Supporting Information for "The Robustness Trade-offs of Institutional Friction in Urban Socio-Hydrologic Systems: A Dynamical Systems & Control Approach"

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Introduction

The Supporting Information contains the additional methodological insight to replicate the model and additional results. We provide the full model description with all equations and detailed descriptions of the algorithms used in the Urban Water Infrastructure Investment Model, a description of how the Phoenix Metropolitan Area case parameters and initial conditions were set, and a description of the sensitivity analysis setup, including additional non-institutional friction sensitivity analyzes that were performed. Additional results include a summary of the additional sensitivity analyzes performed on other parameters not analyzed in the institutional friction robustness analysis and illustrative time series of institutional friction effects.

Text S1. Full Model Description

Urban Water Infrastructure Investment Model (UWIIM) is a discrete time, dynamical system that simulates the flow of water, investment (dollars), and information in a stylized urban water coupled infrastructure system with annual time steps. The coupled infrastructure system's state in a given year, t, is contained in the vector, x_t (Table S1), which is updated each year according to a set of difference equations that capture the operational and political-economic feedback processes of interest for a general urban water coupled infrastructure system.

The system consists of a homogenous user population of size P_t with a per capita demand, d_t, and a network of hard, soft, and natural infrastructures that manipulate the flow of water and information. Each year, t, the UW-CIS receives water inflows, $Q_{i,t}$, from source i that can be stored, used, or released back into the environment. In the default UWIIM, there are only two sources, one groundwater and one surface water, and each is characterized by two time-varying parameters: mean annual streamflow ($\mu_{i,t}$) and the streamflow's coefficient of variation ($c^v_{i,t}$). For each source i, the system has storage infrastructure defined by its volumetric capacity, $\bar{V}_{i,t}$. $V_{i,t}$ refers to the volume of water present in the storage infrastructure at the beginning of the year. The city withdraws water from $V_{i,t}$ and $Q_{i,t}$ to meet demand and remaining flows in excess of storage capacity are released as flood water, $O^f_{i,t}$, our of the UW-CIS. Two types of hard infrastructure determine how much of the withdrawn water, $O^d_{i,t}$, the system can deliver to users: processing infrastructure and delivery infrastructure. The system's processing capacity is source-specific, $w_{i,t}$, are is defined as a proportion of the maximum volume of water the system can process in a year from source i and the maximum volume of water that can be physically available to the system ($\bar{V}_{i,t} + \mu_{i,t}$). Delivery efficiency, η_t, determines the proportion of processed water that can actually be delivered to users, taking into account lost water or the existence of re-use capacity (if water is net re-used, $\eta_t > 1$).

Two forms of soft infrastructure contribute to system operations: demand management and rate policy. Per capita demand can be lowered in the short-term through temporary behavioral adjustments or long-term technological or cultural adjustments. Short-term efforts directly alter d_t while long-term efforts target the baseline per capita demand $\bar{d}_t$, the demand before taking into account behavior adjustments. Multiple urban water models have distinguished between the short-term behavioral measures and long-term "passive" forms of conservation ((M. Garcia et al., 2016)). Since we model a homogenous population, rate policy is contained within a targeted per capita rate ($/person), $\hat{\pi}_t$, and a proportion of the per capita rate that comes from fixed charges, $\beta_p^{(\pi)}$ rather than volumetric charges. Each year, the PIP uses rate revenue to cover operating costs, $C_t^{(o)}$, invest in infrastructure, $J_t^{(o)}$, and service debt C_t^d.

There are two types of exogenous drivers that can disrupt UW-CIS operations: population growth and water inflow change. Both can be defined by the model user to satisfy a desired city context or scenario.

The UWIIM models the political-economic feedback loop through a series of controller feedback loops (CFBLs) that make changes to the infrastructure system to meet desired supply and financial goals. As Anderies (2015) lays out, CFBLs provide a way to mathematically formulate information processing in action situations. We model three representative action situations as controllers: short-term measures, long-term investment, and rate-setting. Each controller, j, processes perceived error, $e_{j,t}$, between the desired system state, γ_j, and the current system state (assuming perfect measurement), x_t, through a three-step algorithm, $G_j(e_{j,t}, x_t)$, that outputs actions, $u_{j,t}$, into the CIS (e.g., investments or rate policy changes). Our approach uniquely accounts for the way institutional friction can give rise to disproportionate information processing (Workman et al., 2009; Jones & Baumgartner, 2005a) through the use of an attention-response function in the first step of $G_j(\cdot)$.

1. The Operational Feedback Loop

1.1. Supply & Demand

Any urban water system is primarily tasked with ensuring that there is available supply of sufficient quality to meet system demand. In the UWIIM, supply, S_t, and demand, D_t, are auxiliary variables given in flow units (volume per year) that can be derived from the state variables of a given year, x_t. We define S_t as the volume of water that can be delivered to users in a given year, an annual metric of *potential*, rather than *actual* deliveries. S_t is the product of the volume of water available to be used by the system in a given year, A_t, and the delivery efficiency, η_t.

$$S_t = \eta_t A_t \tag{1}$$

A_t is the sum of available water from each source, $A_{i,t}$.

$$A_t = \sum_i A_{i,t} \tag{2}$$

For each source, $A_{i,t}$ is the minimum of two types of availability: legal, $A^l_{i,t}$, and processing, $A^w_{i,t}$.

$$A_{i,t} = \min(A^l_{qt}, A^w_{qt}) \tag{3}$$

$A^l_{i,t}$ is calculated by multiplying the amount of water physically available to the system in storage, $V_{i,t}$, and inflow, $Q_{i,t}$, by parameters a^v_i and a^q_i, respectively, and summing the result. The equation is

$$A^l_{i,t} = a^v_i V_{i,t} + a^q_i Q_{i,t} \tag{4}$$

The parameters represent the proportions of inflow and stored water legally available to the city for annual use. Processing availability ($A^w_{i,t}$) reflects the maximum water that can be processed in a year from each source given the city's processing infrastructure, $w_{i,t}$, and is given by,

$$A^w_{i,t} = w_{i,t}(\bar{V}_{i,t} + \mu_{i,t}) \tag{5}$$

If the city had full infrastructure capacity ($w_{i,t} = 1$), the maximum amount of water that could be processed by the city in a year, absent physical or legal limitations, is the sum of expected water coming into the system through source i during year t, $\mu_{i,t}$, and the total storage capacity for i, $\bar{V}_{i,t}$, assuming that the storage is full. $w_{i,t}$ represents the proportion of this hypothetical maximum that is actually able to be processed in a given year, so $A^w_{i,t}$ is, thus, the product of $w_{i,t}$ with ($\bar{V}_{i,t} + \mu_{i,t}$). Note, $A^w_{i,t}$ may be used to take into account quality concerns because treatment capacity is a sub-component of a system's processing capacity. Other availability concerns can be included in this modular definition by adding another variable to the minimum determination. These can include, for instance, operational availability associated with reservoir operations or hedging policies (e.g., (M. Garcia et al., 2016; Mazzoleni et al., 2021)).

Total system demand, D_t, is the product of P_t and d_t. It represents the total volume of water demanded by users in a given year within the UW-CIS before taking into account short-term measures to curtail demand within a year. In this sense, D_t is the expected annual demand for year t at the beginning of the year.

$$D_t = d_t P_t \tag{6}$$

Because the UWIIM uses an annual time step, but short-term measures can occur within a year, the demand by the end of the year can be lower only if short-term measures are enacted by the PIP within the year. The short-term curtailments are measured in volume per year units and contained in the variable $u_{1,t}$, which is the policy output of the short-term measures action situation (Equation 68). $\tilde{d}_t$ and $\tilde{D}_t$ refer to the ending per-capita demand and total demand, respectively, in year t after taking into account short-term water conservation measures.

$$\tilde{d}_t = d_t - u_{1,t} \tag{7}$$

$$\tilde{D}_t = \tilde{d}_t P_t \tag{8}$$

1.2. Infrastructure Dynamics

Multiple types of infrastructure in the UWIIM govern the flow of water, information, and investment dollars in the Operational Feedback Loop. Each infrastructure, indexed by k, has a variable that corresponds with its capacity. $I_{k,t}$ is the vector, for a given year

t, that is indexed by k and contains the capacity variable for each infrastructure. Some infrastructures like processing capacity are source-specific, so there is a unique capacity for each source. Below, we show a default definition of $I_{k,t}$ with only two water sources: surface (s) and ground (g). We assume ground storage (e.g., an aquifer) does not depend on investment, so only V_t^s is included.

$$I_{k,t} = \left(\bar{d}_t \ \eta_t \ \bar{V}_t^s \ w_t^s \ w_t^g \ \mu_t^s \ \mu_t^g\right) \tag{9}$$

Each infrastructure's capacity changes over time according to a common difference equation where each year, it decays according to a decay parameter, δ_k, and increases when investment occurs ((Hansen, 2009; Muneepeerakul & Anderies, 2020; Homayounfar et al., 2018; Muneepeerakul & Anderies, 2017)). We also include a term, $E_k(t)$, that captures any exogenous changes to the infrastructure capacity that the model user wishes to insert. The difference equation for $I_{k,t+1}$ is given by,

$$I_{k,t+1} = (1 - \delta_k) \cdot I_{k,t} + H_k(u_{2,k,t}, x_t) + E_k(t) \tag{10}$$

In the UWIIM, an investment is converted, for each infrastructure type, from dollars to an annual volumetric capacity (e.g., volume of water that can be processed in a given year or volume of water that needs to be conserved through demand management in a year) before it becomes an *output* of the investment action situation $u_{2,k,t}$. However, since each infrastructure capacity variable, $I_{k,t}$, may have different units depending on the infrastructure type (e.g., processing versus storage infrastructure), when $u_{2,k,t}$ is implemented in the CIS, the function $H_k(u_{2,k,t}, x_t)$ transforms the volumetric amount to the relevant units for each infrastructure k. Below are the definitions of $H_k(\cdot)$ for each infrastructure type in the default, two source, setup.

For long-term demand management,

$$H_1(u_{2,k,t}, x_t) = \frac{-u_{2,1,t}}{P_t} \tag{11}$$

For delivery efficiency,

$$H_2(u_{2,k,t}, x_t) = \frac{u_{2,2,t}}{2A_t} \tag{12}$$

For surface storage capacity,

$$H_3(u_{2,k,t}, x_t) = u_{2,3,t} \tag{13}$$

For surface processing capacity,

$$H_4(u_{2,k,t}, x_t) = \frac{u_{2,4,t}}{\bar{V}_t^s + \mu_t^s} \tag{14}$$

For ground processing capacity,

$$H_5(u_{2,k,t}, x_t) = \frac{u_{2,5,t}}{\bar{V}_t^g + \mu_t^g} \tag{15}$$

For mean inflow, there is no conversion needed because both $u_{2,k}$ and I_k for inflow are given in AFY of inflow.

Surface storage capacity and mean inflow from both surface and ground water are already represented in volumetric terms, so the transformation is an identity expression. Long-term demand management is in units of annual volume per capita, so the investment must be normalized by population. Additionally, conservation decreases demand, so we multiply the volumetric investment by -1. Delivery efficiency refers to the proportion of available water that can actually be used, so it must be normalized by that available volume. Processing capacity, for both surface and ground water, must be normalized by the maximum possible water that could be processed in a year, mean inflow ($\mu_{i,t}$) and storage capacity ($\bar{V}_{i,t}$).

When an infrastructure investment is made beyond maintenance ($u_{2,k,t} > H^m_{k,t}$) and the infrastructure type does not get immediate implementation ($\tau^i_k > 1$), the model keeps track of planned infrastructure investments in a state vector with $\tau^i_k - 1$ entries for each infrastructure type k that does not have immediate implementation time. Each year, the implemented investment, $\tilde{H}_{k,t}$ is the sum of maintenance investment $H^m_{k,t}$ and the planned non-maintenance infrastructure investment for that year. After a planned investment is implemented, it is removed from the state vector, and each planned investment behind it in the queue is moved up while the investment made in t is stored at the end of the queue associated with type k.

1.3. Water Users

We assume that baseline per capita demand, $\bar{d}_t$, does not endogenously increase as baseline demand management (or "passive" conservation) changes do not have a tendency to rebound in the long-term like behavior-based conservation does ((M. Garcia et al., 2016; Gonzales & Ajami, 2017)). Instead, baseline demand only can decrease through background, passive conservation (exogenous) or long-term investments (endogenous) following Equation 10.

The actual per capita demand (d_t) can deviate from $\bar{d}_t$ when there is short-term curtailment, $u_{1,t}$. Short-term curtailments lower $\tilde{d}_t$, the per-capita demand by the end of the year (post-curtailment), according to Equation 7, and then, the per capita demand for next year d_{t+1}, is set by the following difference equation:

$$d_{t+1} = \tilde{d}_t \left[1 + \alpha \left(1 - \frac{\tilde{d}_t}{\bar{d}_t} \right) \right] \tag{16}$$

In this way, d_t logistically converges back to $\bar{d}_t$ at a rate determined by the parameter α if there are no more short-term curtailments. This is the rebound effect modeled in past socio-hydrologic models of urban water use ((Gonzales & Ajami, 2017)).

Depending on the model user's intentions, the function $N(x_t)$ can be defined to reflect a particular population growth context, so the P_t difference equation is given by,

$$P_{t+1} = P_t + N(x_t) \tag{17}$$

In the default UWIIM, we opt for a basic logistic population growth equation to define $N(x_t)$ as,

$$N(x_t) = r(1 - \frac{P_t}{\kappa_t}) \tag{18}$$

where the population grows towards a carrying capacity, κ, at the intrinsic growth rate r, both being exogenously set parameters (similar approaches in (M. Garcia et al., 2016, 2020; Liu et al., 2015; Elshafei et al., 2014)).

1.4. Water Balance

The amount of water flowing into the CIS in year t from source i is $Q_{i,t}$. $Q_{i,t}$ is an exogenous driver that can be modeled flexibly to fit a certain hydrologic context of interest to the model user. The default UWIIM models $Q_{i,t}$ with a first-order auto-regressive model also used by Garcia et al ((2016)) and defined as,

$$Q_{i,t+1} = \rho_i(Q_{i,t} - \mu_{i,t}) + c_i^v \mu_{i,t}\sqrt{1-\rho_i^2}N(0,1) + \mu_{i,t} \tag{19}$$

where the coefficient of variation (c_i^v) and auto-correlation (ρ_i) are parameters. $N(0,1)$ is a random number sampled from a standard normal distribution. Many utilities do not have access to the full flow that passes through their system, so $\tilde{Q}_{i,t}$ accounts for the partial access legally available to the utility and is given by,

$$\tilde{Q}_{i,t} = a_i^q Q_{i,t} \tag{20}$$

where the parameter a_i^q specifies the proportion of physically available inflow available to the city to annually use. Volumes of water physically present in storage are $V_{i,t}$ and they change over time with $\tilde{Q}_{i,t}$ and outflows ($O_{i,t}$) in the following difference equation:

$$V_{i,t+1} = V_{i,t} + \tilde{Q}_{i,t} - O_{i,t} \tag{21}$$

Outflows, from each source i, come in two forms: outflows used to satisfy demand ("use", $O_{i,t}^d$) and flood releases ($O_{i,t}^f$). They are summed together to determine $O_{i,t}$.

$$O_{i,t} = O_{i,t}^d + O_{i,t}^f \tag{22}$$

Depending on the priority of water sources for a given utility, the UW-CIS will increase $O_{i,t}^d$ at the highest priority source until it meets demand (taking into account delivery efficiency, η_t, and any short-term curtailments) or reaches the limit set by $A_{i,t}$. Then the next highest priority source is used. Along with priority order (i reflects this order), the θ_i parameter allows for the model user to specify baseline proportions of lower priority sources that a utility will use during a year regardless of high priority annual availability (e.g., using flexible groundwater wells to meet peak days). This logic is contained within the following definition of $O^d_{i,t}$:

$$O^d_{i,t} = \min\left[\left(1 - \sum_{i'>i}\theta_{i'}\right)\left(\frac{\tilde{D}_t}{\eta_t} - \sum_{i'<i} O^d_{i',t}\right), A_{i,t}\right] \tag{23}$$

Flood flows are calculated for surface water when the volume in the reservoir would otherwise surpass the storage capacity ((Mazzoleni et al., 2021; M. Garcia et al., 2020)), or more precisely,s

$$O^f_{i,t} = \max\left[V_{i,t} + a^q_i Q_{i,t} - O^d_{i,t} - \bar{V}_{i,t}, 0\right] \tag{24}$$

1.5. Water Financing

1.5.1. Revenue

We assume the PIP uses generated revenue from user-charged rates to, in order of priority, cover operating costs, service debt, and make infrastructure investments. In the UWIIM, the only means to raise revenue for the public infrastructure provider (PIP) is water rates paid by the water users. Utilities in the U.S. often deploy both a connection charge and a volumetric charge, to cover the fixed costs and per-unit costs of providing water (AWWA, 2017). For a general urban water system, revenue generated from connection charges varies with population, P_t, and revenue generated from volumetric charges varies with demand, $\tilde{D}_t$. We use the post-curtailment demand for volumetric charges to account for the impact of water conservation on revenue noted by other socio-hydrologic models (e.g., (Rachunok & Fletcher, 2023)).

Given a volumetric rate of π^d_t and a per-user rate of π^p_t in year t, revenue, R_t, is the following:

$$R_t = P_t(\pi_t^p + \tilde{d}_t \pi_t^d) \tag{25}$$

In the UWIIM, the PIP makes rate changes, contained in $u_{3,t}$ (Equation 73), based on perceived costs in the next year $(t+1)$. When making this decision, the PIP must predict what the population and demand in the following year will be. Because the PIP cannot predict coming water use curtailments, we assume that the PIP predicts per capita demand will resemble the baseline, $\bar{d}_t$ (Equation 53). We assume the PIP knows the population growth equation and therefore, can accurately predict P_{t+1} (Equation 52). We thus define $\hat{R}_t$ as the planned revenue that motivated $u_{3,t-1}$ and $\hat{\pi}_t$ as the expected per capita revenue by normalizing $\hat{R}_t$ by P_t. The following two equations define $\hat{R}_t$ and $\hat{\pi}_t$:

$$\hat{R}_t = P_t(\pi_t^p + \bar{d}_t \pi_t^d) \tag{26}$$

$$\hat{\pi}_t = \pi_t^p + \bar{d}_t \pi_t^d \tag{27}$$

With any rate change decided upon in year t, the planned per capita rate in $t+1$, is therfore, given by the following difference equation:

$$\hat{\pi}_{t+1} = \hat{\pi}_t + u_{3,t} \tag{28}$$

With this definition, each year, the PIP would have to choose (i.) what the desired revenue ($\hat{R}_t$ or $\hat{\pi}_t$) is and (ii.) what portion of the desired revenue should come from volumetric versus connection charges. To simplify the latter choice, we assume that the PIP seeks a constant proportion $\beta_p^{(\pi)}$ of $\hat{\pi}_t$ from fixed charges, defined as,

$$\beta_p^{(\pi)} = \frac{\pi_t^p}{\hat{\pi}_t} \tag{29}$$

We use the above definition of $\beta_p^{(\pi)}$ and Equation 27 to define π_t^p and π_t^d in terms of $\hat{\pi}_t$ and $\beta_p^{(\pi)}$ in the following way:

$$\pi_t^p = \beta_p^{(\pi)} \hat{\pi}_t \tag{30}$$

$$\pi_t^d = \frac{\hat{\pi}_t (1-\beta_p^{(\pi)})}{\bar{d}_t} \tag{31}$$

Substituting these two equations into Equation 25 yields the following equation for R_t:

$$R_t = P_t \hat{\pi}_t (\beta_p^{(\pi)} + (1 - \beta_p^{(\pi)}) \frac{\tilde{d}_t}{\bar{d}_t}) \tag{32}$$

Consistent with the above logic, if there are no curtailments or per capita demand has converged back to the baseline after a curtailment ($\tilde{d}_t = \bar{d}_t$), actual revenue will match planned revenue ($R_t = P_t \hat{\pi}_t = \hat{R}_t$). Increasing short-term curtailments decreases $\tilde{d}_t$ and thereby, decreases R_t.

1.5.2. Cost Types

Each year, revenue, R_t, is used to cover three types of costs in the annual cash flow of the CIS, which sum to C_t: operating costs (C_t^o), debt service requirements (C_t^d), and direct infrastructure investment from the operating budget (J_t^o). This is line with the common "cash needs approach" to utility rate-making (AWWA, 2017). In the UWIIM, we assume a non-profit-directed PIP, who just seeks to cover costs, C_t, with R_t, so the following holds,

$$R_t = C_t = C_t^o + C_t^d + J_t^o \tag{33}$$

In reality, utilities often keep cash reserves and experience changes in net position as revenues and costs (from operating and non-operating sources) rarely exactly match (AWWA, 2017).

1.5.3. Operating Costs

Operating costs, C_t^o, are frequently studied in the econometric literature on water utilities and point to the economies of scale inherent to large-scale water provision (e.g., (Beecher, 2013; Destandau & Garcia, 2014; Mosheim, 2014)). To account for these economies of scale associated with both volumetric scale ($\bar{D}_t$) and number of users (P_t), we fit the following operating costs function to operating cost data, not including depreciation and amortization, reported by our case studies in their Comprehensive Annual Financial Reports (CAFRs) in 2010 to 2020 ((City of Phoenix, 2022b; City of Scottsdale, 2022a; Town of Queen Creek, 2022)):

$$C_t^o = g_o P_t^{z_p} \bar{D}_t^{z_d} \tag{34}$$

We use $\bar{D}_t$, the baseline demand, instead of $\tilde{D}_t$ because the infrastructure needed to meet baseline demand, in excess of $\tilde{D}_t$, is not completely abandoned in the event of a demand reduction and still requires upkeep as the utility plans to return to it when demand converges back to baseline after the shortage year. g_o is a normalizing constant, and z_p and z_d are the scale parameters for population and demand.

1.5.4. Debt Service

J_t^o only refers to infrastructure investments that come directly from annual operating cash flow (R_t). Infrastructure investments, in the UWIIM, can also come from issued bonds, J_t^b, to provide capital when the utility does not have the necessary cash. Debt service costs, C_t^d, that stem from previously issued bonds are the sum of principal, C_t^p, and interest, C_t^i, payments made by the utility in year t as required,

$$C_t^d = C_t^p + C_t^i \tag{35}$$

We define c_t^p and c_t^i as the annual principal and interest payments associated with bonds that were issued in year t. In this sense, C_t^p and C_t^i are the sum of c^p and c^i from unpaid bonds. If we assume that all bonds are issued with the same life, τ_b, the sum for C_t^p and C_t^i will always need to look to the last τ_b years in the following way:

$$C_t^p = \textstyle\sum_{t'=t-\tau_b}^{t-1} c_{t'}^p \tag{36}$$

$$C_t^i = \textstyle\sum_{t'=t-\tau_b}^{t-1} c_{t'}^i \tag{37}$$

We define c_t^d as the sum of c_t^p and c_t^i for the bond-sourced investments in year t. With this, we re-write Equation 35 as,

$$C_t^d = \sum_{t'=t-\tau_b}^{t-1} c_{t'}^d \tag{38}$$

We assume that, on average, the city pays the principal in equivalent installments over tau_b. Given that the total bond-sourced investment used in year t is J_t^b, such equivalent installments of the principal are equal to $\frac{J_t^b}{\tau_b}$ dollars per year. The annual interest payment is then $i_b J_t^b$ given the assumption that all bonds are issued with the same interest rate i_b. Together, these assumptions allow us to define c_t^d as the following:

$$c_t^d = \left(\frac{1}{\tau_b} + i_b\right) J_t^b \tag{39}$$

Substituting this into Equation 38 and taking the constants (τ_b and i_b) out from the summation, we can express C_t^d, as a function of prior bond-funded infrastructure investments, given by,

$$C_t^d = \left(\frac{1}{\tau_b} + i_b\right) \sum_{t'=t-\tau_b}^{t-1} J_t^b \tag{40}$$

To simplify the dimensionality of UWIIM, as opposed to recording J_t^b for each year of the model run in x_t, we define one state variable $\tilde{J}_t^b$ that records the mean bond investment from the past τ_b years as,

$$\tilde{J}_t^b = \frac{1}{\tau_b} \sum_{t'=t-\tau_b}^{t-1} J_t^b \tag{41}$$

Following this definition, $\tilde{J}_t^b$ is operationalized in the UWIIM by initializing it at the start of the model run and then updating it each year with the year's bond-supported investments, J_t^b in the following difference equation:

$$\tilde{J}_{t+1}^b = \frac{1}{\tau_b}\left[(\tau_b - 1)\tilde{J}_t^b + J_t^b\right] \tag{42}$$

Thus, C_t^d can be calculated in the UWIIM directly from $\tilde{J}_t^b$ by substituting Equation 41 into Equation 40 and yielding the following:

$$C_t^d = (1 + \tau_b i_b)\,\tilde{J}_t^b \tag{43}$$

1.5.5. Costs for Infrastructure Improvements and Maintenance

As discussed in the Infrastructure Dynamics sub-section, infrastructure capacity variables are represented in different units, but in the UWIIM, the PIP makes investment decisions based on the volumetric units of supply needed to meet γ_l, and outputted in $u_{2,k,t}$ (see Action Situation sub-section). The amount of financial investment (in dollars) required to achieve a certain volumetric increase in an infrastructure's capacity is very difficult to generalize for a certain infrastructure type (e.g., delivery infrastructure) because project details and city context factor greatly into the levelized (per volume) cost of an infrastructure investment. It is for this reason that the few dynamic models of urban water infrastructure investments that exist (see review in (Trindade et al., 2020)) specify the cost for a specific project rather than an infrastructure type. However, with predictive humility and for the sake of pursuing general insights, for each infrastructure, k, we define the cost, $J_{k,t}$ of increasing its volumetric capacity an amount $u_{2,k,t}$ as the following power law relationship contained in the function, $F_k\left(u_{2,k,t}\right)$:

$$J_{k,t} = F_k\left(u_{2,k,t}\right) = g_k\left(u_{2,k,t}\right)^{z_k} \tag{44}$$

Since the marginal costs of delivery efficiency investments increase with added delivery efficiency (especially as $\eta_t > 1$), the $J_{k,t}$ power law equation for η uses the interaction $\eta_t u_{2,2,t}$ (because $k = 2$ with η) as the exponential base.

$$J_{2,t} = F_k\left(u_{2,2,t}\right) = g_k\left(\eta_t u_{2,2,t}\right)^{z_k} \tag{45}$$

Many economists that study utility cost functions treat the infrastructure context of a utility ("capital stock") in volumetric terms regarding the supply capacity afforded by the total infrastructure portfolio of a city (e.g., (Destandau & Garcia, 2014; S. Garcia & Thomas, 2001; Hansen, 2009)). Additionally, the power law functional form allows for the consideration of scale relationships as size of the infrastructure investment increases. In theory, the two parameters of the power law can be manipulated by the model user to fit a desired infrastructure context or series of expected infrastructure investments.

Since each infrastructure's capacity will decay without investment (Equation 10), if the PIP wishes to keep each infrastructure at its current level, an annual maintenance investment is required, $\hat{H}^m_{k,t}$. We calculate this with the inverse of the $H(\cdot)$ functions defined in the Infrastructure Dynamics sub-section in the following equation:

$$\hat{H}^m_{k,t} = H_k^{-1}\left(-\delta_k I_{k,t}\right) \tag{46}$$

The cost of this needed maintenance investment simply comes from the application of the cost function (Equation 44) to $\hat{H}^m_{k,t}$, given by,

$$\hat{J}^m_{k,t} = F_k\left(\hat{H}^m_{k,t}\right) \tag{47}$$

2. The Political-Economic Loop

Actors in the the Political Economic Loop (PI and PIP agents) take actions to alter the infrastructure system operated by the Management Loop to achieve desired goal performance states. We model this goal-directed information processing in the UWIIM by defining controller feedback loops (CFBLs), a helpful tool for modeling dynamic action situations in social-ecological systems (e.g., Anderies et al., 2007; Rodriguez et al., 2011; Anderies, 2015; Bakarji et al., 2017). A CFBL consists of (i.) a dynamic system (in our case, the urban water system) that outputs a performance state of interest (in our case, the supply-demand balance) and (ii.) a mechanism of feedback control that measures the output of interest, compares it to a goal, and then responds with calculated action back into the system (Anderies et al., 2007; Rodriguez et al., 2011; Anderies, 2015). We model three action situations in the UWIIM that serve as mechanisms of feedback control: short-term measures, long-term investment, and rate-setting. The key innovation that the UWIIM offers to the use of CFBLs in social-ecological system modeling is the addition of the *attention* filter to the controller. Further discussed in the Action Situation subsection, this feature captures the influence of disproportionate and bounded attention that is well-documented in Punctuated Equilibrium Theory (Workman et al., 2009). The three action situations (or "controllers") are configured into an information processing network with short-term actions and long-term investment occurring in parallel and rate-setting occurring after investment is proposed. Each action situation, in reality, is a collection of many networked adjacent action situations (Deslatte et al., 2021; McGinnis, 2011), but we aggregate this information processing based on the emergent policy output of interest (e.g., an annual investment plan or a new rate policy).

2.1. Goals, Signals, & Error

The three controllers, indexed by j, each have their own performance goal of interest, γ_j. The $M_j(x_t)$ functions translate the state of the system, x_t, to measure the performance output of interest. Short-term curtailment and long-term investment both examine the ratio of supply to demand, but they differ on the level of future projection. The short-term controller ($j = 1$), since it only concerns the balance of supply and demand within the year t, uses the ratio of supply to demand in t. In the UWIIM, we assume that in the short-term, the utility simply hopes to meet supply with demand ($\gamma_1 = 1$). $M_1(x_t)$ is thus defined as,

$$M_1(x_t) = \frac{S_t}{D_t} \tag{48}$$

The long-term investment controller ($j = 2$) focuses on the projected supply and demand ratio τ_p years into the future given x_t (see Variable Projection sub-section). To provide a buffer for potential unforeseen supply and demand changes, utilities may wish to keep a buffer ($\gamma_2 > 1$) between supply and demand in the long-term. $M_2(x_t)$ is thus defined as,

$$M_2(x_t) = \frac{\hat{S}_{t+\tau_p}}{\hat{D}_{t+\tau_p}} \tag{49}$$

The rate-making controller ($j = 3$) uses the projected debt service capacity ratio (DSCR) of the next year ($t + 1$) given projected revenue, operating costs, and proposed investments (see Variable Projection sub-section). The DSCR is often used as a constraint on a utility's bond issuance capacity as the city sets a minimum coverage ratio in its financial policies ((AWWA, 2017)). γ_3 is this minimum DSCR, and $M_3(x_t)$ computes the DSCR for any system state, x_t, in the following equation:

$$M_3(x_t) = \frac{\hat{R}_{t+1} - \hat{C}^o_{t+1}}{\hat{C}^d_{t+1}} \tag{50}$$

Controllers respond according to the perceived error between system state and goal state (Anderies et al., 2007). Thus, the error, $e_{j,t}$ between each $M_j(x_t)$ and γ_j is calculated every year as,

$$e_{j,t} = \gamma_j - M_j(x_t) \tag{51}$$

2.1.1. Variable Projection

Cities make projection about their system state to inform their investments. In the UWIIM, we allow for the PIP to project the current state x_t a certain number of years, τ_p, to calculate the expected state of the system $\hat{x}_{t+\tau_p}$ in the future. Population is the only state variable of which we allow the PIP to have omniscent knowledge. This is because population in the UWIIM, if it only changes based on $N(t)$ (Equation 18) is a simple logistic growth process that many utilities and planning agencies have the capacity to model. The following equation is used by the PIP to project population in τ_p years:

$$\hat{P}_{t+\tau_p} = \frac{\kappa}{\frac{\kappa - P_t}{P_t}\exp(-r\tau_p) + 1} \tag{52}$$

Since the PIP cannot predict short-term measures when making long-term planning, the PIP assumes $\hat{d}_{t+\tau_p} = \bar{d}_t$. This yields the following prediction for total system demand:

$$\hat{D}_{t+\tau_p} = \hat{P}_{t+\tau_p}\bar{d}_t \tag{53}$$

The PIP projects processing capacity and surface storage infrastructure, assuming that existing infrastructure is maintained and knowing investments that have been planned up until t, in the following equations:

$$\hat{w}_{i,t+\tau_p} = w_{i,t} + H_{3+i}^{-1}\left(\sum_{t'=1}^{\tau_p} \tilde{H}_{k,t'}\right) \tag{54}$$

$$\hat{\bar{V}}_{t+\tau_p} = \bar{V}_t + H_3^{-1}\left(\sum_{t'=1}^{\tau_p} \tilde{H}_{k,t'}\right) \tag{55}$$

We use the inverse of the $H_k(\cdot)$ functions to convert the investment in volumetric units into infrastructure relevant units. For delivery efficiency, the PIP makes the same assumptions as other infrastructure, but to account for the changing water availability needed to compute $H_2^{-1}(\cdot)$, the PIP undergoes a recursive projection algorithm with $\hat{V}_{i,t+\tau_p}$, described below.

The PIP projects the actual volume present in storage, $\hat{V}_{i,t+\tau_p}$, in the same recursive algorithm (see attached code) that takes into account planned investments in delivery efficiency and processing capacity and the current use from source i, $O^d_{i,t}$. The PIP assumes that all infrastructure will be maintained over the projection period and inflows are at current mean ($\hat{Q}_{i,t'} = \mu_{i,t}$). For each projected year (t' where $t' = 0$ refers to t), the PIP undergoes the following routine for the PMA example:

1. Calculate $\hat{A}^s_{t'}$: the planned water availability from all surface water sources in t' given planned investments in surface water processing capacity (Equation 54).

2. Calculate $\Delta\hat{A}^s_{t'}$: the added surface water availability as measured by the difference between $\hat{A}^s_{t'}$ and $\hat{A}^s_{t'-1}$.

3. Calculate $\hat{A}_{t'}$: the total water availability, taking into account any net changes to the stored groundwater, $\mu^g_t + Q^b_{t'-1} - O^g_{t'-1}$, and $\Delta\hat{A}^s_{t'}$. $Q^b_{t'}$ is assumed to be the same as Q^b_t.

4. Calculate $\hat{\eta}_{t'}$: the delivery efficiency given planned investments for t' and $\hat{A}_{t'-1}$, defined as,

$$\hat{\eta}_{t'} = \eta_{t'-1} + H_2^{-1}\left(\tilde{H}_{k,t'}, \hat{A}_{t'-1}\right) \tag{56}$$

5. Calculate $O^g_{t'}$: the groundwater use for the following year given $\hat{\eta}_{t'}$ and $\Delta\hat{A}^s_{t'}$ in the following equation:

$$O^g_{t'} = \frac{\hat{\eta}_{t'-1}}{\hat{\eta}_{t'}} \left(O^g_{t'-1} + \Delta\hat{A}^s_{t'-1} \right) - \Delta\hat{A}^s_{t'} \tag{57}$$

The final projected groundwater volume, $\hat{V}^g_{t+\tau_p}$ is then given by the sum of net groundwater storage change in each projection year, defined as,

$$\hat{V}^g_{t+\tau_p} = \tau_p \left(\mu^g_t + Q^b_t \right) \sum_{t'=1}^{\tau_p} O^g_{t'} \tag{58}$$

Since the PMA example assumes minimal surface water storage, $\hat{V}^s_{t+\tau_p}$ is always zero.

$\hat{A}_{t+\tau_p}$, like A_t in the Supply sub-section, is a sum of projected available water from each source. Each sources projected available water is also the minimum of the projected types of available water (legal and technical). The expected values for inflows are always $\mu_{i,t}$. The PIP calculates each type of projected availability, $\hat{A}^l_{i,t+\tau_p}$ and $\hat{A}^w_{i,t+\tau_p}$, according to the following equations.

$$\hat{A}^l_{i,t+\tau_p} = a^v_i \hat{V}_{i,t+\tau_p} + a^q_i \mu_{i,t} \tag{59}$$

$$\hat{A}^w_{i,t+\tau_p} = \hat{w}_{i,t+\tau_p} \left(\hat{\hat{V}}_{i,t+\tau_p} + \mu_{i,t} \right) \tag{60}$$

On the financial side, since rate policy can change each year, the utility projects the expected revenue, operating costs, and annual debt service requirement into the next year ($\tau_p = 1$). Revenue projections use the current expected per capita rate (as per the current rate policy) with the projected population, as calculated in Equation 52. Together, the revenue projection is given as,

$$\hat{R}_{t+1} = \hat{P}_{t+1}\hat{\pi}_t \tag{61}$$

Operating costs use population and demand with Equations 52 and 53 in the following:

$$\hat{C}^o_{t+1} = g_o \hat{P}^{z_p}_{t+1}\hat{D}^{z_d}_{t+1} \tag{62}$$

Debt service requirements use the projected average debt service capacity for the next year, based on Equation 42 and given the proposed investments from the investment action situation, J_t ($u_{2,k,t}$ transformed into dollar units with Equation 70). Since some of this investment can be paid with operational funds up to $\bar{J}^o_t$ (Equation 75), we subtract $\bar{J}^o_t$ from J_t to get $\hat{J}^b_t$ as,

$$\hat{J}^b_t = J_t - \bar{J}^o_t \tag{63}$$

This then allows us to calculate $\hat{C}^d_{t+1}$ using $\hat{J}^b_t$ and $\tilde{J}^b_t$ in the following equation:

$$\hat{C}^d_{t+1} = \tilde{J}^b_t(1 + \tau_b i_b - \frac{1}{\tau_b} - i_b) + \hat{J}^b_t(\frac{1}{\tau_b} + i_b) \tag{64}$$

2.2. Action Situation Controllers

All action situation controllers follow two steps to produce an action, $u_{j,t}$, given perceived error ($e_{j,t}$) and the state of the system x_t. The first step generates attention attributable to $e_{j,t}$ and the second step, based on that attention, responds to the error and system state with a response. The output $u_{j,t}$ is stored in a general array in the computational model at each year t, so the dimensions of each j output in t do not have to match. For instance, the investment action situation output, $u_{2,k,t}$ is a vector of investments for each infrastructure while the rate setting output, $u_{3,t}$, is a single value that indicates the rate change for the next year.

Our approach builds on the foundation established in Punctuated Equilibrium Theory by the original Jones and Baumgartner attention dynamics model ((2005b)), which models policy response as a function of a dynamic input signal and three parameters: an amplification parameter, an efficiency parameter, and a friction parameter. Since the input signal in their model is a standard normal random variable, the amplification parameter linearly translates the input to an appropriate response. The amplification response that we are modeling is nonlinear, and described in the second step. The other two parameters in the original model modify how much of the signal is perceived by the hypothetical agent. They model a simple threshold response with the friction parameter acting as the threshold. Below the threshold, the efficiency parameter linearly decreases the signal perception. Above the threshold, the signal is fully registered. We opt for a continuous function over the error domain, detailed in the first step, also reliant on two parameters that are conceptually similar.

2.2.1. Step One: Generate Attention

Socio-hydrologic models (e.g., (Yu et al., 2017; M. Garcia & Islam, 2021; M. Garcia et al., 2016; Di Baldassarre et al., 2013; Mazzoleni et al., 2021)) have often used the concept of awareness or memory (often denoted "M") to quantify the attention of actors in the social system. Our attention variable is conceptually similar, but we alter the dynamical definition of it to account for institutional friction. Each controller, j, being a human-driven action situation, is subject to disproportionate information processing challenges where actions pursued are not necessarily proportional to the actual scale of a problem (error) ((Workman et al., 2009; Jones & Baumgartner, 2005b)). We model attention for each controller, $Y_{j,t}$, as a proportion (takes values in $[0, 1]$) of the error that will ultimately be registered by the controller. If $Y_{j,t} = 1$, the error is fully perceived by the controller and a "proportional" response to the error can be calculated. If $Y_{j,t} = 0$, there will be no perceived error. We model attention's relationship to error as a sigmoid that is continuous over all possible values for $e_{j,t}$, and as $e_{j,t}$ increases, $Y_{j,t}$ converges to 1 (full attention). The sigmoid is defined as follows,

$$Y_{j,t} = \frac{1}{1 + \exp(-\lambda_j(e_{j,t} - \epsilon_j))} \tag{65}$$

Institutional information processing is largely disproportionate because all actions carry costs associated with gathering information (information costs), searching for a solution (search costs), coming to an agreement on that solution (decision costs), and implementing that solution (transaction costs) ((Jones & Baumgartner, 2012; Jones et al., 2003; Workman et al., 2009)). We, like Jones and Baumgartner (2005b) aggregate these costs into an institutional friction parameter or *institutional costs*, denoted here as ϵ_j. Jones & Baumgartner ((2005b)) use the efficiency parameter to decrease the signal's strength (linearly) if the signal is below the cost threshold. We use a *response elasticity* parameter, λ, to define the slope of the sigmoid as it converges to full attention (higher λ means steeper slope). In this sense, we argue that λ can be thought of as the *institutional ambiguity* present within the system that distorts the actors knowledge of how close their system state is to the hypothetical threshold. If there was very low ambiguity (high response elasticity), the institutional agents would be able to respond fully to the optimal action point (when $e_{j,t} \sim \epsilon_j$), but ambiguity creates partial responses before and after ϵ_j.

Mathematically, in Equation 65, ϵ_j is always the $e_{j,t}$ value that yields $Y_{j,t} = 0.5$, and λ_j determines how quickly the sigmoid approaches zero on the left hand side of ϵ_j and one on the right hand side.

2.2.2. Step Two: Calculate Response

The response of each controller j, $u_{j,t}$ is the output of a nonlinear function $G_j(e_{j,t}Y_{j,t}, x_t)$ that takes the attention-modified error $(e_{j,t}Y_{j,t})$ and the system state, x_t, as the input. Each $G_j(\cdot)$ has two steps: (i.) calculate a potential response that meets the perceived error, $\hat{u}_{j,t}$ and (ii.) filter that potential response given any saturation constraints, $sat_j(\hat{u}_{j,t}, x_t)$. Thus, $u_{j,t}$ can be defined as,

$$u_{j,t} = G_j(e_{j,t}Y_{j,t}, x_t) = sat_j(\hat{u}_{j,t}, x_t) \tag{66}$$

The short-term action response (G_1) follows prior socio-hydrology models conception of short-term conservation. As referenced above, we note that our attention variable closely resembles the often used salience variable that inspires conservation (lowering per capita demand) according to a logistic decay function with inherent effectiveness rate, α, and minimum per capita demand, d_{min}, parameters ((M. Garcia et al., 2016; Mazzoleni et al., 2021; Gonzales & Ajami, 2017)). Thus, we define the potential short-term conservation action, $\hat{u}_{1,t}$, as,

$$\hat{u}_{1,t} = d_t\alpha\left(1 - \frac{d_{min}}{d_t}\right)Y_{1,t} \tag{67}$$

This relationship stems from the logic that it is harder to achieve conservation as the system reaches its demand limit. In the current version of the UWIIM, we do not model any constraints on the short term response for the saturation function because the minimum per capita demand is already accounted for in the logistic decay functional form ($sat_1(\hat{u}_{1,t}, x_t) = \hat{u}_{1,t}$). With this logic, we have the following definition of $G_1(\cdot)$:

$$u_{1,t} = G_1(e_{1,t}Y_{1,t}, x_t) = \hat{u}_{1,t} \tag{68}$$

The investment action situation's response, $u_{2,k,t}$, is a vector of investments for each infrastructure k in volumetric units (the amount of supply capacity gained by the investment). Note, for demand management related investments, decreases in demand are functionally considered supply gains. The potential response, $\hat{u}_{2,k,t}$ is driven by the total perceived supply gap between supply and demand, which is the product of the perceived error, $e_{2,t}Y_{2,t}$, and the projected demand, $\hat{D}_{t+\tau_p}$ (Equation 53), because the error is normalized by it. In addition, we assume that as long as there are available financial resources, the PIP will always invest in maintenance ($\hat{J}^m_{k,t}$ and $\hat{H}^m_{k,t}$), so we add it to $\hat{u}^i_{k,t}$. $\hat{u}^i_{k,t}$ is thus defined as,

$$\hat{u}_{2,k,t} = \beta_{k,t}e_{2,t}Y_{2,t}\hat{D}_{t+\tau_p} + \hat{H}^m_{k,t} \tag{69}$$

Attention dynamics, in this case, only affect expansion of infrastructure capacity, not maintenance. We distribute the supply gap across each infrastructure k with a distribution coefficient $\beta_{k,t}$, which represents the infrastructure investment strategy or preferences of the city being modeled. Default β_k values are set as parameters, but $\beta_{k,t}$ varies with time because investments can be re-distributed from infrastructures that have reached their maximum capacities (see attached code for exact algorithm). Unused investments due to maximum capacity are simply transferred to infrastructures not near their maximum capacity according to their default relative priority (β_k). Note, for demand management, decreases in demand reduce error at a faster rate than supply because $e_{2,t}$ is demand normalized. To account for this, the supply gap assumed by demand management is divided by γ_j to get the actual demand change pursued.

The investment action situation is constrained in its action situation by the year's investment capacity or maximum possible annual investment, $\bar{J}_t$ (Equation 82). Since this constraint is in dollar units, the supply needs to be converted to the financial cost of addressing that perceived need, $\hat{J}_{k,t}$. Therefore, in the investment action situation, the controller transforms the supply need (in volumetric units) for each infrastructure, $\hat{u}_{2,k,t}$, into financial need (dollars) with the cost functions for each infrastructure (Equation 44). We compile the total financial need, $\hat{J}_t$, by summing the investment costs need from each infrastructure type in the following equation:

$$\hat{J}_t = \sum_k F_k \left(\hat{u}^i_{k,t}\right) \tag{70}$$

The controller compares the total financial need to $\bar{J}_t$ in the saturation function and then outputs the result transformed back into supply units (F^{-1}) in the following equation:

$$sat_2 \left(\hat{u}_{2,k,t}, x_t\right) = F^{-1} \left[\min \left(\hat{J}_t, \bar{J}_t\right)\right] \tag{71}$$

where $F(\cdot)$ is a one term power law function with powers less than 1, so it has an inverse function.

The rate-setting action situation returns the change in per capita rate policy, $\hat{\pi}_t$, to address the perceived revenue gap $e_{3,t} Y_{3,t} \hat{C}^d_{t+1}$. The error and attention variables, like investment, are unitless, so multiplying by $\hat{C}^d_{t+1}$ is necessary to describe the revenue gap in dollar units. The potential revenue increase, $\hat{u}_{3,t}$, is the product of the perceived revenue gap divided by the projected population in the next year, $\hat{P}_{t+1}$, because $\hat{\pi}_t$ is in units of dollars per capita. The following equation, thus, defines $\hat{u}_{3,t}$:

$$\hat{u}_{3,t} = \frac{e_{3,t} Y_{3,t} \hat{C}^d_{t+1}}{\hat{P}_{t+1}} \tag{72}$$

The saturation function checks that the potential rate increase is less than the maximum rate increase percentage tolerated by the socio-political system, ψ_r, a parameter, in the following equation:

$$sat_3(\hat{u}_{3,t}, x_t) = \min\left(\hat{u}_{3,t}, \psi_r \hat{\pi}_t\right) \tag{73}$$

2.2.3. Investment Capacity

The PIP can make investments in infrastructure in year t with capital earned by bond issuance, J^b_t, or the net cash available, J^o_t, after paying for operating costs and debt service requirements. Thus, J_t is the sum of the two investment types, defined as,

$$J_t = J^o_t + J^b_t \tag{74}$$

We define $\bar{J}_t$ as the investment capacity of the PIP in year t, or the maximum investment (in dollars) that the utility can make in any given year. It is derived from the maximum bond issuance capacity, $\bar{J}^b_t$, and the maximum investment from net revenue, $\bar{J}^o_t$, which are both separately constrained. Since we assume that the utility cannot draw a deficit, $\bar{J}^o_t$ is the remaining revenue available after paying for operating costs and debt service requirements, given by,

$$\bar{J}^o_t = R_t - C^o_t - C^d_t \tag{75}$$

Bond investments are constrained by the need to keep the debt service coverage ratio above γ_r, the goal debt service coverage. Since we assume that the PIP, on average, pays off bonds in equal installments over the bond's life, we can examine the predicted debt service costs in $t+1$, which must satisfy the minimum debt service coverage ratio, γ_r. We re-arrange the debt service coverage ratio definition (Equation 50), treating γ_r as the constraint on C^d_{t+1} as follows,

$$C^d_{t+1} \leq \frac{\hat{R}_{t+1} - \hat{C}^o_{t+1}}{\gamma_r} \tag{76}$$

We use $\hat{R}_{t+1}$ instead of R_{t+1} because the PIP does not know if short-term curtailment will occur in $t+1$. The projected operating costs for $t+1$, $\hat{C}^o_{t+1}$, follows the form described in the Variable Projection sub-section. We then substitute equation 43 for C^d_{t+1} and isolate J^b_{t+1} to get the following:

$$\tilde{J}^b_{t+1} \leq \frac{\hat{R}_{t+1} - \hat{C}^o_{t+1}}{\gamma_r\left(1 + \tau_b i_b\right)} \tag{77}$$

We then substitute equation 42 for J^b_{t+1} and isolate J^b_t. Since we defined $\bar{J}^b_t$ as the maximum of J^b_t, the constraining inequality can be converted to an equality in terms of $\bar{J}^b_t$ as follows,

$$\bar{J}^b_t = \frac{\tau_b\left(\hat{R}_{t+1} - \hat{C}^o_{t+1}\right)}{\gamma_r\left(1 + \tau_b i_b\right)} - (\tau_b - 1)\tilde{J}^b_t \tag{78}$$

$\hat{R}_{t+1}$ depends on population increase or an increase in the rate policy. We use $\hat{P}_{t+1}$ (Equation 52) for expected population increase. Since possible rate increases are limited by the maximum allowable percent rate increase ψ_r, we can calculate what the maximum possible value of $\hat{R}_{t+1}$ is, denoted now as $\bar{R}_{t+1}$ and defined as follows,

$$\bar{R}_{t+1} = \hat{P}_{t+1}\psi_r\hat{\pi}_t \tag{79}$$

Since $\bar{J}_t^b$ is a maximum, it follows that $\bar{R}_{t+1}$ should be used for $\hat{R}_{t+1}$ since the rate-making action situation follows the investment action situation, limiting knowledge of what rates will be when making investment decisions. Substituting $\bar{R}_{t+1}$ into Equation 78 yields the following:

$$\bar{J}_t^b = \frac{\tau_b\left(\bar{R}_{t+1} - \hat{C}_{t+1}^o\right)}{\gamma_r\left(1+\tau_b i_b\right)} - (\tau_b - 1)\tilde{J}_t^b \tag{80}$$

We now substitute Equations 80 and 75 into Equation 74 to get the following equation for $\bar{J}_t$:

$$\bar{J}_t = \frac{\tau_b\left(\bar{R}_{t+1} - \hat{C}_{t+1}^o\right)}{\gamma_r\left(1+\tau_b i_b\right)} - (\tau_b - 1)\tilde{J}_t^b + R_t - C_t^o - C_t^d \tag{81}$$

We then substitute Equation 43 for C_t^d and combine like terms to get the definition of $\bar{J}_t$ used in the UWIIM code and manuscript as follows,

$$\bar{J}_t = \frac{\tau_b\left(\bar{R}_{t+1} - \hat{C}_{t+1}^o\right)}{\gamma_r\left(1+\tau_b i_b\right)} + R_t - C_t^o - (1+i_b)\,\tau_b\tilde{J}_t^b \tag{82}$$

3. Performance & Robustness Metrics

3.1. Performance Metrics

We record two performance metrics for each year of a model run: reliability and rate burden.

Reliability refers to the percent of demand that the city's water system can meet without needing to impose temporary water use restrictions. We adopt a similar metric to Ajami et al ((2008)) where we record the proportion of baseline demand in year t, $\bar{D}_t$, that can be met by available supply, S_t. This proportion is stored in ω_t for each year and is defined as,

$$\omega_t = \frac{S_t}{\bar{D}_t} \tag{83}$$

The second performance metric is the annual water rate paid by users at the end of the model run (π_{end}). This captures the financial burden placed on users to keep the CIS at a satisfying condition given experienced hydrologic shocks. Public water utilities, like Phoenix Water, have, among other considerations not modeled in the current UWIIM, dueling goals to provide reliable supply while also keeping rates low ((Richter et al., 2013; Hughes, 2022; Lach et al., 2005)). While we set up the Phoenix scenario so that major investment will very likely be needed, which often necessitates rate increases, we monitor this performance metric and its sensitivity to understand if there is an over-response by the PIP to the CAP shock (too much investment for similar reliability benefits).

Over the whole model run, I aggregate the reliability and rate time series in three ways: the mean reliability ($\tilde{\omega}$), the minimum reliability (ω_{min}), and the rate policy at the end of the model run (π_{end}).

3.2. Robustness Metrics

To measure robustness, we follow the example of Anderies et al ((2007)) and Rodriguez et al ((2011)) to create *sensitivity* measures. By sensitivity, we refer to the ratio of percent change in a performance metric to the percent change in an input. In our Phoenix example, the shock is the change in water inflow from the CAP, and we examine two performance metrics, thus creating two sensitivity measures: reliability and ratepayer financial burden.

Note, the performance metrics and sensitivity measures are calculated to summarize an entire model run (in the Phoenix case, a fifty year time-frame). With just one input change, each performance metric gets its own sensitivity measure: minimum reliability (Ω_{min}), mean reliability ($\tilde{\Omega}$), and ratepayer financial burden at the end of simulation (Π_{end}). For a performance metric calculated over model run m, Z_m, which corresponds to a CAP shock defined by s_m (Equation 85), the following equation defines the robustness or sensitivity, B_m,

$$B_m = \frac{1}{s_m}\left(\frac{Z_m - Z_0}{Z_0}\right) \tag{84}$$

where Z_0 represents the null performance metric of the city to no CAP shock ($s = 0$).

Text S2. Phoenix Metropolitan Area Case Description

4. Fitting the Water Management Model to the Phoenix Context

4.1. Common Hydrologic Stressor: Colorado River Supply

All cities modeled in the Phoenix Metropolitan Area have a unique allocation of the Colorado River delivered by the the Central Arizona Project (CAP). As we write this manuscript, the Bureau of Reclamation has announced that 2023 Colorado River Operations will follow the Tier 2a shortage obligations, prescribed by the 2007 Interim Guidelines and the 2019 Drought Contingency Plan (BoR, (2022a)). As argued by multiple scholars ((Wheeler et al., 2022)), regulatory agencies ((DOI, 2022)), and water providers ((Goddard & Atkins, 2022)), the DCP shortage obligations are not enough to meet the pressing state of the Colorado River, which the Bureau has reported may require a 2-4 MAFY basin-wide cut in use (DOI, 2022). The Bureau has undergone a Supporting Environmental Impact Statement (SEIS) process to reform the 2007 guidelines (Bureau of Reclamation, 2022c) and published a draft (D-SEIS) in April (Bureau of Reclamation, 2023).

Much of the basin's future remains in limbo as negotiations continue till the projected August finalization of the SEIS, but without a basin-wide compromise, such a cut, if mandated, would threaten the CAP's allocation (around 1.7 MAF). Arizona water leaders have pledged that they would, of course, not accept such a course of action given the threats to key municipal and tribal users (agricultural users are already being affected by DCP obligations), but Alternative 1 in the D-SEIS, if pursued, could result in a complete cut of CAP 4th priority water for 2024 (Bureau of Reclamation, 2023).

To account for this period of serious uncertainty about an immediate issue, we define a simple series of scenarios for the CAP's future at the municipal provider level. As we write this manuscript, the amount of CAP water available to municipal users has been constant over time because municipal and tribal users occupy the highest priority of CAP users. However, any cuts beyond Tier 2a begin to threaten municipal allocations. μ_2 is the annual water (AFY) that is delivered to municipal users in the Phoenix Active Management Area by the CAP, including both low and high priority use. Our scenario is a simple step-wise disturbance function that decreases $\mu_{2,k,t}$ by a proportional parameter s at time t^*, and that change is sustained for the rest of the model run. Recall, $E^{\mu}(\cdot)$ is the function that contains exogenous changes to mean inflow. For our scenario, it is defined as follows,

$$E_{\mu_2}(\bar{\mu}_{2,t}, t) = \begin{cases} s\bar{\mu}_{2,t} & t = t^* \\ 0 & otherwise \end{cases} \tag{85}$$

Since groundwater allocations are made without taking into account the dynamic state of the local aquifer, we do not model the impact of CAP shortage on groundwater availability. Sophisticated groundwater modeling of the Phoenix Activate Management Area and predictive use modeling in the event of shortage is beyond the scope of this study.

We set s values to reflect possible changes to CAP availability in this uncertain period of Colorado River politics. As a default, we assume that there will be a Tier 3 shortage by 2024 ($t^* = 14$ if $t_0 = 2010$). The current directives from the Bureau of Reclamation indicate that the Tier 3 cuts are not nearly enough to address the current dire state of Lakes Mead and Powell ((Bureau of Reclamation, 2022b)), so this assumption represents the *floor*. A Tier 3 shortage carries with it a 720 KAFY cut for Arizona ((CAP, 2021)), which, in prior Tier 1 and 2a shortages, falls almost entirely on CAP due to its junior status as a water user. We define Δ_{CAP} as the shortage (in AFY) that the CAP has to take. Since μ_2 in our setup is reflective of municipal CAP deliveries in the PMA, we need to calculate what amount of Δ_{CAP} will affect μ_2. For any hypothetical shortage taken by Arizona in its Colorado River allocation (in AFY), Δ_{AZ}, we use the following steps to calculate the s parameter used in the representative scenario.

1. **Arizona Allocation to CAP Allocation:** In Arizona, there are three tiers of users that are higher in priority than CAP (a P4 user). From past models used in the 2007 shortage sharing agreements ((Bureau of Reclamation, 2007)), we estimate an average priority 1-3 use of 1.11 MAFY. Subtracting that from Arizona's allocation of 2.8 MAFY, we get 1.69 MAFY available for fourth priority users like CAP. According to additional Arizona shortage sharing agreements ((ADWR, 2007)), other fourth priority users on the Colorado River have agreed to share shortages with CAP such that they are at least guaranteed their proportional allocation of remaining available water. Their existing non-shortage allocation is 164652 AFY, and dividing this by 1.69 MAFY yields a proportion of 0.098. In the event of a CAP shortage, the non-CAP on-river fourth-priority users are expected to use the minimum of either their proportion of the remaining available water or their typical annual use, which was estimated in the shortage sharing agreements to be 79,350 AFY. After accounting for priority 1-3 use and on-river fourth priority use, the remaining water is available for CAP. Δ_{CAP} is the difference between CAP's typical use amount, around 1.595 MAFY ((CAP, 2022b)), and this remaining available water after accounting for a 5% evaporation loss ((Bureau of Reclamation, 2007)).

2. **Allocating CAP Water:** Within the CAP system, 1.418 MAF of water is dedicated to sub-contracts with four levels of users. The highest priority goes to users that have tier three (P3) Arizona rights but get their allocation delivered through the CAP, and it is 68.4 KAF. The next two levels are treated as equally high priority: municipal & industrial (M&I) users and Indian users, which together hold 981,902 AF of annual sub-contract rights. The remaining sub-contracts are held by Non-Indian Agriculture (NIA) users, totalling 364,698 AF. A municipal user may have access to an array of rights from each tier. CAP water in excess of the 1.418 MAF of sub-contractual obligations is treated as excess water and used for multiple other uses including agriculture and recharge obligations for CAGRD. In our scenario, CAP meets its obligations in priority order given its available water for the year. If there is not enough water to meet M&I and Indian obligations, the water is split according to the sharing protocol outlined by the Arizona Water Settlements Act ((108th Congress, 2004)). To simplify the model, since P3 CAP rights are small portion of Phoenix and Scottsdale's total CAP rights, we group CAP water into high priority (M&I and P3), and low priority (NIA) water available to municipalities (no Indian water).

3. **Isolating the PMA Share:** We distinguish the volume of water available to PMA users from the total high and low priority water available to municipalities by examining the proportion of high (P3 and M&I) and low rights held by users in the Phoenix Active Management Area, according to the CAP sub-contract database (CAP, 2022a). Those proportions are 0.535, and 0.192, respectively. Now, we have the total water available to PMA users in any shortage year. Dividing the difference between this and μ_2 by μ_2 gives

an estimate for the s proportion associated with a hypothetical Colorado River shortage for Arizona (Δ_{AZ}).

We opt for the Tier 3 shortage as our default scenario, which is associated with a 720 KAF cut to Arizona's allocation. According to our assumptions, this would imply a default s value of 0.284 (Table S2).

Due to the heavily regulated nature of the Colorado and Salt-Verde systems, the variation of inflow (captured in $C^{v}_{i,t}$) is not a concern outside of controlled cuts described above. Thus, we keep $C^{v}_{i,t}$ for both surface water and groundwater at a constant near zero value (to prevent dividing by 0 errors).

4.2. City-Specific Water Context

Designations of Assured Water Supply (DAWS), completed for most PMA cities in 2010, provide a commonly formatted set of water resource information at the city level. We, thus, set 2010 as the start year for all model runs and used DAWS estimations to set model parameters and initial conditions related to the water resource portfolio of Scottsdale ((ADWR, 2013)) and Phoenix ((ADWR, 2010)). Queen Creek does not have a DAWS, but they have a Certificate of Assured Water Supply (CAWS) for their 2011 system ((ADWR, 2011b)) and a CAWS for the H20, Inc. system ((ADWR, 2011a)) that they acquired in 2013, which provide similar groundwater availability information. We triangulated these official ADWR filings with published ADWR user-specific supply and demand data for the Phoenix AMA ((ADWR, 2022)) and publicly available water resource plans for each city ((City of Phoenix, 2011, 2021; Sunrise Engineering, Inc., 2017; Scottsdale Water, 2021)). Water resource plans published after 2010-2011 allow us to make sure that the initial conditions that we set for the cities to resemble 2010 in the

UWIIM application do not cause the city's to take significantly different paths from 2010 to 2022.

There are three possible water sources available for the three cities being modeled: SRP delivered surface water, CAP delivered surface water, and local groundwater. For each of the three sources, we define a total annual inflow to users in the PMA: 900 KAFY of SRP water ((City of Phoenix, 2021)), 369 KAFY of CAP water ((ADWR, 2022)), 690 KAFY of local groundwater recharge ((ADWR, 2022)). The CAP and groundwater inflows represent the annual average from 2000-2021 of reported inflows in the Phoenix AMA database. The CAP inflow represents municipal Phoenix AMA users only to insure that the shortage volume is accurately calculated based on municipal priority (see previous sub-section) while the groundwater inflow is not user-specific. This is because the local aquifer cannot be siloed into relevant users, so all users that share an aquifer affect each other's use.

Since the cities receive surface water from bulk water providers, we assume that surface water storage is negligible for each city ($V_0^s = V_t^s \sim 0$). City-specific groundwater storage in 2010 (V_0^g) was estimated from their DAWS or CAWS, which specifies a 100-year safe-yield allocation (total volume, not annual use). In addition to this safe-yield estimate, we add long-term storage credits accrued by the city before 2010 (recorded in their DAWS or CAWS). For Queen Creek, a major update for their groundwater availability in the past decade has been the purchase of 175 KAF of groundwater extinguishment credits ((Ferris & Porter, 2019)) that add to this total available storage but does not appear in their 2010-2011 position. Since we do not allow for cities to modify their source water in this application of the UWIIM, we add these credits do Queen Creek's initial storage availability.

Since the model requires a storage capacity ($\bar{V}_t$), we set the surface storage capacity to a very small number, near zero, to prevent dividing by zero, and the ground storage capacity to be double the safe yield volume (if the city does not use any groundwater over 100 model years, they will fill their storage) since the model runs used in this analysis do not go beyond 100 years. The chosen capacities do not affect the model dynamics because the cities do not invest in them.

Each city requires unique legal availability parameters, a_i^v and a_i^q, for each water source i. As mentioned, surface water volume is negligible in our PMA case, so we set $a_{1,2}^v = 1$ for SRP ($i = 1$) and CAP ($i = 2$), noting that $V_{1,2} \sim 0$, to give the cities full access to essentially nothing. For SRP and CAP inflows, a_i^q is simply the proportion of the total inflows from each source that the city has access to, given their ADWR filings described above and CAP sub-contract registry ((CAP, 2022a)). Since SRP rights are land-specific, only a certain portion of a city's demand (corresponding to the proper land parcel) can utilize their SRP allotment, ξ_1. We derive ξ_1 from Scottsdale and Phoenix water resource plans ((City of Phoenix, 2022a; City of Scottsdale, 2022b)). However, Phoenix and Scottsdale have additional access to SRP water associated with an expansion of Roosevelt dam after the initial Kent Decree allotments. This water comes from storage capacity added to the Salt-Verde reservoir system after the Kent Decree and can be used anywhere in the city's service area, referred to as New Conservation Space (NCS) and Gatewater. Since these water allotments are surplus water, their availability is subject to temporal variability in Salt-Verde hydrology, which this version of the UWIIM does not model. Instead, we use the average availability of NCS water and Gatewater reported in the two cities' DAWS to define $a^q_{1,NG}$, the proportion of all SRP water entering the PMA that is each city's average NCS and Gatewater availability. In the model, total SRP water entering the PMA does not change over time, so the total inflow is always μ_1. With these conditions in mind, SRP legal availability for each city in the PMA is defined as follows,

$$A^l_{1,t} = \min\left(a^q_1\mu_1, \frac{\bar{D}_t}{\eta_t}\xi_1 + a^q_{1,NG}\mu_1\right) \tag{86}$$

Since a^q_1 includes NCS water and Gatewater, $a^q_{1,NG}$ only needs to be considered in the second term of the minimum statement. For CAP availability, we further divide a^q_2 (the total proportion of non-shortage CAP inflows available to a city) into the proportion of low priority priority CAP water, $a^q_{2,L}$, and the proportion of high priority CAP water, $a^q_{2,H}$, available to the city as given by the CAP sub-contract registry (see previous subsection for definitions of high and low priority). Thus, available CAP water for a city is given as,

$$A^l_{2,t} = a^q_{2,H}Q^{(H)}_{2,t} + a^q_{2,t}Q^l_{2,t} \tag{87}$$

Any available CAP water that is not used in the year that it is available can be stored or "banked" by the city in its groundwater storage, Q^b_t. It is treated as simply another local groundwater inflow for the city's groundwater water balance and is defined as,

$$Q^b_t = A^l_{2,t} - O^d_{2,t} \tag{88}$$

For groundwater, since safe yield is concerned with balancing groundwater withdrawals with predicted inflows, we assume that the annual allocation of groundwater use given to each city (their 100-year volume of assured water divided by 100 years) is the average groundwater inflow attributable to their city ($a_3^q \mu_{3,t}$). We use μ and not Q because the allocations are not dynamically set based on annual inflows. Since our calculations of local available groundwater storage (V_t^g) are at the city-level, we assume that the city can use all of its available stored water ($a_3^v = 1$) in excess of the safe yield allowance. Recall, V_0^g is the amount of total groundwater use granted to each city in 2010 for its 100-year assured water supply, so if $V_t^g = 0$, the city has used up its total 100-year allowance of groundwater use. Additionally, we account for Queen Creek's participation in the Central Arizona Groundwater Replenishment District (CAGRD) ((Ferris & Porter, 2019)), which is any agency operated by CAP to offset groundwater use in member areas that exceeds safe yield determinations through groundwater replenishment, by adding initial volume to V_0^g equal to Queen Creek's projected demand in excess of its CAWS allowance given its initial per-capita demand and its projected population growth since population growth is exogenous to the model's dynamics. Taking all of this into account, the following equation determines $A_{3,t}^l$.

$$A_{3,t}^l = a_3^q \mu_{3,t} + a_3^v \max\left(0, V_t^g - 100 a_3^q \mu_{3,t}\right) \tag{89}$$

We derive initial groundwater processing capacity of each city from the reported volumetric pumping capacity reported in city designations and city water resource plans. For Phoenix's groundwater pumping capacity, we include both Phoenix operated wells (23 KAFY) and SRP wells that Phoenix can has an agreement with to access their groundwater rights (20 KAFY). We assume that Phoenix and Scottsdale can fully process their available surface water ($w_0^s = \bar{w}^s$) and Queen Creek cannot ($w_0^s = 0.0005$). We do not set Queen Creek's to zero because we need slight initial capacity to calibrate the cost functions described in the next section. This is why Queen Creek relies solely on groundwater use during the 2010-2020 decade ((Sunrise Engineering, Inc., 2017; Town of Queen Creek, 2012)).

D_0 is assumed to be the total demand or deliveries to users made by the utility in 2010. Most utilities, however, report the volume of water used (extracted from available sources) in their water resource plans and the same is reported in the ADWR database for the Phoenix Active Management Area (AMA) ((ADWR, 2022)), which does not account for system losses or local re-use. We first total the city's annual use (AFY) from the ADWR data in 2010 (Use_0). Then, we extract deliveries, D_0, by subtracting losses (L_0) and adding reported local re-use amounts in 2010 (RU_0), as follows,

$$D_0 = Use_0 + RU_0 - L_0 \tag{90}$$

d_0 is D_0 divided by the 2010 population (P_0) as follows,

$$d_0 = \frac{D_0}{P_0} \tag{91}$$

The delivery efficiency for each city is, on average, the volume of water delivered to city users per water used from its sources. To determine an initial delivery efficiency (η_0) for each city, we gathered information on the loss rate of water in cities and the capacity to locally re-use reclaimed water. Starting in 2016, AMA reporting required cities to report their loss rate (percentage), so we calculated an average loss rate across the available reporting years for each city, l. For Phoenix and Scottsdale, we use the effluent capacity reported in their DAWS for the initial re-use capacity, A_0^r, and for Phoenix, add its "three-way exchange water" ((City of Phoenix, 2011)), which refers to effluent water that Phoenix has exchanged for 20KAFY of SRP delivered water but is still recorded as effluent water in right. For Queen Creek, we set $A_0^r = 0$ to reflect that they did not have re-use capacity in 2010. The equation for η_0 is then defined as follows,

$$\eta_0 = (1 + l)^{-1} \left(1 + \frac{A_0^r}{A_0}\right) \tag{92}$$

Since Phoenix and Scottsdale are primarily surface water systems, θ_g was empirically derived from historic surface water and groundwater production reported in water resource plans ((City of Scottsdale, 2022b; City of Phoenix, 2022a)). Rather than assuming $\theta_g = 1$ for Queen Creek because they do not use any surface water in 2010, we set $\theta_g = 0.075$ like Scottsdale because their surface water resources are primarily CAP-based like Scottsdale. This does not matter for Queen Creek's initial use because they do not have any processing capacity to use surface water in the first place.

We set the minimum per-capita demand parameter to be reflective of the local demand profile. Beginning with the California requirement of 43 GPCD for satisfactory household service (Feinstein, 2018), we assumed that the proportion of the total demand going to residential use would be the same at the minimum demand level, thus dividing 43 GPCD by the percentage of local demand that goes to residential use.

4.3. City-Specific Population Growth Context

Population growth parameters (r and K) were set based on a logistic fit of annual population data from city Comprehensive Annual Financial Reports (CAFRs). The per capita limit to annual revenue, $\bar{\pi}$ was just set to be \$1000 for all cities to allow the stress to accumulate beyond affordability limits. In the analysis phase, we compared the generated π values with common affordability standards.

4.4. Common Infrastructure Settings

The remainder of the infrastructure parameters are the same across the cities modeled. Table S5 lists the common default values and their justification. Decay rates on all infrastructure types (δ) were set to 0.05. Depreciation is a difficult parameter to generalize across cities and infrastructure types. We opt for 0.05 because it sits between the value of 0.1 used in previous CIS models ((Homayounfar et al., 2022; Muneepeerakul & Anderies, 2017)) and the lower range of (0.0125, 0.02) used in the general water infrastructure cost model that inspires our investment cost function ((Hansen, 2009)). We additionally confirm that 0.05 is consistent with the default investment cost function parameters for the PMA and expected infrastructure costs, and we perform sensitivity analysis on the parameter to demonstrate its functional relevance in the UWIIM. The rate does not matter significantly in the current model setup because we assume that the utility maintains infrastructure states if they have sufficient financial resources. The time to implement investments τ^i was estimated from the Phoenix Capital Improvement Plans ((City of Phoenix, 2022b)) by averaging the planned time between investment and finished construction of capital projects, organized by our infrastructure types. Demand management investments have the shortest time (2 years) and delivery efficiency improvements have the longest time (4 years). The limits for infrastructure improvements were estimated from current technological context. Maximum delivery efficiency ($\bar{\eta}$) is assumed to be 1.5 (with Equation 92) across all cities to reflect a situation where the city reclaims and reuses 60% of use, which is generous given current PMA cities reclaim around 40% of use before considering treatment, and has a loss rate of only 5%. For maximum processing capacity, we calculate the processing capacity necessary to fully process their legal allotment from each source in a year as follows,

$$\bar{w}_{i,t} = \frac{A^l_{i,t}}{\bar{V}_{i,t} + \mu_{i,t}} \tag{93}$$

5. Fitting the Financial Model to the Phoenix Context

We fit the financial model using a combination of empirical investment, revenue, bond issuance, and operating cost data for the three cities studied: Phoenix, Scottsdale, and Queen Creek. The final sub-section provides summary tables of the parameters and initial conditions used.

5.1. Operating Cost Function

Operating cost data was gathered from each city's CAFRs from 2010 to 2020 (City of Phoenix, 2022b; City of Scottsdale, 2022a; Town of Queen Creek, 2022). Due to the significant amount of change faced by Queen Creek in the past decade, including the acquisition of two water systems, CAFR data before 2010 was not considered. Service population data for each city was gathered from a combination of Arizona Department of Water Resources data (ADWR, 2021) and the SDWIS (US EPA, 2022). Total deliveries made in each year, D_t, were calculated according to reported water uses and loss rates in the ADWR AMA data (ADWR, 2022). Using equation 34, we fit a log-log regression accounting for city effects, ξ_c and time effects, ξ_t, to account for inflation. c is the city index as follows,

$$\log C^o_{ct} = \log g_o + z_{op} \log P_t + z_{od} \log D_t + \xi_c + \xi_t t + \varepsilon_{ct} \tag{94}$$

We assume independent, normally distributed errors, ε_{ct}. ξ_t and ξ_c are used with the calculated g_o to make a specific normalizing coefficient g_o for each city given 2010 US dollars as follows,

$$g_{oc} = g_o \exp\left(\xi_c + 2010\xi_t\right) \tag{95}$$

The regression results are summarized in Table S7. The chosen model achieved an r^2 of 0.992. The population, deliveries, and city effects estimates are significant to p¡0.01. Likely due to the small time range of the data, the time effects (hypothesized to related to inflation) were not significant. To justify our inclusion of both demand and population as factors, we show regression results for alternative models including population only and demand only.

To visualize the results, we provide the fit of the population and demand model to the data in Figure S1.

5.2. Revenue & Rates

Initial revenue settings for each city require us to set $\hat{pi}_0$, the initial goal per capita rate, and the proportion of rate revenue that comes from fixed or connection charges β_p^π. We gather revenue data from each city's CAFR in 2010 and divide that revenue by the 2010 population to estimate $\hat{pi}_0$. Within this process is the assumption that there are no short-term demand curtailment measures in 2010 that would make the actual revenue not equal to the target revenue. We then calculate β_p^π with the Water Rates Dashboard for Arizona provided by the Environmental Finance Center at University of North Carolina ((UNC Environmental Finance Center, 2022)). For each city, the dashboard provides the fixed costs associated with a monthly residential bill and the monthly residential bill associated with a given gallons per month (gpm) of usage. We use the d_0 calculated above to calculate an average monthly water usage and extract the resulting bill from the dashboard. We divide the fixed costs by the total average bill for each city to get β_p^{π}. Note, this process may not capture the complexity associated with block rate pricing and higher fixed costs for larger users, but the significance of this choice can be addressed by performing sensitivity analysis on $\beta_p^{(\pi)}$. Also, the dynamic controller mechanism in the UWIIM ensures that even if our initial calibration is incongruous with other parameters, the city can correct using investment and rate policy changes to get the system to its goal state before the CAP shock, which does not occur for 14 years ($t^* = 14$).

5.3. Infrastructure Investment Costs

We collected infrastructure investment data from the Capital Improvement Plan (CIP) of Phoenix (City of Phoenix, 2022b) for 2010-2021. We grouped investment projects into the categories of infrastructure relevant to the model to get a total investment in each infrastructure type (delivery efficiency and processing capacity). Combined with the AMA database (ADWR, 2022), we were able to create annual data for $J_{k,t}$ and the change in volumetric supply capacity attributable to the infrastructure type k, $H_{k,t}$.

From the $J_{k,t}$ time series, we calculated an average proportion of Phoenix capital investments that go to delivery infrastructure of 0.66 and a proportion of 0.33 for processing infrastructure. Other infrastructure projects take up the remaining 0.01 proportion. Conservation investments do not appear in the CIP, so we attribute the remaining 0.01 to conservation investments. We define these investment proportions for each infrastructure type as ϕ_k in the cost function (Equation 44) calibration discussed below.

5.3.1. Demand Management Investments

Since Phoenix does not list its conservation investments in its financial records, we have little city-specific data to use for calibrating the long-term demand management cost function parameters. To simplify the effort, we assume that there are no returns to scale for increasing conservation investments $z_{\bar{d}} = 1$. To derive a useful $g_{\bar{d}}$ value, we turn to reports from the Southern Nevada Water Authority, a similar regional example to the PMA cities, and their conservation rebate program, which saw a reduction of 39 KAFY in annual demand from 2000-2018 with \$230M ($J^{(\bar{d})}$) in reported investment (Southern Nevada Water Authority, 2019). Given SNWA time series for system demand, per-capita demand ($\bar{d}_t$), and population (P_t) over that period of time, we extracted an annual $H^{(\bar{d})}$ (average annual change in demand in AFY associated with the conservation investment) associated with the rebate. The program achieved 38,668 AF of conservation in 18 years, which implies an annual conservation of 2148.222 AFY ($H^{(\bar{d})}$).

Then, we calculated the background decay rate $\delta_{\bar{d}}^{SNWA}$ required to maximize the likelihood of the demand and population time series data from SNWA in the following equation:

$$\delta_{\bar{d}}^{SNWA} = -\frac{1}{\sum_t \bar{d}_t}\left(39 + H^{(\bar{d})}\sum_t \frac{1}{P_t}\right) \tag{96}$$

With those, we were able to derive the SNWA normalization coefficient $g_{\bar{d}}$ associated with the rebate program as follows,

$$g_{\bar{d}} = \frac{J^{(\bar{d})}}{H^{(\bar{d})}} \tag{97}$$

However, to account for the fact that the local Phoenix region did not experience the same decrease in demand from 2000-2018 that SNWA did, we calculate a local $\delta_{\bar{d}}$ for the Phoenix region, given the same $g_{\bar{d}}$. This is because we do not have data on conservation investments, but we do have time series data of Phoenix population and demand. Due to the significant acquisitions of service territory in Queen Creek, the time series data is not useful, but we were able to fit a power law model for the Scottsdale and Phoenix demand time series data accounting for city-unique effects. We compare the power law model to a linear model (Table S8). The power law model is given by,

$$\log d_t = \log \xi_c + \delta_{\bar{d}} \log t \tag{98}$$

The linear model is given by,

$$d_t = \xi_c + \delta_{\bar{d}} t \tag{99}$$

Both models performed well with their adjusted r^2 values being both 0.997. Given the similarity, we opt for the power law model to reflect the general model of background demand decay in the socio-hydrology literature (e.g., (M. Garcia et al., 2016; Gonzales & Ajami, 2017)). For the most part, the area's per-capita demand did not change significantly over the sample time period, and for the sake of the model analysis, background demand decay is not expected to play a significant role in the city's response to CAP shocks. It is reassuring that the modeled decay rate (-0.0003) is the same as the SNWA extracted decay rate since, again, they are close regional neighbors.

5.3.2. Hard Infrastructure Investments

For hard infrastructure, we need to ensure that the infrastructure investment cost function is consistent with the investment capacity parameters (τ_b and i_b) and initial conditions ($\tilde{J}_0^b$).Using Equation 41, we can calculate the initial average annual bond investments, $\tilde{J}_0^b$, from C_0^d and the τ_b and i_b parameters. We derive τ_b and i_b from the average bond life and interest rate of bonds issued by the City of Phoenix to cover water system improvements, reported in the city's CAFRs from 2010-2021.

The key assumption for our initial calibration is that at the start of the model run (2010), all three cities are investing to maintain their infrastructure capacity ($J_0 = \hat{J}_0^m$), or expressed as an equation with c being the city index,

$$J_{c,0} = \hat{J}_{c,0}^m = J_{c,0}^o + \tilde{J}_{c,0}^b \tag{100}$$

From the city CAFRs and the above described operating cost calibration, we have an estimate for R_0, C_0^o, and C_0^d. With these initial values, not all cities have a debt service coverage ratio of at least 2 (γ_r), so to keep our assumption of infrastructure maintenance, we calculate J_0^o to be $(\gamma_r - 1)C_0^d$, so that if the city's DSCR is below γ_r, the rate-setting controller will seek to raise rates to a point where both the DSCR is at γ_r and the utility is maintaining infrastructure with an average annual bond-sourced investment of $\tilde{J}_0^b = J_0^b$.

We allocate $J_{c,0}$ to infrastructure types k with the above calculated values of ϕ_k in the following equation:

$$J_{c,k,0} = \phi_k J_{c,0} \tag{101}$$

Additionally, with the initial values of infrastructure capacity in each city detailed in the Water Resources calibration, a given δ_k, and the $H_k(\cdot)$ equations listed in the Infrastructure Dynamics sub-section, we calculate the annual maintenance need (in the volumetric capacity units associated with H_k) required for each city, $\hat{H}_{c,k,0}^m$ by infrastructure type k. This is the capacity that would be lost each year if there was no maintenance investment.

Since we have three cities, we have three data points of $\hat{H}^m_{c,k,0}$ versus $J_{c,k,0}$ for each infrastructure type. We first calculate z_k directly from the three data points (in log-log form) using the general expression for fitting a power parameter in a power law model as follows,

$$z_k = \frac{Cov\left(\log(\hat{H}^m_{c,k,0}), \log(J_{c,k,0})\right)}{Var\left(\log(\hat{H}^m_{c,k,0})\right)} \tag{102}$$

Encouragingly, each infrastructure type (delivery efficiency and processing capacity) provided a z_k less than one, implying returns to scale as the size of the investment increases (decreasing marginal investment cost).

Since there is not enough data to have a confident g_k, we treat g_k as a city specific parameter, $g_{c,k}$, also reflecting the fact stated above that investment costs can be quite city-specific. We calculate $g_{c,k}$ for each city given its $\hat{H}^m_{c,k,0}$, $J_{c,k,0}$, and z_k values in the following equation:

$$g_{c,k} = \frac{(\hat{H}^m_{c,k,0})^{z_k}}{J_{c,k,0}} \tag{103}$$

We combine processing capacity for surface and groundwater to get a mutual $g_{c,k}$ value because Phoenix does not separate them in their CIP.

With this calibration process, the investment cost function parameters still rely on a given δ_k parameter. We use a default value of 0.05 because it is a commonly used default depreciation rate in capital investments. Using this value yields a g_η value that implies a capital cost per acre-foot of around \$5,700, which is about double the per acre-foot capital costs reported in re-use facility projections in California ((Cooley & Phurisamban, 2016)) and Arizona ((Carollo & City of Flagstaff, 2017)). This makes sense because we group distribution infrastructure (another costly category of infrastructure investment) into delivery efficiency, so expansions to delivery efficiency that hypothetical re-use solutions would provide would likely also carry with it alterations to distribution infrastructure. Regardless, we run sensitivity analysis experiments that vary δ_k to discern if there is a significant role that this parameter choice plays on our findings.

5.3.3. Investment Allocations

The investment allocations in the UWIIM are steered by β_k parameters that signify the proportion of supply needs that are filled by each infrastructure type. Since we assume cities will always seek to maintain existing infrastructure states, β_k only relates to investments that expand infrastructure capacity. We begin with an assessment of investment priority from recent water resource and infrastructure master plans of the cities and then choose β_k values to reflect that priority order.

Across all three cities, groundwater processing infrastructure is the highest priority of the three types we are examining as they prepare for shocks to surface water supplies (Scottsdale and Phoenix) (City of Phoenix, 2021; City of Scottsdale, 2022b) or expanding demand (Queen Creek) (Sunrise Engineering, Inc., 2017). Thus, we set β_{w_g} to be 0.7 for Phoenix and Scottsdale and 0.9 for Queen Creek. Queen Creek's groundwater priority is set higher because their 2017 master plan uses groundwater capacity, only, to meet committed demand and only notes the potential of other options like surface water or re-use. We confirmed the 0.9 setting by comparing Queen Creek's simulated groundwater capacity in 2022 given our above defined population growth scenario to the city's 2022 committed groundwater capacity in the 2017 plan ((Sunrise Engineering, Inc., 2017)), both of which are around 35 KAFY. Since Queen Creek does not reveal a clear preference for deciding between the re-use and surface processing, we set Queen Creek's default β_η and β_{w_s} to both be 0.04. We assume Scottsdale and Phoenix possess the necessary surface water treatment capacity, so $\beta_{w_s} = 0$. Phoenix and Scottsdale have the capacity to expand re-use, but it is much more difficult than expanding groundwater capacity due to existing exchange agreements with their reclaimed water ((City of Phoenix, 2021)). Thus, we set $\beta_\eta = 0.2$ for Phoenix and Scottsdale. This leaves 0.1 for demand management priorities in Phoenix and Scottsdale, and 0.02 in Queen Creek.

Since this is not meant to be a decision support model that closely reflects reality, choosing β_k is just a means to set a reasonable baseline to test the influence of institutional friction. Recall, the β_{kt} updating algorithm ensures that when the limit of an infrastructure capacity is reached, the PIP pursues the other options in proportion of their remaining priority level.

Text S3. Sensitivity Analysis Setup

While we calibrate the financial and water resources context of each city, many of the institutional design parameters are more difficult to calibrate since they can refer to more intangible phenomena like institutional friction. Fortunately, sensitivity analysis (Table S10) is at the core of our work presented here as we are interested in the way uncertainty of the institutional context actually affects the robustness of a city's water system to changes in CAP availability. We do note that some institutional parameters have grounded default values. Each of the goal parameters γ_j has a basis in PMA water management. Short-term measures are only put in place when there is not enough supply to meet demand ($\gamma_1 = 1$). Investments are driven by a long-term supply buffer of 20% above projected demand ($\gamma_2 = 1.2$), which we pulled from interviews with PMA water resource managers. Financial decisions are driven by a minimum debt service coverage ratio of 2, which is stated in Phoenix rate-planning ((Rafelis, 2021)). We set the default rate increase limit, ψ_r, to be 15% since 2000, the most that Phoenix has raised rates within a year (as measured by the average monthly bill) is 13%.

Institutional friction remains an illusive parameter to calibrate to complex institutional contexts. For institutional costs, ϵ_j, we assume no institutional costs as a default for all action situations ($\epsilon_j = 0$). For short-term measures and investment, we vary it in $[0, 1]$ because beyond $\epsilon_{1,2} = 1$, we are implying that the controller would not act if all projected demand was impacted by a shortage. We use the same variation range for rate-making because beyond $\epsilon_3 = 1$, we are implying that the controller will not act until there is only enough net revenue available to cover current debt service obligations.

With the institutional response elasticity, λ_j, since it is a coefficient in the exponential term of Equation 65, discerning units for empirically grounding it is difficult. We opt for an approach that relates the λ_j setting to the range of error values that will generate a significant attention response. When error is exactly equal to ϵ_j, $Y_{j,t} = 0.5$. The response elasticity, λ_j, defines how quickly the attention-response curve on either side of ϵ_j converges to 1 (maximum attention) on the right side ($e_{j,t} > \epsilon_j$) and 0 (no attention) on the left side ($e_{j,t} < \epsilon_j$). Assuming that $Y_{j,t} > 0.1$ (over 10% of the actual error is perceived) is significant, we re-arrange Equation 65 to solve for the value of λ_j that will cause a certain range of error Δe_j to generate attention above 0.1 on the left side of ϵ_j. Since we are dealing with the default values of λ_j, we set ϵ_j to its default value (zero) and thus, use the following equation to intuit a value of λ_j for a given Δe_j:

$$\lambda_j = \frac{1}{\Delta e_j} \ln(9) \tag{104}$$

For example, a Δe_j value of 0.2 implies that error values that are 0.2 less than ϵ_j will still generate significant attention. This would require a λ_j value of about 11. We begin with our extreme cases to determine a suitable variation range for λ_j. We assume that the highest ambiguity (lowest response elasticity) case is associated with a Δe_j value of 0.5 where the PIP still pays significant attention to cases where there remains uncertainty surrounding available supply to cover half of projected demand. This is associated with a λ_j value of about 4. At the other extreme, we examine the case associated with a Δe_j value of 0.01, which can be though of, in the investment action situation for instance, as a situation where uncertainty only surrounds 1% of projected demand. This is associated with a λ_j value of about 220. To set a default value, we use a Δe_j of 0.1, which has a λ_j

value of 22 associated with it. Since short-term actions, especially in the PMA, allow for more direct, responsive, emergency power held by the director of the water department (e.g., (City of Phoenix, 2015)), we increase the elasticity of the default λ for short-term curtailment to 110, which is associated with a Δe of around 2%. Again, a core focus of this work is sensitivity analysis of these institutional friction parameters, so setting default values is not as important as understanding the implications of their variation on system robustness.

I offer a basic one-at-a-time sensitivity analysis of other potentially impactful parameters to provide context to the findings discussed above (with Table S10 & Figure S3).

For Phoenix and Scottsdale, minimum reliability sensitivity is not significantly impacted by any of the other parameters, indicating that the controller was well-designed to respond to the unique error context of a given parameter set. Queen Creek's reliability is sensitive to short-term curtailment responsiveness (α and ϵ_1) because they may need to turn to short-term measures during the high growth period. Additional work should investigate the interaction between short-term processes and investment, which has been explored in water resources modeling (e.g., Trindade et al., 2020), while also accounting for institutional friction. Also for Queen Creek, the lead time required for investments affects their timing to keep up with the high growth period, and the long-term supply goal can create an over-reaction response that depletes available groundwater credits faster.

Since keeping rates low is not a goal of any of the controllers, the model's rates are understandably more sensitive to other parameter variations in all three cities. The goal of this modeling study, though, is not to predict rate outcomes, but to explore the relationship between operational capacity, institutional friction, and robustness in comparison across the cities. Additional work, can explore multidimensional sensitivity analyses that pairs institutional friction parameters with each of the potentially impactful rate-making parameters (e.g., goal DSCR).

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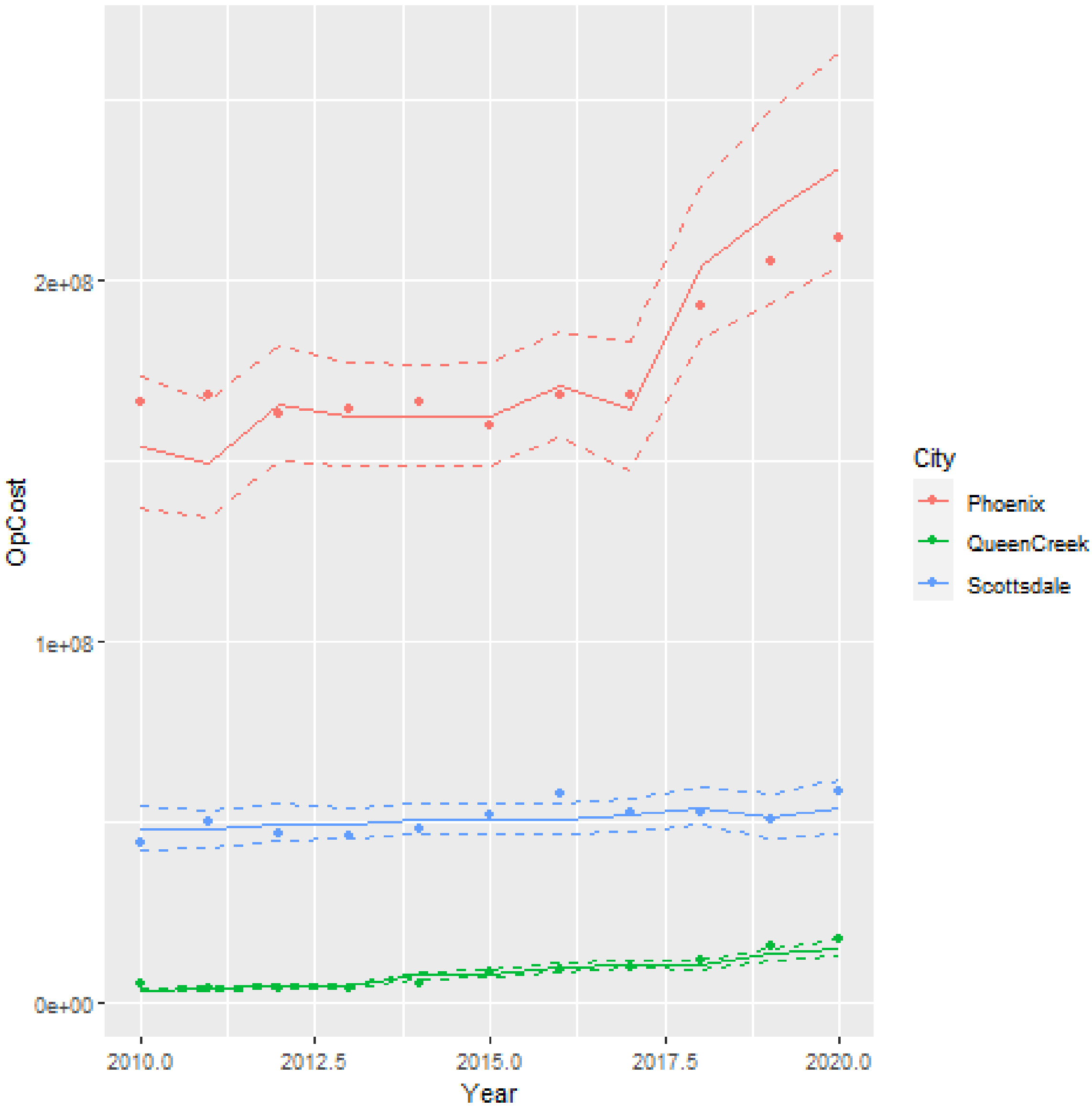

Figure S1. Fit of the Operating Costs model for the Phoenix Metropolitan Area. Dashed lines display residual standard error range.

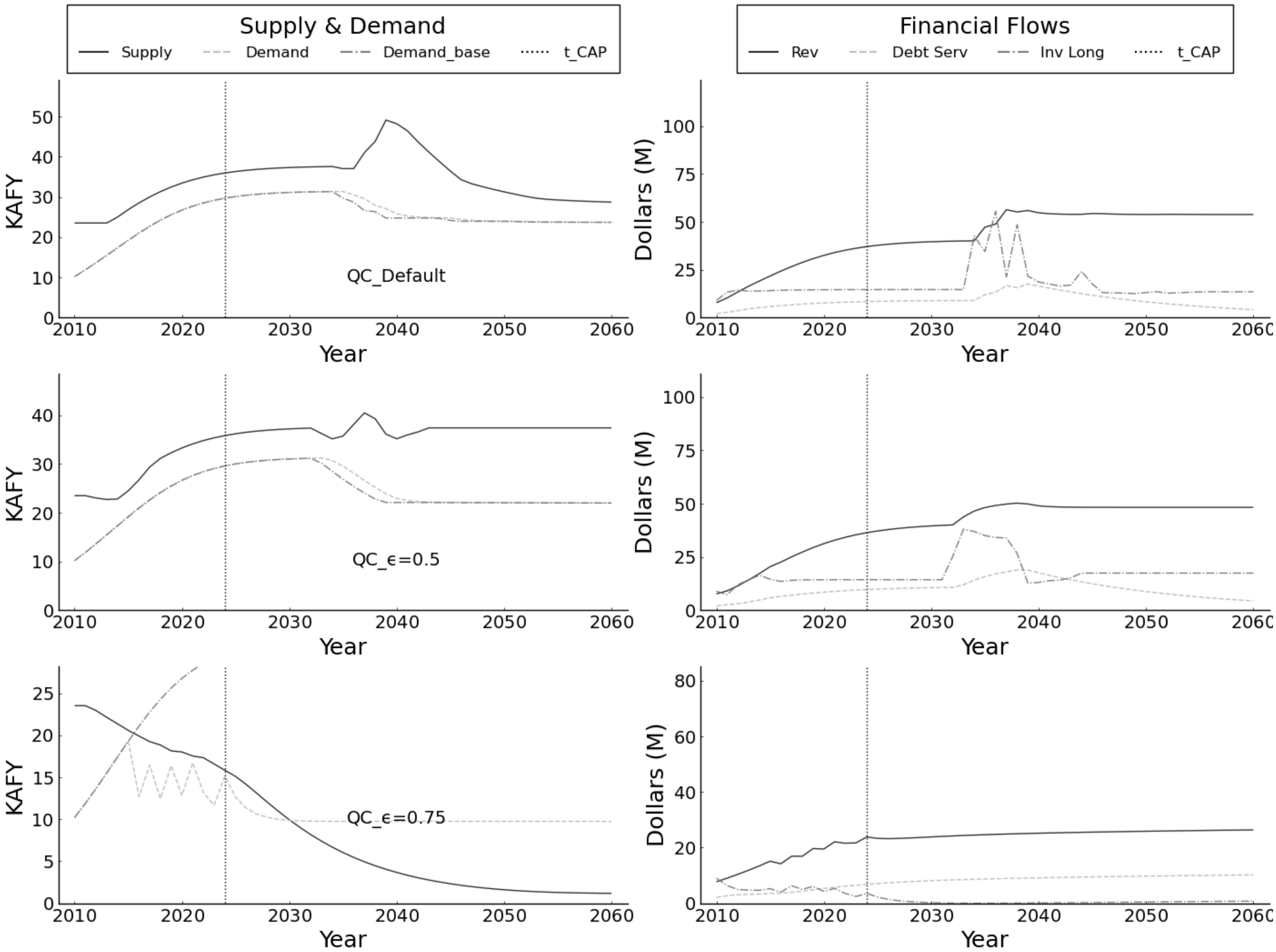

Figure S2. Time series comparison of Queen Creek's response to a 10% CAP Shock ($s = -0.1$) given default and two alternative rate-setting institutional costs settings ($\epsilon_3 = 0.5$ and $\epsilon_3 = 0.75$).

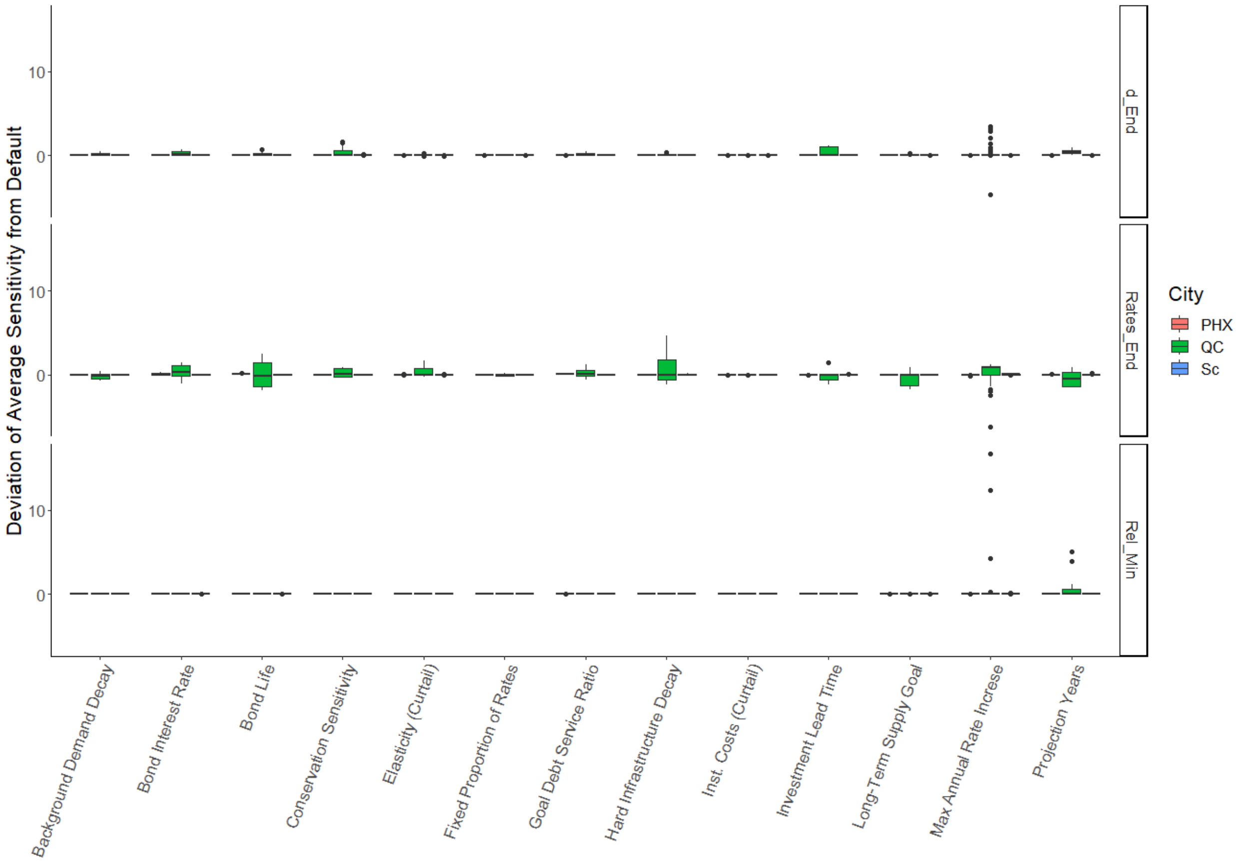

Figure S3. Summary of additional sensitivity analysis done on non institutional friction parameters. Mean reliability sensitivity was not significantly affected by the additional parameters for all cities (Supporting Information).

Table S1. Summary of UWIIM State Variables (x_t)

Variable Name	Symbol	Units	Difference Equation
Water Inflow			
Mean Inflow	$\mu_{i,t}$	Vol/yr	Equation 10
Actual Inflow	$Q_{i,t}$	Vol/yr	Equation 19
Storage			
Physical Volume in Storage	$V_{i,t}$	Vol	Equation 21
Storage Capacity	$\bar{V}_{i,t}$	Vol	Equation 10
Processing & Delivery			
Processing Capacity	$w_{i,t}$	Unitless	Equation 10
Delivery Efficiency	η_t	Unitless	Equation 10
Finance			
Per Capita Revenue	$\hat{\pi}_t$	\$/person/yr	Equation 28
Average Annual Investment from Bonds	$\tilde{J}_t^b$	\$/yr	Equation 42
Water Users			
Actual Per Capita Demand	d_t	Vol/person/yr	Equation 16
Baseline Per Capita Demand	$\bar{d}_t$	Vol/person/yr	Equation 10
Population	P_t	persons	Equation 17

Table S2. Example s Calculations for Hypothetical Colorado River Shortages

Δ_{AZ}(KAF)	Q_{CAP}(MAF)	Q_H(AF)	Q_L(AF)	$Q_{2,H}$(AF)	$Q_{2,L}$(AF)	Q_2(AF)	s
0	1.595	707223	364698	378641	70022	448663	0
592	1.033	694390	0	371454	0	371770	-0.172
720	0.911	604462	0	321095	0	323624	-0.284
1057	0.608	411604	0	213094	0	213094	-0.525
1738	0.063	62587	0	19124	0	19124	-0.957

Table S3. City-Specific Water Resources Initialization

Variable	Type	Units	PHX Value	S Value	QC Value	Justification
θ_g	Parameter	unitless	0.024	0.075	0.075	WRP
ξ_1	Parameter	unitless	0.5	0.17	0.0	WRP
a_1^q	Parameter	unitless	0.3088	0.02111	0.0	D/CAWS
$a_{1,NG}^q$	Parameter	unitless	0.06367	0.0	0.0	D/CAWS
$a_{2,L}^q$	Parameter	unitless	0.5324	0.0472	0.0594	D/CAWS, CAP
$a_{2,H}^q$	Parameter	unitless	0.3894	0.2055	0.0013	D/CAWS, CAP
a_3^q	Parameter	unitless	0.05357	0.03114	0.02135	D/CAWS
w_0^s	Init. Cond.	unitless	0.2855	0.0702	0.0005	WRP
w_0^g	Init. Cond.	unitless	0.005315	0.006977	0.006737	WRP
V_0^g	Init. Cond.	AF	3940489	2244374	1764135	D/CAWS
η_0	Init. Cond.	unitless	0.9742	1.0562	0.9339	ADWR
d_0,$\bar{d}_0$	Init. Cond.	GPCD	163.17	338.75	282.85	ADWR
d_{min}	Parameter	GPCD	64.18	66.15	56.58	WRP

PHX = Phoenix; Sc = Scottsdale; QC = Queen Creek; WRP = Water Resource Plan; CAFR = Comprehensive Annual Financial Report; D/CAWS = Designation/Certificate of Assured Water Supply; CAP = Central Arizona Project; ADWR = Arizona Department of Water Resources.

Table S4. City-Specific Population Initialization

Variable	Type	Units	PHX Value	S Value	QC Value	Justification
r	Parameter	unitless	0.088	0.143	0.240	CAFR, ADWR
κ	Parameter	persons	1686528	242300	101553	CAFR, ADWR
P_0	Init. Cond.	persons	1458275	217943	32197	CAFR, ADWR

Table S5. Water Management Parameter Default Values for All PMA Cities

Name	Symbol	Def. Value	Reasoning
Streamflow			
Maximum SRP Inflow	$\bar{\mu}^{SRP}$	900000	[AFY] (City of Phoenix, 2021)
Maximum CAP Inflow	$\bar{\mu}^{CAP}$	448663	[AFY] (CAP, 2021)
Maximum Groundwater Inflow	$\bar{\mu}^{g}$	690602	[AFY] (ADWR, 2022)
Groundwater Inflow Variation	C^v_g	0.001	Very low, near zero
Surface Inflow Variation	C^v_s	0.001	Very low, near zero
Max Proportion of Ground Storage Legally Available	a^V_g	1	No limits
Max Proportion of Surface Storage Legally Available	a^V_s	1	No limits (little surface storage anyways)
Demographic/Social Context			
Short-Term Demand Sensitivity	α	0.5	Average of ((Gonzales & Ajami, 2017)) post-2013
Long-Term Demand Background Decay	$\delta_{\bar{d}}$	0.0003	PMA Demand Trends
Hard Infrastructure Parameters			
Hard-Infrastructure Decay (η, $\bar{V}$, w)	δ_k	0.05	See Section 5.3.2
Max Surface Storage Capacity	$\bar{V}^s_{max}$	10^{-5}	[AF] Very low, near zero
Implementation Time	τ^i_k	3	Average of Phoenix CIP projects ((City of Phoenix, 2022b))

Table S6. Financial & Political-Economic Parameter Default Values for All PMA Cities

Name	Symbol	Def. Value	Reasoning
Actor Goals			
Short-Term Supply Goal	γ_1	1	Enough to meet present demand
Long-Term Supply Goal	γ_2	1.2	Interviews, Phoenix
Debt Service Coverage Ratio	γ_3	2	Phoenix Policy (Rafelis, 2021)
Long-Term Projection Range	τ_p	5	Guide for immediate investment needs (e.g., (Sunrise Engineering, Inc., 2017))
Choice Constraints			
Max Possible Rate Change	ψ^r	0.15	Phoenix Rate History
Institutional Friction			
Short-Term Curtailment Elasticity	λ_1	110	See Section 6
Long-Term Investment Elasticity	λ_2	22	See Section 6
Rate-making Elasticity	λ_3	22	See Section 6
All Action Situation Institutional Costs	ϵ_j	0	See Section 6, No costs
Investment Capacity & Cost Parameters			
Bond Life	τ_b	15	CAFR
Bond Interest Rate	ι	0.04	CAFR
Delivery Efficiency Returns to Scale	z_η	1.01266	See Section 5.3.2
Processing Capacity Returns to Scale	z_w	1.04019	See Section 5.3.2
Demand Management Returns to Scale	$z_{\bar{d}}$	1	Simplifying Assumption
Operating Cost Function Parameters			
Population Returns to Scale	z_{op}	0.5581	CAFR Data for Case Cities
Demand Returns to Scale	z_{od}	1.0303	CAFR Data for Case Cities

Table S7. Phoenix Metro Area Operating Costs Regression Results

	Dependent variable:		
	OpCost_log		
	(1)	(2)	(3)
Pop_log	0.558***		0.976***
	(0.165)		(0.143)
Del_log	1.030***	1.685***	
	(0.280)	(0.238)	
CityQueenCreek	1.761***	1.873**	0.069
	(0.607)	(0.711)	(0.477)
CityScottsdale	1.101***	0.861***	0.609**
	(0.268)	(0.303)	(0.279)
Year	0.004	0.005	0.023**
	(0.010)	(0.012)	(0.011)
Constant	−10.350	−12.344	−41.484**
	(18.793)	(22.022)	(20.192)
Observations	33	33	33
R^2	0.992	0.989	0.989
Adjusted R^2	0.991	0.988	0.987
Residual Std. Error	0.128 (df = 27)	0.151 (df = 28)	0.154 (df = 28)
F Statistic	703.566*** (df = 5; 27)	637.742*** (df = 4; 28)	605.087*** (df = 4; 28)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table S8. Phoenix Metro Area Background Demand Decay Rate Regression Results

	Dependent variable:	
	d Linear	d_log Power
	(1)	(2)
CityScottsdale	0.195***	0.721***
	(0.003)	(0.011)
Year	−0.0002	−0.0003
	(0.001)	(0.003)
Constant	0.673	−1.034
	(1.384)	(5.774)
Observations	14	14
R^2	0.998	0.997
Adjusted R^2	0.997	0.997
Residual Std. Error (df = 11)	0.005	0.021
F Statistic (df = 2; 11)	2,510.194***	1,973.278***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table S9. City Specific Financial Parameters and Initial Conditions

Variable	Type	Units	PHX Value	Sc Value	QC Value	Source
$\tilde{J}_0^b$	Init. Cond.	\$/yr	69694375	12500000	1322425	CAFR
$\hat{\pi}_0$	Init. Cond.	\$/person/yr	238.36	398.11	241.06	CAFR
β_p^π	Parameter	unitless	0.6322	0.3586	0.5801	UNC EFC, (2022)
β_η	Parameter	unitless	0.2	0.2	0.04	WRP
β_{w_s}	Parameter	unitless	0.0	0.0	0.04	WRP
β_{w_g}	Parameter	unitless	0.7	0.7	0.9	WRP
$\beta_{\bar{d}}$	Parameter	unitless	0.1	0.1	0.02	$\sum_k \beta = 1$
g_o	Parameter	$\frac{\$}{AFY \cdot person}$	0.1435	0.4316	0.8346	CAFR, ADWR

Table S10. Institutional Design & Other Parameter Sensitivity Analysis Ranges

Variable Name	Symbol	Units	Default	Range	Increment
Hydrologic Shock (Inflow)					
Magnitude of CAP Shock	s	unitless	-0.284	$[-1, 0]$	0.01
Institutional Friction					
Institutional Response Elasticity (Short-Term)	λ_1	unitless	110	$[4, 220]$	log range, $n = 50$
Institutional Response Elasticity (Other)	$\lambda_{2,3}$	unitless	22	$[4, 220]$	log range, $n = 50$
Institutional Costs (Rate-Setting)	ϵ_3	unitless	0	$[0, 1]$	0.02
Institutional Costs (Other)	$\epsilon_{1,2}$	unitless	0	$[0, 0.5]$	0.01
Additional Sensitivity Analysis					
Projection Years	τ_p	years	5	$[1, 10]$	1
Goal, Investment	γ_2	unitless	1.2	$[1, 1.2]$	0.01
Goal, Rate-Setting	γ_3	unitless	2	$[1.5, 2.5]$	0.01
Rate Increase Limit	ψ_r	unitless	0.15	$[0, 0.5]$	0.01
Hard Infrastructure Decay Rate	δ_k	unitless	0.05	$[0.01, 0.1]$	0.01
Investment Lead Time (Hard)	τ_i	years	3	$[1, 5]$	1
Fixed Proportion of Revenue	$\beta_p^{(\pi)}$	unitless	City-Specific	$[0, 1]$	0.01
Bond Life	τ_b	years	15	$[5, 30]$	1
Interest Rate	i_b	unitless	0.04	$[0.01, 0.1]$	0.01
Conservation Sensitivity	α	unitless	0.5	$[0, 1]$	0.01
Background Demand Decay	$\delta_{\bar{d}}$	unitless	0.0003	$[0, 0.001]$	