly et al. 2008). Without strategic investment, increasing failures of physical assets, or components, and resulting service outages can occur without the means to properly respond. Serious questions remain as to whether our currently deployed infrastructure can remain functional as climate changes and during extreme events, the latter when people may need critical services the most.
In arid and semi-arid regions with hot temperatures, potable water delivery is an infrastructure system of particular concern. Water is a critical resource, not just for drinking, but often for industries that drive economies (such as manufacturing and agriculture), and even for power including for coal generated, hydropower, and natural gas (Guhathakurta and Gober 2007, Bartos and Chester 2014, Hwang and Lansey 2015, Berardy and Chester 2017, Eisenman et al 2016). This is particularly true in the semiarid Southwest US where scarce water resources are transported long distances, populations have and are forecasted to grow significantly, agriculture remains a major activity, and thermoelectric power generation continues to supply a large fraction of energy (Bartos and Chester 2015). If there is a continuation of the current path of global emissions, projections up to a 5 °C increase in average temperatures in the Southwest by the end of the century may occur, relative to the last century (RCP 8.5 avg) (Melillo et al 2014). If radiative forcing is instead stabilized shortly after the year 2100 without overshooting the long-run radiative forcing target level, there is projected to be an average 3 °C increase (RCP 4.5) (Melillo et al 2014). There has been a great deal of work to understand how the accessibility of water resources might change as populations and climate change (Garfin et al 2014). However, there remains a dearth of knowledge of how water infrastructure—in distribution systems in particular—might perform under increasing local temperatures and what that means for water delivery reliability. Evidence accumulates that increasing temperatures affect the reliable operation of components within water infrastructure, and the failure of one or more components could lead to cascading effects (Bondark et al 2018). Temperature affects component wear that results in the potential for overheating of motors (Banerjee et al 2020). The Perses model is designed to simulate the reliability of water distribution systems into the future under long-term exposure to different temperature projections. The model is programmed in Python v2.7 and interfaces with EPANET, a US EPA-designed hydraulic solver (United States Environmental Protection Agency 2020). Multiple temperature scenarios are used as inputs, including a baseline (where historical temperatures persist, i.e., no climate change) and future projections with changing temperatures based on global circulation model (GCM) ensembles (IPCC 2021). Perses stochastically fails components of water distribution systems which are sensitive to temperature—namely motors and electronics within pumps, along with PVC and iron pipes—in each time step based on their temperature exposure and robustness, and then assesses the state of components in EPANET to track the consequential service outages, considering daily demand patterns and hydraulic flows.
The program tracks the time of failed components and repairs according to given repair times. The results show a comparison of the increases in pipe and pump failures and how water outages increase under different temperature change scenarios. Two case studies are used to evaluate the effects of temperature on component failures and service outages in water distribution systems in cities under current and future extreme heat scenarios similar to those in the US Southwest. The model is then used to explore adaptation strategies relating to the probability of failure and repair times. An overview of the process is shown in figure 1. Due to data availability and modeling constraints, Perses does not consider all dynamics present in real-world water systems which contribute to failure and repair (e.g. traffic loading, changes in pipe roughness, etc). Perses instead focuses on temperature-influenced dynamics of failure. Therefore, the key insight from Perses is the difference in failures for a water system between scenarios of future temperatures.

2.1. Developing temperature profile inputs

Seven temperature profiles downscaled to the city level are used as inputs into Perses to capture future climate uncertainty. We compare the results from six temperature profiles informed by GCMs to those from a baseline temperature profile of the continuation of historical temperatures (Bureau of Reclamation 2013). The temperature profiles informed by GCMs incorporate uncertainty about the future emissions profile, the variables, interactions, and initial conditions within alternative models of each representative concentration pathway (RCP) scenario (IPCC 2019). Daily maximum temperature futures are characterized by RCP 4.5 and RCP 8.5 scenarios from the Coupled Model Intercomparison Project Phase 5 (CMIP5) model set. CMIP5 is the model ensemble for the IPCC 5th Assessment Report (Laboratory 2008). RCP 4.5 is used as a reasonable minimum case, representing a stabilization of emissions by the end of the century. RCP 8.5 assumes rapidly increasing concentrations of emissions. Minimums, averages, and maximum temperatures of all runs in each RCP scenario were considered to incorporate the uncertainty of variables, interactions, and initial conditions. Therefore, the temperature profiles informed by GCMs are RCP 4.5 minimum, RCP 4.5 average, RCP 4.5 maximum, RCP 8.5 minimum, RCP 8.5 average, and RCP maximum. Daily temperatures from GCMs are downscaled to hourly levels by assuming a sinusoidal curve between the maximum and minimum daily temperatures. Using an updated CMIP6 would not necessarily produce significantly different results if diurnal temperature extremes remained relatively consistent for the region of study from CMIP5 (Bourdeau-Goulet and Hassanzadeh 2021).
2.2. Modeling component probability of failure

The characterization of the probability of failure of motors and electronics within pumps and PVC and iron pipes is used to determine whether components have failed in each time step of the simulation. Probability distribution functions (PDFs) of failure are generated using the procedure developed in Bondank et al. (2018) by (1) providing variable inputs into temperature-degradation-failure equations (Banerjee et al. 2008, Cowern 2000, Csanyi 2015, Rockwell Automation AG 1998, Hoffman 2017, Kreeley and Coulton 2012, Whittle and Stahmer 2005, Volk et al. 2000, Randall-Smith 1992, Hua et al. 1999, Toroz and Uyak 2005, Graham et al. 2009) and (2) running Monte Carlo simulations holding each temperature constant (Bondank et al. 2018). Possible future temperature scenarios and ranges of operational parameters representing uncertainty in preventative maintenance practices were used as inputs to these equations. The complete list of ranges of input parameters characterizing operating conditions can be found in Bondank et al. (2018) (table S7 [https://stacks.iop.org/ERIS/2/045002/mmedia]). To determine the probability in each timestep of the simulation, a separate PDF was generated for each daily temperature within the range of daily temperatures from the projections (0 °C–57 °C). To evaluate the cumulative probability of failure at each time step, the PDFs are converted into cumulative distribution functions (CDFs) by integrating over each time step as shown in SI figure S1. It can take many years of accumulated degradation for there to be 100% chance of failure, especially in iron pipes (given their long lifetimes relative to other components) under low-temperature exposures.

Each temperature-failure CDF represents the probability of failure of a component over time when exposed to a consistent temperature. In reality however, components are exposed to diurnal and seasonal cycling of temperatures over their lifetimes. Therefore, to determine the probability of failure of components in each timestep of the simulation, the temporal aspect of temperature exposure is considered. ‘Exposure’ represents the temperature a component is exposed to, weighted by the amount of time the component is exposed. To calculate exposure values, we multiply duration and magnitude to get units of degree-unit time (°C · Δt) as
shown in equation (1).

\[
\text{Exposure} \ [°C \cdot \Delta t] = \text{magnitude} \ [°C] \cdot \text{duration} \ [\Delta t].
\] (1)

This formulation of exposure assumes that magnitude and duration both have linear relationships with exposure. This is a reasonable assumption because this formulation of exposure is used in other contexts, for example in the heat effects on human health (Hoehne et al. 2018). If there are any interactions between duration and magnitude for the water system context, it may be the case that duration and magnitude have a non-linear relationship with exposure. For example, the magnitude might increase as the duration increases due to the feedback of additional heat generated from component degradation over time. It could also be the case that duration could have a non-linear relationship with exposure due to outside aging factors. Without data to analyze the exact nature of the relationship between exposure and its factors, it is uncertain as to which relationship is most accurate. Future studies could explore the results of employing an assumption of non-linear relationships between magnitude and duration of exposure.

A probability distribution was then generated for each type of component to reflect the effects of different exposure values on failure over the component’s lifespan. To generate these exposure-failure CDFs, probabilities from the temperature-failure CDFs with different discrete values of durations and magnitudes of temperatures, but with the same exposure values, were binned together and averaged. The average probability of failure of each exposure bin is calculated cumulatively from one bin to the next. Each one-unit-larger exposure bin adds the average of the additional probabilities incurred from having each discrete temperature which is included in the bin exposed for one year longer duration than in the last exposure bin. Each exposure bin thus has an equal to or greater probability of failure than the last bin according to these incremental increases. The output exposure-failure CDFs are shown in figure 2. They represent the probability of failure for each type of component given certain levels of exposure. Though the figure shows duration in units of years, the model calculates exposure based on 1 h increments. Each component has a different sensitivity to temperature exposure and therefore it takes different amounts of exposure for the probability of failure to equal one. At this stage, the probability distributions of motors and electronics are averaged into one exposure-CDF for a pump component to match what is modeled in the hydraulic solver described in section 2.4.

### 2.3. Modeling component states

In each time step, the simulation tracks the dynamic state of components relating to exposure, probability of failure, individual robustness, and operational state (failed or functional). Time steps of the simulation are 1 h increments because there are no significant sub-hourly temperature and failure dynamics. The failure state of a component in any given time step is based on the probability of failure given its current exposure state, its level of individual robustness, and whether the repair time has passed if it had already failed in the previous time step. Component exposures are tracked over time by the simulation as they fail and become repaired. Once failed, the component will be assigned a duration for that failure, which models the time to identify, isolate and repair the outage. The model allows multiple components to be failed in the same time step. The repair times are the same for multiple simultaneous failures as for single failures, though in reality repair times would likely increase proportional to distance between failures or nature of the hazard. When components are repaired, their exposure returns to zero. This assumes that repairs restore the component functionality to new. For pipes, the repair function of Perses more realistically represents replacements because the exposure of a whole pipe segment is reset to zero when its functional status is restored. The lengths of pipe segments in the model have not been designed to realistically undergo replacement from failure after a break. Therefore, since more length of pipe is replaced from breaks in the model than in real-world systems, the number of pipe failures occurring in the simulation is likely underestimated. However, the percent difference in pipe failures between
temperature scenarios in a water distribution system with high-quality pipes is expected to be similar to one with lower quality pipes. To get a more accurate estimate of the absolute number of failures, pipe networks could be modeled with a segment at specified lengths. Additionally, in this model, pipes are replaced using the same material as the previous pipe, and there are no preventative pipe or pump replacements. The omission of these dynamics causes an overestimation of failures. With data about the evolution of preferred pipe types over time and preventative replacement dynamics, Perses could be further amended to estimate the number of pipe failures more accurately.

Each component’s cumulative exposure is tracked in each time step to evaluate its probability of failure using the exposure CDF curves. To do this, temperature profiles are used to determine the temperature experienced in each time step. The temperature values of the time step are multiplied by the duration of the time step to get the current exposure value (equation (1)). The exposure values are iteratively summed together to get a current overall exposure value. This follows the mathematical representation of degradation of components as a function of the cumulative exposure, equation (2), that was introduced in Bondank et al. (2018) (Bondank et al 2018). Because exposure is cumulative, the effects on the component probability of failure are lasting. For example, if a component experiences high exposure early on in life, it will have a high probability of failure for the rest of its life until it is repaired.

\[
rd = \int_{t_1}^{t_2} \alpha \cdot T_e^\beta \, dt. \tag{2}
\]

Where \( r_d \) is the rate of degradation from exposure (lifespan/°C), \( T_e \) is the temperature experienced by the component (°C), and \( \alpha \) and \( \beta \) are the linear and exponential parameters of degradation.

The determination of whether a component has failed in a certain time step is then performed by comparing the probability of failure of the component population (i.e. all pumps or all PVC pipes) at the current exposure state to the component’s individual ‘robustness factor’, which is a random value from a uniform distribution ranging from 0 to 1 representing the component’s survivability compared to other components of its type. Heterogeneities in components of the same type could arise from differences in construction quality, surrounding soil condition, or inconsistent treatment in operation across components. Due to constraints in computing complexity and data availability, these dynamics are not individually modeled for each component. Instead, a uniform distribution is used to characterize these heterogeneities and randomize effects on components. The process of comparison of population probability of failure and individual robustness factors is shown in figure 3. A component is determined to be in a failed state when its probability of failure is greater than its robustness factor. Robust components need more exposure to fail and less robust components need less exposure to fail.

2.4. Modeling service outages
The results of the component failure analysis are input into the hydraulic solver (EPANET) to estimate service outages in each time step. Service outages are defined in this study as time steps in which a demand node pressure drops within 20–40 psi (service loss outage) or below 20 psi (vacuum pressure outage) (Mays 2000).
Pressures at these levels are recognized to cause issues with providing water at adequate quantities and quality (which we will call service loss outages here), though pressure drops do not necessarily dictate a loss of water quantity. EPANET is used as the hydraulic solver because it is the model of record for the United States Environmental Protection Agency and because it is widely used by both academics and industry professionals. EPANET’s algorithm uses consumer demands as inputs and outputs pressures in the network. Therefore, outages are represented in terms of pressure outages. An EPANET network file is passed to Perses to generate component attributes automatically, and Perses runs EPANET using the EPANET 2.2. Programmer’s Toolkit files.

When components are failed, they are shut off by changing their attributes within EPANET. Pipe statuses are set to ‘closed’ which represents the response team isolating the break by shutting the pipe’s valve. Emitters are added to one node of the broken pipes to model water outages before operators can shut off valves to isolate the break. The magnitude of loss is modeled to be similar to what is experienced in fire-flow using a coefficient of 100 (100 times the maximum flow expected) (Mays 2000). Pumps are turned off by setting their status to ‘closed’ as well. The change in status of components causes consequential pressure outages in nodes. Multiple service outages can occur in one time step if multiple demand nodes are below pressure thresholds. The number of nodes that have outages is counted in each time step. Before counting service outages, however, 48 h is run at the beginning of the simulation to obtain the correct output once the system equilibrates. EPANet allows for demands to vary by the hour according to daily demand patterns. Since the demand patterns are in 1 h increments, the hydraulic time steps are also in 1 h increments. Perses currently models the scenario of consistent daily demands and static network layouts over the 100 years simulation period. This assumes no significant change in demographics, use patterns, expansion, or spikes in demand from extreme heat which could contribute to worse outages during failures. If data were to become available, considering projections of these factors in Perses would increase the accuracy of the outage estimates.

3. Case studies

Two case studies are used to evaluate the effects of temperature on component failures and network service outages under extreme heat scenarios like those in the US Southwest. A full set of network data including spatial topography of components, pump and demand curves, nodal elevations, tank sizes, and pipe diameters for a Southwestern city would be ideal for this study, but none were publicly available. As such, a system based on the number of components in the City of Phoenix, Arizona network without any topological or water flow information is first used for only a component failure analysis without assessment of service outages. We call this the large-scale system. The large-scale system has populations of components representative of those in the City of Phoenix: 113 pumps and 61,500 pipes (7000 total miles of pipe with 600-foot segments) (City of Phoenix 2018, City of Bellingham 2009). Without information about the distribution of pipe materials, we modeled half of the pipes as iron and the other half as PVC. To evaluate service outages, which require a realistic network geometry, we study a widely available network from North Marin County in California. We call this network the small-scale network and the layout is shown in SI figure S2. The small-scale network has been widely used for research purposes and is provided in the EPANET user manual (Sakarya and Mays 2005, Vasconcelos et al 1997, Rossmann 1994, Goldman and Mays 2005). The network consists of 91 nodes, 115 pipes (of which we estimate 17 are PVC and 98 are iron from the roughness factors), 3 storage tanks, 2 reservoirs, and 2 pumps, and serves a suburban population of around 53,000 people (Sakarya and Mays 2005). Nodal demands range from 0.87 to 1856 gallons per minute. The small-scale network allows for the assessment of supply and demand while the large-scale system characterizes only supply effects. The modeled version of North Marin’s network contains the larger pipes of the real network which are dendritic (tree-like) in nature without loops to create redundancies. Additionally, the modeled length of pipe segments and intervals of isolation valves are likely longer than in the real system. Thus, the number of service outages from any one pipe failing is likely overestimated. Therefore, it is thus ideal to use as granular a network model as possible.

The case studies are also characterized by the component ages and component repair times. The ages of pipes and pumps in Phoenix are unknown, and as such it is assumed that the large-scale and small-scale systems were built in 1950, corresponding to the start of significant population growth and provision of new infrastructure in the City of Phoenix (Rex 2000). The Perses simulation thus begins with new components in 1950 for both the small-scale network and the large-scale system. Repair times are set at 88 h for pipes, 5 h for motors, and 4 h for electronics, consistent with the mean-time-to-repairs reported in the literature for US water systems (Cullinane 1989). A sensitivity assessment is developed using varying repair times. The time associated with waiting for parts or the need to repair collateral damage outside the water distribution system is not included in these mean repair times but could be significant.

For both case studies, the current and projected future temperature profiles for the City of Phoenix, Arizona, are used. Projections have 1/8-degree spatial resolution and were averaged spatially within the region.
bounded by latitudes 33.3125 to 33.8125 and longitudes −122.1875 to −111.9375 (2414 km² that represent the City of Phoenix). There are 19 different climate models and 42 total runs (which include different variables, interactions, and initial conditions assumptions) in the RCP 4.5 emission scenario and 20 climate models with 41 total runs in the RCP 8.5 emissions scenario. See SI table 1 for a list of the climate models and runs. The baseline projections are observed historical temperature data from 1950–2016 that are repeated into the future, in order to most accurately characterize past failures (NOAA 2016). By using observed instead of projected historical data, we do not control for any bias in climate models which might generate small deviations between back-casted values and observed historical data. SI figure S3 shows plots of the different temperature profiles over time. The averages of the scenarios show a clear increase in temperatures into the future with RCP 4.5 average rising from roughly 30 to 32.5 °C and RCP 8.5 average to 35.5 °C by end-of-century.

4. Results

4.1. Long-term increases in failures in the large-scale system

In the large-scale system, future PVC pipe, pump, and iron pipe failures exceed estimates for the baseline case. Figure 4 shows the projections of cumulative component failure overtime under the minimum, average, and maximum climate projection scenarios as compared to the baseline. By 2099, the anticipated increase in failures from the average temperature profiles of the RCP 4.5 and 8.5 scenarios are 1%–5% more pump failures, 2%–5% more PVC pipe, and 3%–7% more iron pipe failures above the baseline scenario. The bounds of possibility from the extremes of variables, interactions, and initial conditions assumptions within RCP 4.5–8.5 models are at maximum a 19%–23% increase in pump failures, 18%–21% increase in PVC pipe failures, and 38% increase in iron pipe failures. The minimum bound of RCP 4.5–8.5 is a 13%–16% decrease in pump failures, a 14%–17% decrease in PVC pipe failures, and a 24%–28% decrease in iron pipe failures.

Components have different responses to cumulative heat exposure. Pumps and PVC pipes have a similar linear profile of yearly failure rates. Iron pipes experience exponential failure rates because of increases in the rate of corrosion and therefore the rate of degradation of lifespan over time, and not simply the instantaneous percent of degradation of lifespan as is the case with pumps and PVC pipes (Volk et al 2000). A result of this difference in behavior of failure is that the first iron pipe to fail after the system is built is in 1977 whereas the first pumps and PVC pipes fail right away, in the year 1951. Though the trends of yearly failure are different between pumps and PVC pipes and iron pipes, all components reach 100% of baseline temperatures at the same time—in the average RCP it is 99.7% through the simulation, and in maximum RCPs its 98.9% through the simulation. After these times, the exceedance of baseline failures of iron pipes increases above that of pumps and PVC pipes.

The exceedance of baseline failures in the average RCP scenarios reveals potential challenges for budgeting, management, and maintenance. If emissions and climate model scenarios at or above the average are realized and budgets are not adjusted to include the increased need for preventative or corrective maintenance, either additional service outages will occur or a last-minute reshuffling of municipal funds may mitigate service outages but result in a lingering overall budget deficit (Farmer 2014). Because budgets are generated based on past expenditures and new projects, there is no formal process to include projections of increased failure rates (Ginley and Klein 2017). If utilities continue with this process, they will need to foresee the pattern in the increased failures before they can budget for adaptation options. A survey of water utilities reveals that action is taken once extremes have been experienced (Heyn and Winsor 2015). The timing of the occurrence of increased failures could be important for whether utilities sense the increased rates of failure and can incorporate the increase into their future budgets. In the case of iron pipes, the large threshold of exposure needed to cause failure could cause situational surprise (Eisenberg 2018) by the end of the century if there are large numbers of iron pipes installed around the same time (as modeled in the case study), are not preventatively replaced, and suddenly fail before their expected lifespans. This effect would be lessened in cases where iron pipes were installed in different time periods or if there is a preventative replacement program. Because the cumulative failure curves for pump failures and PVC pipes are linear, if monitoring failure rates, utilities will know soon that pumps and PVC pipes are failing more frequently and may be able to incorporate it into future budgets. Some utilities in the Southwest already report that they experience an increase in PVC and pump failure with extreme heat and therefore expect further increases from climate change (Heyn and Winsor 2015).

Historical data show that the model estimates of component failures under baseline temperature conditions are reasonable. The data available cannot provide complete validation or calibration for the model, however, due to the mismatch of industries, location, and type of stressors the data characterize. The historical average failure rate of motors across a variety of industries in the US is on average 3%–12% every year under current temperature conditions (Banerjee et al 2008). The average annual pump failure rate from the large-scale model under baseline conditions is 1.69% per year, which is near the historical range. The historical failure rate of
polyethylene pipes in Las Vegas in 2005 was 6.5% over the year (Las Vegas Valley Water District 2016, Heyn and Winsor 2015, Ralph et al 2016). The average failure rate of PVC pipe from the large-scale model under baseline conditions is 1.72%. Furthermore, current annual iron pipe break rates are reported to be 6% on average in the United States (Las Vegas Valley Water District 2015). The average failure rate of iron pipe from the large-scale model under baseline conditions is 0.001%. The discrepancy in historical pipe break data and the modeled annual pipe failure rates show that temperature-related mechanisms of failure do not contribute as much to failures relative to other mechanisms of pipe failure—like freezing conditions, inadequate bedding support, or live loads caused by traffic, which are not modeled in this study (Hu et al 2010). However, the simulated model results appear reasonable given the external failure rates. Failure data on components in the water industry and under the same operational conditions as assumed would be needed to fully validate the model.

4.2. Long-term increases in failures in a small-scale network

In the small-scale network, future PVC pipe failures exceed estimates for the baseline case, and the criticality of infrastructure components becomes apparent. Figure 5 shows the projections of cumulative component failure and service outages over time under the minimum, average, and maximum climate projection scenarios as compared to the baseline. By 2099, the anticipated increase in failures from the average temperature profiles of the RCP 4.5 and 8.5 scenarios is zero for pumps and iron pipes, and a 0.5%–2% PVC increase above the baseline scenario. The bounds of possibility from the extremes of variables, interactions, and initial conditions assumptions within RCP 4.5–8.5 are at maximum no increase in pump or iron pipe failures and a 12%–15% increase in PVC pipe failures. The minimum bound of RCP 4.5–8.5, where temperatures are below baseline, is a 50% decrease in pump failures, and a 14%–16% decrease in PVC pipe failures.

In the small-scale network, there is a smaller population of components than in the large-scale system and therefore, there are fewer overall component failures. Because of this, the times between component failures are longer and produce stepwise cumulative failure curves. Smaller utilities may not experience the increases in failure because they have fewer assets and therefore fewer chances of failure. Trends of increases in component failure should therefore be interpreted from the large-scale system. Additionally, though there are no projected increases in pump failures, the failures happen sooner under average and maximum projections than under baseline conditions. This could also be problematic because if failures happen sooner than expected under baseline conditions, they might not be covered in the budget in the years that the failures occur.

Service outages (20–40 psi) and vacuum pressure service outages (below 20 psi) that constitute inadequate pressure for domestic and commercial use are projected to not increase under average conditions. The outputs from the extremes of weather pattern assumptions within RCP 4.5–8.5 are at maximum a 16%–26% increase in service outages and vacuum pressure service outages. The minimum bound of RCP 4.5–8.5 is a 5%–6% decrease in service outages and vacuum pressure service outages. Similar to preventative maintenance and capital improvement budgets, if repair/response budgets do not have enough room to allow for the increase in service outages under the maximum RCP temperature scenarios, and find themselves unable to adequately respond, outages could have greater durations, thereby causing greater loss to human health and economic opportunity. Furthermore, if budgets neglect proper corrective maintenance, it could further increase components’ chances of failure in the future (Tobias 1986). This could cause the system to move into a state of deterioration that would be increasingly challenging to manage (Tobias 1986). Unfortunately, there are
no data available on historical instances of water outages to validate findings at the service loss level. However, since we have validated component failures, the outages should be reasonable since they are calculated using a standard hydraulic solver.

Service outages are non-linear and emergent outcomes of the complex interactions between the component failures and the topology and flows within the network. This is evidenced by the fact that the number of service outages in the network from component failures is not proportional to the number of component failures. For example, in year 33 of the simulation, 2 pipes failed and there were a resulting 6511 service outages. But in the year 50, 4 pipes failed and there were only 264 resulting service outages. The nonlinearity is the result of the criticality of the component (Newman 2010). Like other water reliability studies using simulation to find outages, we refer to critical components as ones that cause outages when failed (Su et al 1987, Bao and Mays...
From evaluating where those components are located within the network we find results consistent with studies that rely on the topology of the network—the critical components serve as the sole connection between demand nodes and the source of water, whether it be the reservoir or from the rest of the network (Goulter and Morgan 1985, Wagner et al 1987, Goulter and Coals 1986, Cullinane 1989, Herrera et al 2016). An identification of the criticality of components in the small-scale network can be found in SI section S4.2.

4.3. Evaluating mitigation potential of adaptation strategies

Contextual variables in the simulation that are temperature-independent represent opportunities for exploring how well adaptation strategies could mitigate failures from climate change. The two contextual variables to which failures and outages are sensitive to are the operational parameters used to generate the temperature-failure CDFs and the repair times of components. Ranges of operational parameters that produce relatively low probabilities of failure represent the implementation of improved preventative maintenance strategies. An example of a preventative maintenance strategy in this context is changing the range of internal heating in motors within pumping units. When the internal heating from the friction of the bearings is kept at 100 °C–105 °C via good bearing lubrication practice, the motor has a lower probability of failure than if the internal heating is kept at 105 °C–110 °C via poor lubricating practice (Cowern 2000).

To evaluate how well preventative maintenance and fast repair times could mitigate outages, we compare the percent of additional outages from climate change that were offset by implementing three independent possible adaptation strategies: (1) improved preventative maintenance at 50% above mid-levels, (2) improved repair times at 50% above mid-levels (i.e., 88 and 8 h respectively), and (3) both improved preventative maintenance and repair times 50% above mid-levels. We then explore why those offsets occurred and form recommendations from the findings. As an example, we explore how strategies would offset failures if maximum projections within each RCP were realized. The strategies are compared based on the number of times they offset the additional failures from climate change, which we refer to as the ‘factor of offsets’. Improved preventative maintenance offsets outages by decreasing component failures. For the small-scale network, improved preventative maintenance will provide a 17% offset of additional PVC failures under maximum temperature conditions. These component failure offsets do not translate to offsets of nodal outages. Improved repair times offset service outages directly without offsetting component failures. Implementing improved repair times has a 4-factor offset of all service outages under maximum conditions. These results imply improving repair times is therefore more effective at reducing the number of time periods with outages by reducing the duration of outages and is more effective than preventing component failures.

5. Discussion

The Perses model shows the capability of a dynamic extended period simulation to aid decision-making about climate adaptation by estimating the impacts on consumers. The use of Perses for projecting failures from increasing temperatures in water distribution systems shows that utilities in the Southwestern region of the US that experience high temperatures will likely experience increases in component and consequential service-level outages to consumers. If an allowance is not provided in budgets for the increased need for repair, replacement, and response required from increased failures, and for maintaining the quality of repairs, outages to consumers could be more frequent and could extend even to longer periods.

The knowledge Perses generates could be especially useful for resilient decision-making regarding assessing consequences and management strategies since the American Water Infrastructure Act passed in October 2018 requires US utilities to conduct resilience assessments to natural hazards (US Congress 2018). As utilities in warm regions of the US conduct their assessments, they could use the Perses results especially for improving the ‘consequence analysis’ and the ‘risk and resilience management’ steps in their assessments as suggested by the Risk Analysis and Management for Critical Asset Protection (RAMCAP) Standard for Risk and Resilience Management of Water and Wastewater Systems which serves as guidance for compliance with the new law (Brashear and Jones 2010). The RAMCAP standard calls for an estimation of the duration and severity of service outages that could result from a hazard. This is then used to define resilience as a function of the duration and severity of consequence instead of just the estimation of ultimate consequence. They ask that utilities ‘do not assume that all uncontrollable variables and unpredictable events occur simultaneously’ (AWWA 2010). Therefore, more detailed knowledge of time and space is needed to estimate this aspect. Additionally, the evaluation of the results under different maintenance scenarios using Perses also helps with ‘assessing the options by analyzing the facility or asset under the assumption that the option has been implemented’ by ‘re-estimat[ing] the risk and resilience levels and calculating the estimated benefits of the option’. Utilities could improve the context considered by inputting utility-specific information like the number and topology of components and demand profiles.
The applicability of Perses to water systems decision-making is specific to certain spatial and temporal contexts. Perses applies to a certain type of climate in warm regions that does not experience freezing temperatures (e.g. the US Sun Belt, Middle East, North Africa, and South Asia). In cold regions, the effects of temperature include additional dynamics regarding changing freeze-and-thaw cycles which have a large impact on pipe breaks (Kim 1995). Additionally, Perses is most applicable to the structure of water infrastructure that is currently prevalent in developed countries today. Water systems that incorporate new designs such as decentralization, or more robust materials, for example, would have different responses to increasing temperatures that are not yet characterized in the current version of Perses. Additionally, the current model does not account for changes to infrastructure design or operations during the simulation.

The analysis of adaptation strategies to temperature effects does not consider costs or all of the stressors needed to make complete practical recommendations for utilities. Cost-effectiveness would be a better metric than outage reduction effectiveness for decision-making because it would help to compare outages on more commonly used terms. For example, it is anticipated that though repair strategies are the most effective at reducing outages overall, a level of repair that costs the same amount as a level of preventative maintenance may not be more effective at reducing outages and therefore preventative maintenance would be a more attractive strategy. To allow for this comparison, costs of the strategies of repair and preventative maintenance and their ability to reduce outages at different levels of investment should be estimated. The social and economic costs of outages should also be estimated to fully characterize the cost of not preventing outages. We expect that the cost of repair is dependent on the labor required to do the repair and the cost of replacement parts and that the cost-effectiveness of different levels of preventative maintenance would require characterizing the diminishing marginal returns of improving reliability. Estimating this would be dependent on collecting the following data: utilities’ predictions of component failure times and the actual component failure times—the difference of which characterizes the accuracy of their method of prediction, and the amount invested in each component for preventative maintenance, along with the resulting reliability of the components.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

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