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Drought-Driven Water Insecurity in an Emerging Indian Megacity: A Coupled Multi-Agent Systems Approach for Policy Evaluation

Ankun Wang[1], Christian J. A. Klassert[2], Raphael Karutz[2], Mikhail Smilovic[3,4], Taher Kahil[3], Peter Burek[3], Yuanzao Zhu[2], Heinrich Zozmann[2], Bernd Klauer[2], Karin Küblböck[5], Ines Omann[5], Anjuli Jain Figueroa[6], Yoshihide Wada[7], Rosamond Naylor[8], and Steven M. Gorelick[1]

[1]Department of Earth System Science, Stanford University, Stanford, CA, USA, [2]Helmholtz-Centre for Environmental Research-UFZ, Leipzig, Germany, [3]Water Security Research Group, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria, [4]Institute of Environmental Engineering, ETH Zurich, Zurich, Switzerland, [5]Austrian Foundation for Development Research-ÖFSE, Vienna, Austria, [6]Independent Scholar, Washington, DC, USA, [7]King Abdullah University of Science and Technology, Thuwal, Saudi Arabia, [8]Department of Environmental Social Sciences, Stanford University, Stanford, CA, USA

Key Points:

- Coupled multi-agent systems model quantifies urban water insecurity among socio-economic groups during a mid-century multi-year drought
- Comprehensive supply- and demand-side interventions effectively benefit mid- and high-income residents, leaving urban poor behind
- Strategic implementation of policy interventions creates synergies that significantly enhance urban water security

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

A. Wang,
ankunwang@stanford.edu

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Author Contributions:

Conceptualization: Ankun Wang, Christian J. A. Klassert, Raphael Karutz, Mikhail Smilovic, Taher Kahil, Peter Burek, Yuanzao Zhu, Heinrich Zozmann, Bernd Klauer, Karin Küblböck, Ines Omann, Anjuli Jain Figueroa, Yoshihide Wada, Rosamond Naylor, Steven M. Gorelick
Data curation: Yuanzao Zhu, Anjuli Jain Figueroa
Formal analysis: Ankun Wang, Christian J. A. Klassert, Raphael Karutz, Mikhail Smilovic, Taher Kahil, Peter Burek, Yuanzao Zhu
Funding acquisition: Bernd Klauer, Karin Küblböck, Ines Omann,

Abstract Developing regions face critical water security challenges driven by rapid urban growth, economic development, and climate change. In India, these issues are particularly evident in Pune, the country's 9th most populated city. It is evolving into a sprawling urban agglomeration expected to grow from 7 to 11 million residents by mid-century. The city's aging water-supply system is ill-equipped to ensure water access during droughts lasting 2–3 years, particularly for residents in informal settlements. We present a policy-evaluation model to assess options for addressing future urban freshwater insecurity. The model uses a coupled multi-agent systems approach that integrates human-environment interactions and responses to future drought, population, and economic conditions. Under business-as-usual for a mid-century, multi-year drought, major reservoirs dry up and groundwater levels decrease dramatically. The water use Gini coefficient exceeds 0.5, indicating severe inequality where most low-income individuals face: (a) unaffordable water costs (10%–18% of income), (b) vulnerability (<40 L daily), and (c) prolonged shortages (>6 continuous months). Comprehensive interventions, combining supply- and demand-side measures, cut the water use Gini coefficient in half and lower water costs by two-thirds. Implementing a strategic subset of interventions creates synergies that significantly enhance water security, yet remains insufficient for the low-income population. This study highlights how growing inequalities in urban water access exacerbate water security challenges, even under a suite of mitigating measures. In all scenarios, additional drought emergency supply will be required to address water insecurity of the lowest 10% income population.

Plain Language Summary Prolonged droughts and increasing urban inequality create a growing risk of unprecedented water security challenges in emerging mega-cities. One such rapidly developing major urban agglomeration is Pune, India's 9th largest city. Our research shows that the combined impacts of urbanization and a mid-century multi-year drought under climate change affect all Pune households, but hit hardest are the urban poor living in informal settlements. Through a novel coupled human-natural systems framework, we identify a mix of measures involving water reallocation, an agricultural-to-urban tanker water market, infrastructural improvements, and water regulations that effectively address water insecurity challenges. We further identify synergies that produce beneficial results with fewer implemented mitigating measures, providing guidance critical to policy makers and water managers.

1. Introduction

Urban water supply systems are facing increasing pressure from rising demand, limited freshwater resources, and climate change, threatening water security (D'Odorico et al., 2018; Flörke et al., 2013; Greve et al., 2018; Hoekstra et al., 2018; McDonald et al., 2014). In this study, we define water security as reliable access to sufficient quantities of potable water at an affordable cost to ensure human well-being (Bakker, 2012; Cook & Bakker, 2012).

Yoshihide Wada, Rosamond Naylor, Steven M. Gorelick
Investigation: Ankun Wang, Christian J. A. Klassert, Raphael Karutz, Mikhail Smilovic, Taher Kahil, Peter Burek, Yuanzao Zhu, Heinrich Zozmann, Karin Küblböck, Anjuli Jain Figueroa, Steven M. Gorelick
Methodology: Ankun Wang, Christian J. A. Klassert, Raphael Karutz, Mikhail Smilovic, Taher Kahil, Peter Burek, Yuanzao Zhu, Anjuli Jain Figueroa, Steven M. Gorelick
Project administration: Bernd Klauer, Karin Küblböck, Ines Omann, Yoshihide Wada, Rosamond Naylor, Steven M. Gorelick
Software: Ankun Wang, Christian J. A. Klassert, Mikhail Smilovic, Taher Kahil, Peter Burek, Anjuli Jain Figueroa
Supervision: Bernd Klauer, Yoshihide Wada, Rosamond Naylor, Steven M. Gorelick
Validation: Ankun Wang, Christian J. A. Klassert, Mikhail Smilovic, Taher Kahil, Peter Burek
Visualization: Ankun Wang
Writing – original draft: Ankun Wang, Steven M. Gorelick
Writing – review & editing: Ankun Wang, Christian J. A. Klassert, Raphael Karutz, Mikhail Smilovic, Taher Kahil, Peter Burek, Yuanzao Zhu, Heinrich Zozmann, Bernd Klauer, Karin Küblböck, Ines Omann, Anjuli Jain Figueroa, Yoshihide Wada, Rosamond Naylor, Steven M. Gorelick

Extreme droughts and water shortages have negatively affected more than 80 large cities worldwide since 2000 (X. Zhang et al., 2019). By 2050, one third to nearly one half of the global urban population is projected to face water scarcity, with one-quarter of this population residing in India (He et al., 2021). Recent crises in Cape Town, São Paulo, and Chennai demonstrate how droughts exacerbate existing inequalities through inadequate infrastructure and inequitable water access, disproportionately affecting low-income households (Fernandes, 2018; Millington, 2018; Rusca et al., 2023; Savelli et al., 2023). These events show that urban water insecurity is not only a problem of limited supply, but a complex societal-water challenge that results from interactions among local hydrologic conditions, socioeconomic processes, and water management institutions that govern the access to and provision of freshwater (Frimpong et al., 2024; Krueger et al., 2019; Padowski et al., 2016; Zeitoun et al., 2016).

Analyzing these complex urban water security challenges calls for a systems approach that integrates the non-linear dynamics and interactions among actors, sectors, and systems (Huggins et al., 2022; B. Li & Sivapalan, 2020; X. Li et al., 2018; Reed et al., 2022; Turner et al., 2003). Agent-based and multi-agent systems models have emerged as rigorous tools for simulating human systems dynamics and their interaction with the natural and built environment, particularly in urban water scarcity and security studies (e.g., Bakhtiari et al., 2020; Huber et al., 2021; Klassert et al., 2023; Yoon et al., 2021; Q. Zhang et al., 2023). These approaches explicitly account for the role of individuals, their unique behavioral characteristics, and mutual interactions (Alam et al., 2022; Amaya et al., 2025; An, 2012; De Bruijn et al., 2023; Huber et al., 2019; Kahil et al., 2019; Lin et al., 2022; Troy et al., 2015).

Yet, despite this potential, urban water access inequalities remain underrepresented in water security research (Babuna et al., 2023). Assessing such inequalities using a systems approach has been hindered by limitations in current modeling frameworks. Specifically, many existing agent models are not coupled with physically based hydrologic models for urban water scarcity studies (Schück et al., 2025), apply simplified rather than fully spatially distributed models (Alam et al., 2022), or are loosely coupled at aggregated (e.g., yearly) time scales (Canales et al., 2024). Such limitations reduce the agent model's capacity to simulate spatially distributed and inequitable impacts of policy interventions (Alam et al., 2022). Another challenge is that agents' water use decision is often insufficiently connected with socioeconomic factors such as household income, living conditions and the evolution of urban sprawl, densification, and socioeconomic redistribution of the urban population (e.g., Mashhadi Ali et al., 2017; Yan et al., 2022). Moreover, existing socio-hydrological and decision-support models have focused on aggregated indicators at the city, watershed or regional scale, overlooking impacts on vulnerable households (Rachunok & Fletcher, 2023). As a result, evaluating urban water security challenges from the perspective of inequality, and how policy interventions affect distributional outcomes, especially for low-income households, under future drought and rapid urban growth, remains underexplored.

To address this gap, we develop a comprehensive coupled multi-agent systems model to evaluate potential policy solutions aimed at reducing urban water insecurity. We focus on India's Pune agglomeration, an urban region rapidly becoming a mega-city of over 10 million in a basin comparable in size to Switzerland. It is emblematic of water security challenges around the world under the combined pressures of drought driven by climate change, population growth, and urbanization.

Integrating a high-resolution, fully distributed hydrologic model with spatially explicit human agents, the coupled systems model simulates biophysical processes and agents' decision-making, including households, industrial and commercial entities, regulators, and farmer agents, as well as their interactions and responses to future drought and socioeconomic conditions. Urban agents are represented with detailed socioeconomic attributes using extensive data sets, including quantitative surveys of 1,872 households in and around Pune, and spatially explicit projections of urban development (Karutz et al., 2023; Zhu & Klassert, 2025). This multi-agent approach enables the evaluation of distributional impacts among different socioeconomic groups through a novel suite of well-being metrics developed in this study. We apply the systems model to evaluate the effectiveness of supply- and demand-side policy interventions in the Pune agglomeration, incorporating inputs and feedbacks from local stakeholders and experts. Together, these advances allow for systematic evaluation of how drought impacts and policy interventions affect urban water security and their implications for inequality.

Our results demonstrate that the coupled multi-agent systems model is suitable to capture the complex interplay between water scarcity and urban socioeconomic disparities and how these factors affect water access inequality. The coupled multi-agent systems model components and system-level outputs are validated against historical

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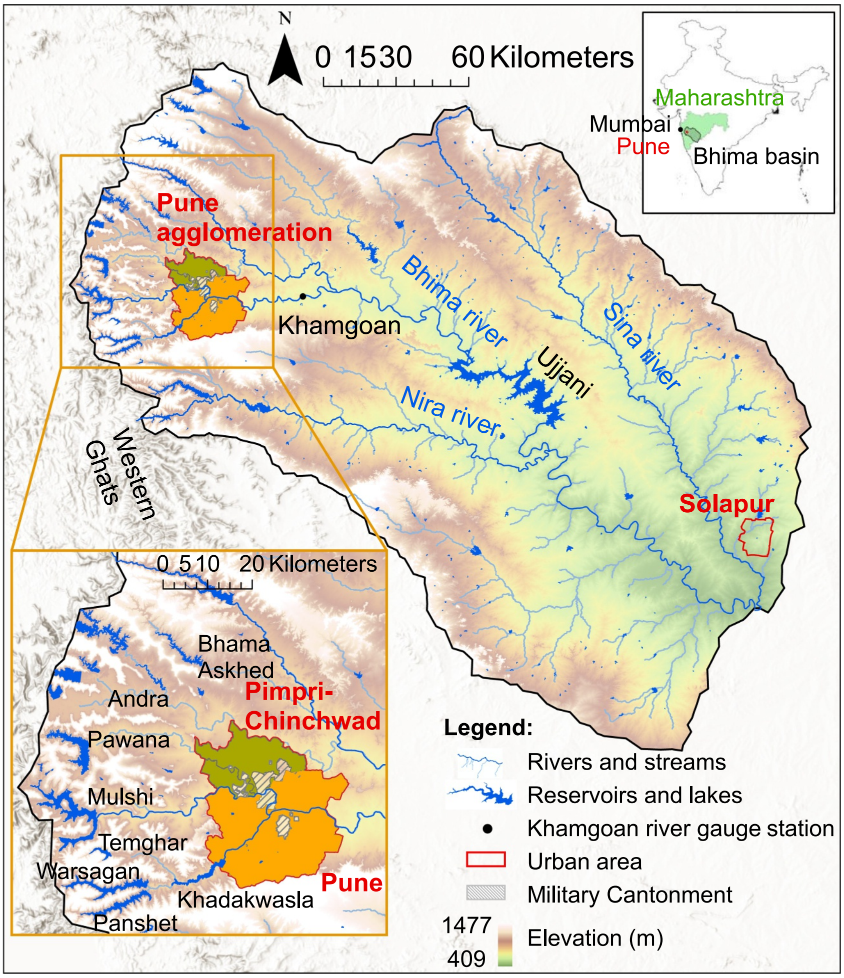

Figure 1. The Pune agglomeration and the Bhima basin. Pune receives its water from the Khadakwasla Complex, consisting of the Khadakwasla dam and a few reservoirs (Temghar, Warsagan, Panshet) that feed into it, while Pimpri-Chinchwad receives water from the Pawana dam. New pipelines are under construction to secure additional supply for the city from two northern reservoirs (Andra and Bhama Askhed). We assume this infrastructure will be in place by mid-century (PMC, 2024; Pune pulse, 2024). Mulshi is a major Tata power dam in the Bhima basin and Ujjani is a major downstream reservoir.

observed data. Under a mid-century, multi-year drought, groundwater and surface water resource availability in the Pune agglomeration decline severely. As a consequence, low-income residents in informal settlements face disproportionately high water stress compared to middle- and high-income groups. Combined supply- and demand-side policy interventions synergistically enhance water security. However, these measures remain insufficient to ensure water access for the low-income residents. Although focusing on the Pune agglomeration, this study provides a comprehensive systems modeling framework for policy evaluation, transferable to rapidly urbanizing regions, largely in the Global South facing similar challenges.

2. Study Area

2.1. Pune Agglomeration and Its Regional Context

Pune is India's ninth most populated city, with its population having doubled since 2000 (United Nations, 2024). It is second only to Mumbai in population within the state of Maharashtra. Its urban development is significantly connected to neighboring Pimpri-Chinchwad, forming a rapidly melding urban center here called the Pune agglomeration. This urban agglomeration is projected to grow from 7 million to 11 million residents by 2050, with its urban built-up area expected to increase by 50% (Karutz et al., 2023).

The Pune agglomeration is located in the northern part of the Bhima basin (45,800 km^2) (Karutz et al., 2022) (Figure 1), a vast region similar in size to Switzerland, with elevations varying from 1,477 m in the Western Ghats mountains to 409 m in the valley to the southeast (Hawker et al., 2022). The basin has a tropical monsoonal climate with annual rainfall ranging from 4,200 mm in the Western Ghat mountains to 415 mm in the much flatter lower basin, averaging 700–850 mm (Integrated State Water Plan, 2018; Jipkate et al., 2020). The basin's surface water is highly managed with 48 major and medium reservoirs having a cumulative live storage capacity of 7.4 billion cubic meters, accounting for more than 80% of the total storage capacity of all reservoirs (Integrated State Water Plan, 2018). Approximately 70% of managed reservoir water goes to agriculture via canals feeding canal-command areas (Garg et al., 2012). Groundwater in the Pune agglomeration is accessed by numerous bore wells and some large-diameter dug wells tapping the basalt aquifer. The basalt aquifer contains aquifer units 10–20 m thick resulting in a total aquifer thickness of 50 m over a depth of 250 m (H. Kulkarni, 2017; H. Kulkarni et al., 2019). Tanker trucks extract groundwater from peri-urban bore wells to supply water to the city. Water use in the basin is dominated by agriculture (80% in 2018) (Integrated State Water Plan, 2018). Sugarcane irrigation accounts for 80% of agricultural water occupying only 20% of the cultivated area (Integrated State Water Plan, 2018; Lee et al., 2020). Domestic and industrial uses comprise 11% of total water use, with the remaining 9% diverted from privately owned Tata Power dams to provide hydropower to Mumbai (Integrated State Water Plan, 2018).

2.2. Water Security Challenges

The Pune agglomeration is facing growing water insecurity (Tholiya et al., 2022). Like all major urban areas in India, the Pune agglomeration is characterized by intermittent water supply, ranging from 24-hr access for only 10% of households to as little as 20 min daily for others (Zhu, Gawel, et al., 2024). Approximately 19% of the population resides in informal settlements (MASHAL, 2011). There, pipe connections are rare and residents must obtain water from other sources, such as public standpipes or purchases from private vendors (Zozmann et al., 2022b). These time- and energy-intensive, manual, self-supply activities exacerbate water unaffordability and inequality (Zhu, Klassert, et al., 2024; Zozmann et al., 2022a).

Water security in the Pune agglomeration is also challenged by haphazard planning and governance, resulting in significant non-revenue water (pipe water leakage and unauthorized use), unregulated groundwater abstraction, an informal tanker water market, and competition for water between urban and a powerful agricultural sector (Karutz et al., 2022; Lee et al., 2020; Zozmann, Morgan, et al., 2022). Overreliance on informal water markets can make residential water access costly and tenuous (Klassert et al., 2023; Srinivasan et al., 2010a). Moreover, the region is drought-prone, where prolonged droughts (e.g., greater than 1-year duration) with consecutive years of low monsoon rainfall lead to surface water scarcity and groundwater depletion, severely impacting urban water supply (Udmale et al., 2016, 2021). Future climate change impacts are likely to worsen water scarcity in the city (Butsch et al., 2017).

3. Materials and Methods

Our policy-evaluation model framework consists of four components: the coupled multi-agent systems model (Figure 2a), scenario sets, intervention portfolios developed through stakeholder engagement, and metrics of resource status and human well-being.

The coupled multi-agent systems model integrates various modules representing components of the coupled human-natural-engineered system and their intricate interconnections. The model consists of two types of modules: (a) biophysical modules that simulate physical processes in the natural and built environment, and (b) human modules that represent human agents that interact and make decisions. Agents are here defined as autonomous entities that make decisions in relation to one another and in response to hydrologic and socio-economic conditions (Yoon et al., 2021). Each agent represents aggregated decision-making, particularly aimed at allocation, use, and management of water resources, rather than individuals.

Scenarios are defined here as factors beyond the direct control of water managers or policy makers. Each scenario set reflects possible future climatological, population, and economic changes. Interventions are policies and policy adaptations made by decision makers to cope with urban water security challenges. This study analyzes a suggested suite of interventions under various scenario sets using the coupled systems model, and the results are

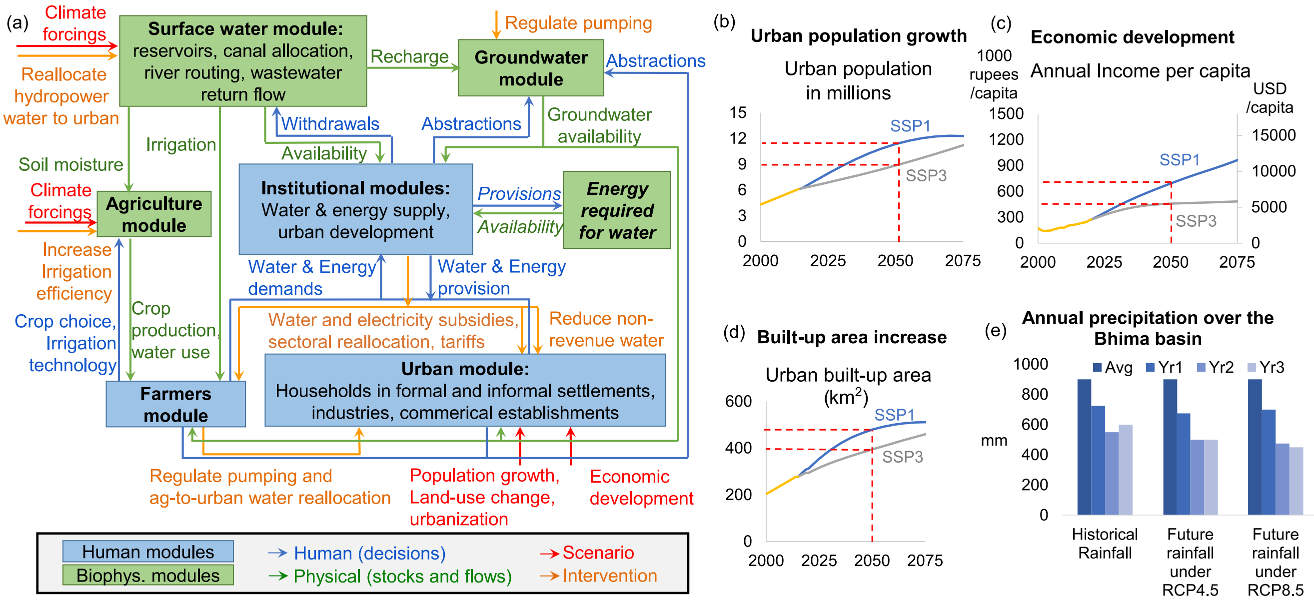

Figure 2. The coupled multi-agent systems model, future scenarios and interventions. (a) The coupled multi-agent systems model consisting of biophysical and human modules, as well as scenarios and interventions. The coupled multi-agent systems model also captures interactions between biophysical and human modules through water stocks and flows and human decision-making processes. Also shown are projections of (b) urban population growth, (c) urban economic development, (d) urban built-up area increase under SSP1 and SSP3, and (e) rainfall averaged over the Bhima basin under historical conditions and adjusted to future climate change scenarios under RCP4.5 and RCP8.5. The first column of each rainfall scenario represents the average rainfall year, and Year 1–3 represents the multi-year drought period.

quantified by metrics showing resource status and societal impacts on human well-being. This forms our policy-evaluation model framework.

The model framework integrates a diverse set of data inputs from the Bhima basin and the Pune agglomeration. This includes climate and hydrologic data from remote sensing (e.g., Beck et al., 2019), global climate models (Rama Nemani/NASA, 2021), reservoir data including 48 managed reservoirs, river gauge stations, and observation wells, as well as crop data from satellites (e.g., Zhao & Siebert, 2015) and agricultural statistics. The model also incorporates data from quantitative household surveys (Zhu & Klassert, 2025), government census, government reports, along with gridded projections of built-up area expansion and population growth, downscaled from global Shared Socioeconomic Pathways (SSPs) (Karutz et al., 2023). Moreover, the model includes spatially explicit data to represent water access infrastructure. A summary of the complete set of data input and detailed explanations of each data set can be found in Table S2 in Supporting Information S1, and in each module description in Supporting Information S1.

3.1. Coupled Multi-Agent Systems Model

The biophysical and human modules further include submodules. The biophysical modules include a surface water module, a groundwater module, an agriculture module, and an energy (required for water) module. The human modules include an urban module, an institutional module, and a farmers module.

3.1.1. Biophysical Modules

The surface water module employs a regionalized version of the Community Water Model (CWatM) (Burek et al., 2020), a hydrologic and river routing model with a spatial resolution of 30 arcsecs (∼1 km). It simulates daily river flow, managed reservoir storage and releases, allocation of reservoir releases to the different water use sectors via the canal network, and wastewater return flow (Supporting Information S1, Methods, Surface water module).

The groundwater module applies the MODFLOW model (Langevin et al., 2017) at a 500-m spatial resolution, and it is dynamically coupled with the surface water module, CWatM (Guillaumot et al., 2022). The transient model simulates the evolution of groundwater levels. The groundwater system is modeled as a homogenous unconfined aquifer with an initial saturated thickness of 50 m, a simplified representation of the aquifer (Supporting Information S1, Methods, Groundwater module). This simplification was necessary due to the lack of more detailed hydrogeologic data, but the model was shown to reproduce changes in heads at measured locations (Guillaumot et al., 2022). Daily groundwater depth is simulated and updated based on recharge from rainfall and river water infiltration as well as abstractions from pumping wells for irrigation and urban uses.

The energy module determines the energy required for water, including farmers' energy demand for pumping and electricity demand from households and commercial and industrial establishments for piped, well, and tanker water supply.

The agriculture module simulates the biophysical crop water use, including irrigation water uses from surface water and groundwater using the FAO crop water use method (Allen et al., 1998), and the resulting crop production, given farmers' crop choices determined by the farmers module. Crop production is a function of crop yield, crop area, crop water requirements (as determined by effective rainfall, evapotranspiration, soil moisture, and irrigation conditions), and surface water and groundwater access. The agriculture module has a unique spatial scale, which is delineated based on the location of talukas (i.e., subdistricts consisting of a collection of villages), and canal command areas (each area receives canal water from its designated reservoir) (Supporting Information S1, Methods, Agriculture module).

3.1.2. Human Modules

The farmers module determines farmer agents' cropping behavior by maximizing farming profits under various land and water availability constraints and under the constraint that they gravitate to planting crops they have planted before (Supporting Information S1, Methods, Farmers module). It applies the Positive Mathematical Programming (PMP) procedure, widely used for agricultural economic policy analysis (Dagnino & Ward, 2012; Howitt, 1995; Nagpal et al., 2024; Röhm & Dabbert, 2003; Yoon et al., 2024). The farmers module uses the same spatial resolution as the agriculture module, which consists of 174 farmer agents located inside and outside canal command areas.

The urban module determines urban agents' monthly water use behavior in cities (Supporting Information S1, Methods, Urban module). It categorizes the urban agents into households in formal and informal settlements, commercial establishments, and industrial establishments. These agents are parameterized with primary survey data of 1,872 households collected in and around Pune (Zhu & Klassert, 2025), India Human Development Survey-II (Desai & Vanneman, 2015), remote sensing data (European Commission, Joint Research Centre (JRC), 2015), as well as census (Asher & Novosad, 2019; Office of the Registrar General and Census Commissioner, India, 2011) and water supply data (PMC, 2014). Water demand by household agents is calculated using an econometric demand function, which considers water price and each agent's socioeconomic status including their income and household size. Commercial and industrial establishment agents' water demand is estimated based on water price, number of employees, and water intensity of business activities. A tiered supply curve is utilized to determine the water supply from each source to satisfy the agent's demand, including supply from the public piped network, private wells, and tanker water markets in peri-urban areas (Srinivasan et al., 2010b). Tanker trucks provide essential supply, particularly during droughts, with prices determined by consumers' willingness-to-pay and typically much higher than municipal water price and water from private wells.

The institutional module represents a collective government agent that aggregates multiple real-world institutional entities responsible for water allocation, regulation, and resource supply across sectors in the Bhima basin. This government agent includes water resources managers who orchestrate reservoir releases such as the Water Resources Department, Government of Maharashtra, and regulatory agencies such as the Maharashtra Water Resources Regulatory Authority (Integrated State Water Plan, 2018). The government agent also includes local suppliers, including urban water utilities (Pune and Pimpri-Chinchwad Municipal Corporations), urban energy utilities, rural water cooperatives (Water User Associations), and tanker water sellers (Integrated State Water Plan, 2018; Karutz et al., 2022; PCMC, 2010; PMC, 2012). Pune is implementing a licensing policy for water tanker drivers and the model assumes all tanker trucks are regulated by mid-century (Punekar News, 2025).

The government agent makes decisions on releases from 48 managed reservoirs based on hydrologic inputs from the surface water module (details of reservoir rule can be found in Supporting Information S1, Methods, Surface water module). It also manages resources supply and distribution based on resources availability and demands from urban and farmer agents. Most importantly, the government agent implements policy interventions including but not limited to tariff increases, infrastructure improvements, pumping regulations, and sectoral water reallocation to cope with drought conditions. These policy interventions are implemented based on defined policy rules derived from existing regulatory frameworks, discussions with Pune's Water Supply Department, and input obtained during stakeholder workshops. Overall, the government agent serves as governing and provisioning actors whose decisions and actions influence urban and farmer agents (Yoon et al., 2022).

3.1.3. Module Coupling and Interactions

The biophysical and human modules exchange information at monthly time steps through two-way coupling. The surface water and groundwater module aggregate water availability into monthly values for the human agents on the same ~1 km grid. Moreover, the surface water module interacts with other modules by quantifying recharge to groundwater, and soil moisture for agriculture. The groundwater model is coupled with human modules where agents make decisions on their groundwater abstraction depending on the cost of pumping, a function of groundwater depth, pumping rate, and energy prices, as well as the cost and availability of surface water.

The government agent determines monthly reservoir releases based on current month's local climate and hydrologic conditions for each managed reservoir. Urban agents, represented within each 1 km grid cell, decide monthly water use based on available reservoir supply, local groundwater depth and pumping costs, as well as tanker water availability from peri-urban areas and tanker water price. Each farmer agent assesses local climate and water availability to make cropping decision for Kharif (monsoon, June–October) and Rabi (winter, November–May) seasons. Farmer agents are each represented at a unique spatial scale, which is then disaggregated into crop land use at a 1 km scale, and they make monthly irrigation water use decisions based on crop water requirements (kept track of by the agriculture module).

Agents' water use values are passed back to the surface water and groundwater module at each monthly time step to update the water resources status for the month. Marching through time, these updated hydrologic conditions become the starting point for the next month. The new conditions then influence how agents make their decisions for the following month.

Scenarios and interventions are imposed and provide external inputs to different modules, for example, meteorological forcing for the biophysical modules, and population growth for the urban module. They do not respond to the coupled systems dynamics, but rather affect the human agents' water access, pumping behavior, and water management decisions, and the overall resources status, on a monthly basis.

Specifically, agents adjust their behavior in response to drought conditions. Based on discussions with stakeholders, government reports, and water-use data, the model assumes that when piped water supply is insufficient, urban agents switch to alternative water sources, including pumping groundwater and purchasing tanker water to accommodate their demand. During droughts, urban agents adjust their reliance on groundwater in response to increased pumping costs due to water table decline. Their reliance on tanker water also responds to tanker water price, which reflects their willingness-to-pay determined by supply and demand. Urban agents will also respond to the drought measures implemented by the government agent, such as a municipal water tariff increase and a cap on pumping. These responses are represented by econometric demand functions and a tiered supply curve. Farmer agents respond to drought conditions by reallocating land among crops within the current season and adjusting irrigation water use. They will also adjust their cropping decisions to interventions such as electricity subsidy changes. These responses are represented through profit maximization using PMP. The government agent adjusts reservoir releases in response to declining hydrologic conditions, allocates water supply across sectors based on reduced water availability and demands, and implements the selected interventions to cope with drought conditions.

The explicit two-way coupling between the fully distributed hydrologic model and diverse human agents, at a fine spatial resolution of 1 km^2 and monthly time steps over all, allows the model to capture nonlinear systems dynamics that cannot be represented in simplified models for system as complex as Pune and the Bhima basin. Stakeholders noted that the detailed and comprehensive model design provided a realistic representation of the city and region. Detailed information for each module is provided in Supporting Information S1, Methods. The standard Overview, Design concepts, and Details + Decision (ODD + D) description (Müller et al., 2013), which

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describes the decision-making logics of the human agents, is provided in the Supporting Information S2, ODD + D Description.

3.1.4. Model Calibration and Validation

The surface water module was calibrated and validated using the Kling–Gupta Efficiency (KGE) metric (Gupta et al., 2009) for monthly river flow (available for monsoon months from June to October) at 16 river gauge stations in the Bhima basin. The calibration period is from 2002 to 2007 and the validation period is from 1996 to 2001, determined based on the availability of continuous historical observed data for all the gauge stations. The calibration used DEAP, an evolutionary computation framework, to calibrate 11 hydrological parameters (Burek et al., 2020). The detailed calibration process, data input, calibrated parameters, and KGE metric results for all the stations can be found in Supporting Information S1, Methods and Table S3. The model exhibited satisfactory performance, with a median KGE of 0.67 during calibration (95% confidence interval of 0.60–0.74), and a median KGE of 0.69 during validation (95% confidence interval of 0.05–0.87). The wide confidence interval during validation is due to the extremely low performance of the Rosa river gauge station, whereas 81% of the stations showed a KGE $>$ 0.62. This station is located on the Sina river within the Bhima basin, in a rural area downstream of the Pune agglomeration, not directly influencing the urban water insecurity results of this study.

Water table changes simulated by the groundwater module were validated for the period 1997–2009, with published results presented in Guillaumot et al. (2022). By comparing the simulated water table with the observed data aggregated from 351 monitoring boreholes in the Bhima basin, the authors concluded that relative groundwater table fluctuations, before and after the monsoon season, were well represented. The validation results showed a normalized root-mean-square error (RMSE) of 41%, calculated as the RMSE as a percentage of the standard deviation of the observed data. However, reproducing the absolute water table depth remained challenging due to the relatively coarse spatial resolution of MODFLOW and the geological complexity of the Bhima basin (Guillaumot et al., 2022). Because the model showed a consistent offset between simulated and observed depths, a fixed bias-correction map was applied, derived from kriged post-monsoon well observations and long-term simulations. Further details are provided in Supporting Information S1.

The total water demand from all household agents was validated against a benchmark assumption of 100 LPCD for the Bhima basin population. The commercial and industrial water demand was validated against the net non-domestic water demand in Pune in 2012 published in the Detailed Project Report for Pune Municipal Corporation 24/7 Water Supply Project (i.e., 99.52 million liters per day) (PMC, 2014). Our PMP agricultural model outputs were validated by comparing simulated farmer agents' crop land use aggregated to Pune and Solapur districts respectively with land use data reported in government sources for the period 2006–2021 (Department of Agriculture, 2023), showing that the model captures the major cropping patterns over time.

While each module was calibrated and validated individually, the coupled multi-agent systems model was validated against observed system-level data. This included validation against historical sectoral water use data in the Bhima basin from both surface water and groundwater, water uses from major reservoirs in the basin, and total water supply in the Pune agglomeration. Simulated sectoral water uses in the Bhima Basin were in agreement with values from the Integrated State Water Plan (2018) (Table S5 in Supporting Information S1). We used the water use data. It is based on an average rainfall year and the surface water use data represents bulk surface water supply including all water losses, based on water balance calculations (Smilovic et al., 2024).

In an average rainfall year (2010–2011), simulated domestic and industrial use was approximately 5% less than reported surface water use and 20% higher than reported groundwater use. However, since domestic and industrial groundwater use is only 186 Mm^3, compared to surface water use being 1,364 Mm^3, the 20% difference is negligible in absolute terms. Simulated agricultural surface water use was 7,328 Mm^3 versus 8,502 Mm^3 observed (14% lower), while groundwater use was 3,440 Mm^3 versus 3,361 Mm^3 observed, showing only 2% difference. Simulated reservoir releases matched well with the observed values from selected reservoir projects (RMSE = 86 Mm^3) (Table S6 in Supporting Information S1). We averaged annual reservoir water uses over the historical period from 2010 to 2019, depending on the data availability, and compare the values with simulated results from the same period. In the Pune agglomeration, total modeled water supply for Pune and Pimpri–Chinchwad closely reproduced reported municipal data within 10% in historical years (Table S7 in Supporting Information S1). Further details are presented in Text S4, Systems model validation in Supporting Information S1.

3.2. Scenario Sets

We examine four scenario sets combining two socioeconomic development projections for 2050, and two climate change severity assumptions analyzed statistically over 2022–2063. These are respectively defined using SSPs and IPCC Representative Concentration Pathways (RCPs). These scenario sets enable us to evaluate the scenario uncertainty, specifically, how the uncertainties in future climate, urbanization and economic growth scenarios affect our analysis on urban water insecurity.

We use regionalized SSP scenarios by Karutz et al. (2023), where SSP1 represents high urbanization, and SSP3 represents a low urbanization scenario. The SSP1, downscaled to the Pune agglomeration, shows a high urbanization rate, high annual urban income growth, and rapid urban built-up area increase. The SSP3 shows the opposite in which urbanization and urban economic development are slow, with a gradual increase in urban built-up area (Figures 2b, 2c, and 2d).

For climate scenarios, we focus on a prescribed 3-year drought that occurred from 2000 to 2003, but we scale it based on projected rainfall statistics that reflect multi-decadal climate change impacts in the future (Figure 2e) (Ekström et al., 2015). Based on the SPI (Standardized Precipitation Index) classification by Mckee et al. (1993), we define a multi-year drought as a period of at least three consecutive years with SPI-12 values below −0.5, including at least one year where the SPI-12 value falls below −1. A 3-year drought is selected to represent a severe yet plausible scenario where prolonged water deficits can lead to cumulative water resources depletion and long-lasting impacts on water security. Given that 3-year droughts have occurred historically in the Bhima basin, during 1984–1987 and 2000–2003 (Udmale et al., 2021), it is reasonable to expect that such 3-year droughts may recur in the future, and could be even more severe under climate change. For future scenarios, we scale the historical 2000–2003 drought using CMIP6 climate model projections under RCP4.5 (moderate climate change) and RCP8.5 (extreme climate change). Historical rainfall is obtained from the MSWEP (Multi-Source Weighted-Ensemble Precipitation) product (Beck et al., 2017, 2019), and the future rainfall from statistically downscaled and bias-corrected GCM output NASA NEX-GDDP-CMIP6 (Rama Nemani/NASA, 2021) (Text S5, Climate in Supporting Information S1).

3.3. Intervention Portfolios Developed Through Stakeholder Engagement

We developed potential policy interventions that emerged from co-creation workshops conducted in 2019 and 2022 in Pune with over 50 local stakeholders including former and current civil servants, academic experts, consultants, and regional NGOs (Küblböck et al., 2022). As some of the policy interventions share common policy objectives and are likely to be implemented in tandem, we group them into six intervention portfolios (Table 1). In the coupled multi-agent systems model, these intervention portfolios are operationalized by the government agent based on defined decision rules.

On the water demand side, we evaluate price regulation and infrastructure management, which require a range of strategies including doubling municipal water price of the highest price tier, doubling electricity costs for both urban and agricultural use, capping well pumping at 40 liters per capita per day (LPCD) when groundwater depletion exceeds 80% of the aquifer saturated thickness, and improving infrastructure to increase irrigation efficiency from 60% to 80%. The price regulation interventions are developed based on stakeholder inputs (Küblböck et al., 2022), and impacts of electricity subsidies on groundwater depletion (Chatterjee et al., 2024). Infrastructure management interventions are supported by the existing regulatory framework under the Maharashtra Groundwater (Development and Management) Act, 2009, which restricts groundwater pumping in over-exploited areas (Government of Maharashtra, 2009), and reflect the current trend of transitioning from conventional irrigation methods to more efficient drip and sprinkler irrigation methods in the Bhima basin (Integrated State Water Plan, 2018).

On the water supply side, we explore enhanced piped supply and agricultural-to-urban water transfer. Enhanced supply involves reallocation to the Pune agglomeration of the Tata Power dam water that currently flows to Mumbai, as suggested by social activists in recent years (Thakkar et al., 2015) and enforcement to reduce non-revenue water from 35% to 20% by the mid-century. Reductions in non-revenue water will be achieved through prevention of unauthorized abstractions and infrastructure maintenance, building on existing efforts in the municipalities and national urban water management guidelines (P. Kulkarni, 2025; National Institute of Urban Affairs, 2021). Agricultural-to-urban water transfer is based on a market where farmers can sell their groundwater

Table 1
Intervention Portfolios (Detailed Explanation of Each Policy Intervention Is in Text S6, Interventions in Supporting Information S1)

Intervention portfolios	Decision rules
Business-as-usual	No interventions
Price regulation	Electricity subsidy reduction for groundwater pumping for urban and agriculture resulting in doubled electricity cost, starting at the onset of the multi-year drought
	Doubled municipal water price of the highest tier, starting at the onset of the multi-year drought
Infrastructure management	Enforce a cap of 40 LPCD in urban groundwater pumping at the locations where groundwater depletion exceeds 80% of the aquifer saturated thickness during the multi-year drought
	Improvement in irrigation efficiency in rural area from 60% to 80%, assumed to have already been achieved by mid-century, even in an average rainfall year
Enhanced piped water supply	Reservoir transfer from Tata dam, triggered when the reservoir storage at the end of the monsoon season could not reach half of its normal peak storage
	Reduction in non-revenue water from 35% to 20%, assumed to have already been achieved by mid-century
Agricultural-to-urban water transfer	Water re-allocation from agriculture to the urban sector through water market, starting at the onset of the multi-year drought
Comprehensive action	Implement all interventions mentioned above simultaneously

to urban households rather than using it for crop irrigation, allowing them to secure income equivalent to their anticipated crop production profits (Rosegrant et al., 2000). The implementation of formal water markets would require legal and institutional reform, such as establishing trading water entitlements, additional institutional arrangements, and metering of groundwater pumping (Venkatachalam, 2008). Finally, the comprehensive action portfolio implements all interventions from both water demand and supply sides. The rationale and possible barriers of implementation of each policy invention is further explained in Text S6, Interventions in Supporting Information S1.

3.4. Metrics

We develop a comprehensive set of metrics to analyze the systems model output, including the resource status as well as human well-being (Table 2). Metrics of resource status focus on the spatial and temporal distribution of

Table 2
Metrics of Resource Status and Human Well-Being

Metrics	Description
Resource status	
Reservoir storage	The state of each reservoir's active storage (Mm^3)
River flow at the outlet	River water discharge at the outlet (m^3/s)
Groundwater depletion	Percentage of remaining saturated aquifer thickness in the city and the Bhima basin
Human well-being	
Per capita water use	Per capita water use of the household population in L/person/day
Inequality	Water use Gini coefficient calculated to measure inequality in the per capita water use of the household population
Unaffordability	Percentage of income spent on water
Vulnerability	Percent of household population receiving water less than 40 L/person/dayon an average annual basis
Shortage duration	Number of consecutive months in a year that people remain vulnerable by receiving water less than 40 L/person/day

reservoir water, groundwater depletion, and river discharge. Metrics of human well-being include per capita water use, inequality in per capita water use, unaffordability, vulnerability, and shortage duration. The objective of the well-being metrics is to evaluate water security outcomes among water users, in this study focusing on urban household agents. The metrics enable the quantification of the differences in water access among socioeconomic groups from multiple dimensions. Specifically, the metrics don't apply to the government agent, as the government agent functions as a collective regulatory and decision-making entity that implements policy interventions rather than experiences water security outcomes.

We note that cost-benefit analysis is beyond the scope of this work. This work focuses on inequalities in water access, rather than aggregated net benefits or overall efficiencies of policies. Moreover, Rachunok and Fletcher (2023) highlighted that utility-scale decision-making aimed at maximizing reliability and minimizing cost can create trade-offs that worsen water affordability for low-income households. This stresses the need to evaluate policies from the perspective of inequality, which is the approach taken in this work.

3.5. Computational Setup

The model simulations for the entire Bhima basin were implemented in Python and executed on the Stanford Sherlock high-performance computing (HPC) cluster. Each run, representing one combination of a scenario set and an intervention portfolio for both the average year and the multi-year drought period, required approximately 12 hr (i.e., 3 hr for 1 simulation year) on a single CPU core. In total, 24 model combinations were simulated in parallel, each run executed independently on separate CPUs.

3.6. Sensitivity Analysis

We performed sensitivity analysis by varying key intervention parameters by ±10% and ±20% compared to their baseline, and evaluating the resulting changes in resources status and well-being metric results. This analysis provides insights into how well interventions remain beneficial over a range of parameter values. For example, the results show that increasing the pumping cap (40 LPCD) by 20% would worsen inequality in per capita water use by 2%, and a further 20% increase in electricity cost for the price regulation intervention would reduce water use inequality by 2.1%. The complete sensitivity analysis results are provided in Table S4 in Supporting Information S1.

4. Results

4.1. Resource Status

The mid-century, multi-year drought greatly reduces freshwater availability under business-as-usual (without interventions). We show the resource status results under extreme climate change and high urbanization as a representative case (Figure 3). During drought years 1–3, major reservoirs supplying the city show dramatic declines in storage levels, notably reducing urban water provision (Figure 3a). Further hydrologic impacts are evident. For example, river discharge at the Khamgoan river gauge station, located just downstream of the city, decreases significantly during the drought years (Figure 3b). The furthest major downstream reservoir (Ujjani) also experiences a dramatic decline in storage, potentially generating negative (third-party) downstream impacts on the Solapur region. Groundwater levels in the Pune agglomeration gradually decline from 5 m below ground surface to 30 m at the end of drought year 3, due to excessive pumping (Figure 3c). Groundwater is further depleted in the surrounding villages by tanker trucks extracting water from peri-urban areas to supplement the city's supply. Intensive sugarcane cultivation is a major source of groundwater depletion in the Bhima basin's rural region (Figure 3d).

It is also interesting to note that the reservoir storage and river discharge begin to recover in the third year. Although rainfall in drought year 3 remains less than year 2 over the Bhima basin, rainfall is greater upstream of the Pune agglomeration, resulting in higher reservoir inflows and downstream discharge. While surface water depletion is no worse than in drought year 2, groundwater levels averaged over the Pune agglomeration and peri-urban area continue to decline throughout the multi-year drought. Moreover, in year 3 of the drought, groundwater depletion becomes more severe over the Bhima basin, as shown in Figure 3d.

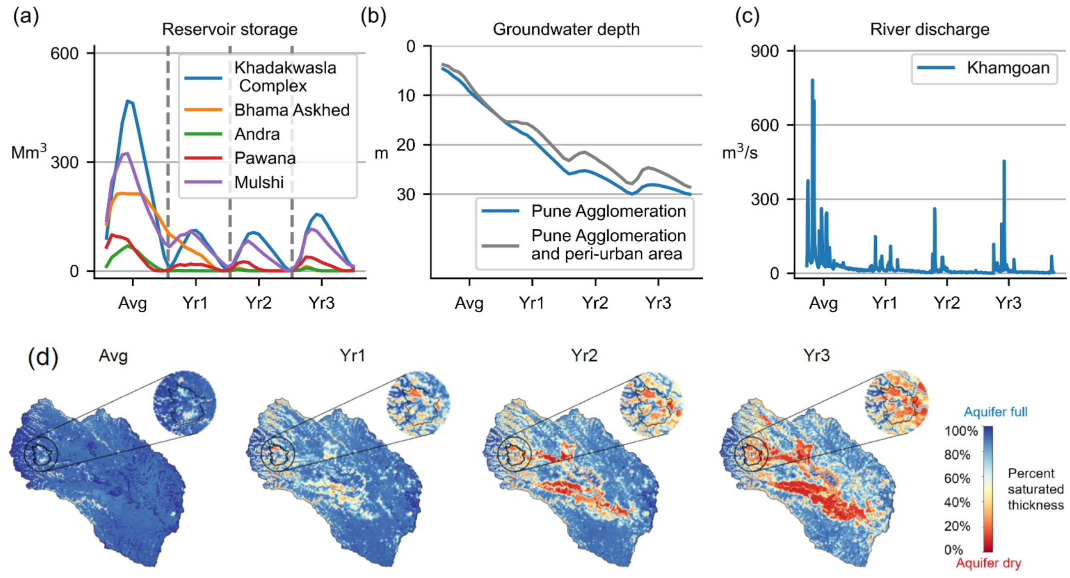

Figure 3. Water resource status under a future multi-year drought, starting from an average rainfall year, under business-as-usual conditions under extreme climate change and high urbanization. Shown are impacts on (a) reservoir storage, (b) urban groundwater level in meters below ground surface, (c) river discharge at the Khamgoan gauge station downstream of the Pune agglomeration, (d) basin-wide groundwater depletion.

4.2. Water Insecurity

Human well-being metrics under business-as-usual show decreasing water security for urban residents across all future climate and urbanization scenarios (Figure 4). We categorize the urban population into low-income (bottom 10%), middle-income (middle 80%), and high-income groups (top 10%) (Figure S3 in Supporting Information S1) (Zhu & Klassert, 2025). The 10% threshold for the lowest income population aligns with previous studies focusing on household water inequality and affordability (e.g., Fankhauser & Tepic, 2007; Yoon et al., 2021), and we apply the same 10% threshold for the high-income population.

Across all drought and urbanization scenario sets, per capita water use by all income groups decreases dramatically (Figure 4a). Low-income residents, who begin at a low water use of around 52 liters per capita per day (LPCD) even in an average rainfall year, drop by over 50% to 23 LPCD, falling well below the critical water-use threshold of 40 LPCD (Klassert et al., 2023; Srinivasan et al., 2013; Yoon et al., 2021). Middle-income residents drop from around 120 LPCD to 50 LPCD and high-income residents' water use falls from 150 LPCD to between 43 and 60 LPCD in drought year 2. Drought year 3 shows similar water uses as year 2. It is instructive to compare these future water use values to water access under historical non-drought conditions, where some residents receive piped water up to 366 LPCD, while others having limited access receive only 51 LPCD (Tholiya & Chaudhary, 2023). An interesting result is that under high urbanization scenarios, high-income residents show lower water use than middle-income residents in drought year 2 and 3 (Figure 4a). This is due to the different locations of income households in the Pune agglomeration relative to their access to water sources. Under all scenarios, high-and middle-income residents obtain well water and tanker water to satisfy their demand, due to insufficient piped supply. However, for high-income residents, groundwater depletion is more severe in their areas and tanker water supply is spatially constrained by tanker delivery limits. This difference in access becomes more pronounced under high-urbanization scenarios. These factors lead to overall water uses from middle-income exceeding those from high-income residents.

The urban population experiences increased inequality in water use during drought years (Figure 4b). The water use Gini coefficient, which measures inequality (where 0 represents perfect equality and 1 represents perfect inequality), doubles from up to 0.25 in the average rainfall year to 0.52 in drought year 2 under extreme climate change and high urbanization. The increase reflects substantial water use inequality. Low-income households, largely residing in informal settlements, bear a disproportionate burden of limited water availability during drought. These low-income households systematically lack affordable access to sufficient water to cope with

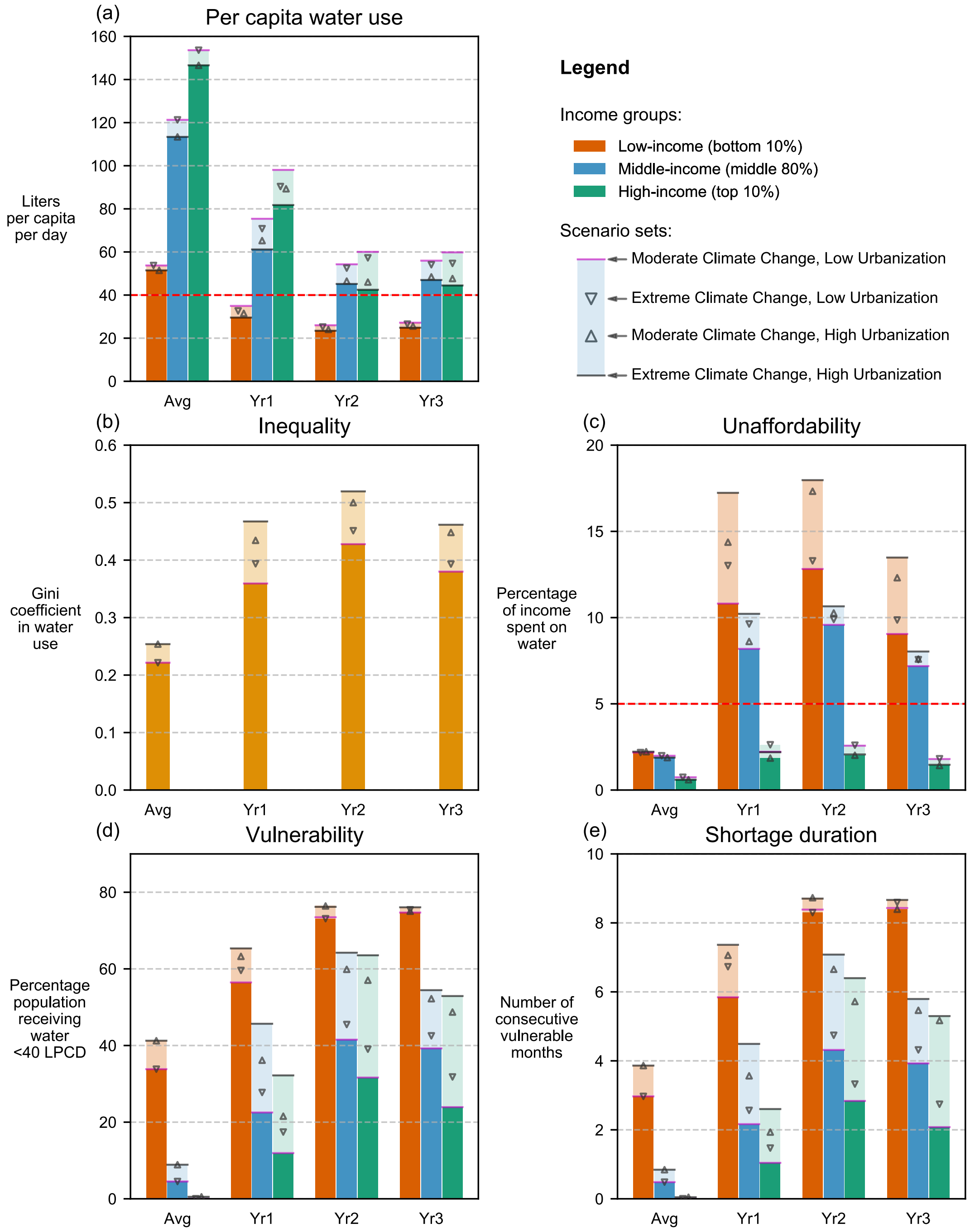

Figure 4. Comparing an average rainfall year and a mid-century multi-year drought, the impacts on human well-being under business-as-usual conditions. Shown are (a) per capita water use by income groups on an annual basis, with the red dashed line indicating the critical water-use threshold of 40 LPCD, (b) inequality in water use (Gini coefficient being 1 represents perfect inequality and being 0 represents perfect equality), (c) unaffordability, with the red dashed line indicating the 5% unaffordability threshold, (d) vulnerability, and (e) shortage duration. The faded bar-segments represent the range across all scenario sets, with the upper and lower bounds indicating maximum and minimum values. Each scenario set is marked by either a line or a triangle symbol.

drought conditions. It is noteworthy that in drought year two, the Gini coefficient of 0.52 for water is even higher than the mid-century projected Gini coefficient for per capita income, which is 0.24, calculated based on household surveys data and SSP projections (Karutz et al., 2023; Zhu & Klassert, 2025). This indicates that water use inequality further amplifies socioeconomic disparities during a future drought. The water use Gini coefficient decreases slightly in drought year 3 compared to year 2 but remains high, reaching up to 0.47.

The cost of water as a percentage of income increases disproportionately across income groups, showing significant unaffordability for low-income residents during droughts (Figure 4c). For low-income residents, water costs surge to 12%–18% of their income in the second drought year across the four scenario sets. This share of income spent on water substantially exceeds the 5% unaffordability threshold defined by the United Nations (2010). Middle-income residents also pay a high proportion of their income (approximately 10%) for water during the second drought year. The situation gets alleviated during the third year with the unaffordability for low-income and middle-income residents dropping to below 13% and 8% respectively. This results from lower tanker water prices as tanker water demand declines with increased piped supply (Figure S4 in Supporting Information S1). On the other hand, high-income residents maintain their percentage below 2%, indicating they are far less affected during the drought years as water remains affordable for them (Rachunok & Fletcher, 2023; Savelli et al., 2023).

Analysis of vulnerability shows that all income groups suffer from critically low water use during the drought years, with the low-income population suffering much more than the middle-income and high-income population (Figure 4d). Over 30% of the low-income population receives water less than 40 LPCD even in the average rainfall year. Across the four scenario sets, the low-income population is in dire straits during the drought period, with 75% receiving less than 40 LPCD during the second and third drought year. This result aligns with the findings of studies in other regions that highlight the vulnerability of urban low-income residents (Millington, 2018; Savelli et al., 2023; Yoon et al., 2021).

Water shortage duration reaches severe levels during drought periods, again particularly affecting low-income residents (Figure 4e). Water shortage duration can extend up to 9 continuous months during the second and third drought year for low-income residents under all scenario sets. Shortage duration can increase up to almost 7 months for middle- and high-income residents in the second year under high urbanization scenarios and decrease to just below 6 months during the third drought year. Even during the first drought year, low-income residents experience 7 continuous months of water use less than 40 LPCD.

4.3. Scenarios Comparison

Comparing human well-being metrics across scenario sets (Figure 4) reveals that urbanization has a greater impact on water insecurity than long-term climate change during a future multi-year drought in the Pune agglomeration, consistent with some previous findings (Schewe et al., 2014; Vörösmarty et al., 2000; Yoon et al., 2021).

To quantitatively compare the relative influence of climate change and urbanization, we calculate how the metric results change when one driver (i.e., climate change or urbanization) varies while holding the other constant. For instance, under drought year 2, consider low urbanization and moderate climate change as the baseline scenario, shifting to high urbanization increases water use Gini coefficient by 16%. Similarly, middle- and high-income residents show marked increases in vulnerability and shortage duration when shifting to high urbanization, with an additional 18% of the middle-income and 24% of high-income residents experiencing vulnerability, lasting 2–3 months longer. On the contrary, shifting to extreme climate change, while holding low urbanization constant, only raises water use Gini coefficient by 5%, while adding 4% of the middle-income and 6% of the high-income to experience vulnerability, lasting 0.5 months longer. These contrasts show that changes in urbanization level have much larger effects on water insecurity than changes in climate change severity, indicating that the near doubling of population places greater stress on water security than climate change during the drought period.

Other well-being metrics (per capita water use, unaffordability) tell the same story. Particularly, the pattern of unaffordability in most cases is driven by increased water demand under high urbanization, leading to greater willingness-to-pay for tanker water and consequently higher water prices (Figure S4 in Supporting Information S1). Unaffordability for high-income residents under high urbanization scenarios is actually lower than that under the low urbanization scenarios, due to their higher projected income under rapid economic development conditions.

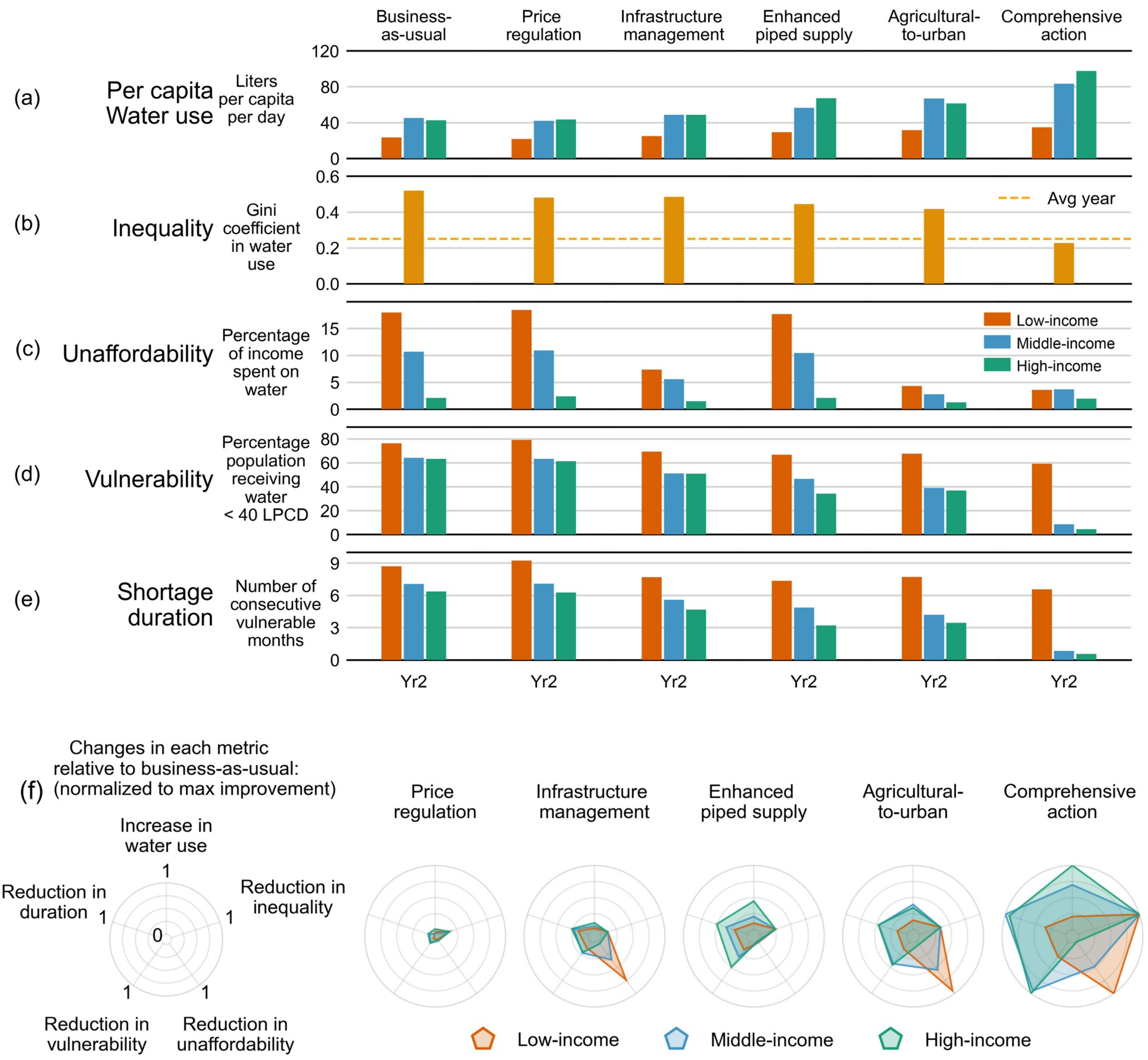

Figure 5. For year 2 of a mid-century multi-year drought, effectiveness of intervention portfolios. It includes increasing (a) per capita water use and reducing (b) inequality in water use, (c) unaffordability, (d) vulnerability, and (e) shortage duration under extreme climate change and high urbanization. The dashed line in (b) indicates the level of inequality in water use in the average rainfall year. It also includes (f) showing changes in each metric relative to business-as-usual. These changes are normalized to a 0–1 scale, where 0 represents no change relative to business-as-usual, and 1 represents the maximum improvement observed across all intervention portfolios and income groups.

4.4. Policy Evaluation

Here, we evaluate the effectiveness of intervention portfolios on human well-being metrics in the second drought year under extreme climate change and high urbanization (Figure 5, results for all the scenario sets are in Figures S5–S10 in Supporting Information S1).

Comprehensive action has markedly improved water security during drought years by increasing per capita water use, especially for middle- and high-income groups (Figure 5a). High-income residents' water use doubles from 43 LPCD to over 90 LPCD and middle-income residents increase from 50 LPCD to 80 LPCD. Averaged water use by low-income residents increases by 60%, but remains below the 40 LPCD threshold.

The reduction in water use inequality is particularly significant, with comprehensive action far outperforming all other intervention portfolios (Figure 5b). Most notably, during the second drought year, comprehensive action actually reduces inequality to below the average rainfall year's level, bringing down the water use Gini coefficient value from 0.52 to 0.23. This significant improvement also indicates that combining individual intervention portfolios into comprehensive action creates synergies that further reduce water use inequality, with effects exceeding the sum of their individual impacts when implemented alone. The combination of supply- and demand-side intervention portfolios creates positively interacting effects by redistributing water access across income groups, reducing financial barriers, and improving the societal benefit of public infrastructure.

Water costs as a percentage of income are significantly lowered by comprehensive action, and this impact is almost entirely attributed to agricultural-to-urban water transfer (Figure 5c). In the second drought year, the cost relative to income drops to 3% for all income groups. Agricultural-to-urban water transfer greatly reduces tanker water prices by providing additional tanker water (Figure S4 in Supporting Information S1). However, the cost percentage overlooks "hidden" forms of unaffordability. While low-income residents spend merely 3% of their income on water, their water use remains dangerously low due to their limited financial condition (Figure S11 in Supporting Information S1), as tanker water prices remain relatively high for them. This is reflected by the limited increase in per capita water use of the low-income group under both agricultural-to-urban water transfer and comprehensive action.

By implementing comprehensive action, vulnerability of middle- and high-income groups declines from more than 60% to about 5% in the second drought year (Figure 5d). However, the low-income group still suffers greatly, with up to 59% of the population remaining vulnerable, receiving inadequate supply in the second drought year. Comprehensive action also significantly reduces water shortage duration, almost eliminating long-term impacts (>1 month) for middle- and high-income groups (Figure 5e). While comprehensive action improves the conditions for low-income residents, they are still severely affected, suffering from continuous vulnerable periods of approximately 6 months in the second drought year. The significant decrease in vulnerability and shortage duration achieved by comprehensive action cannot be attributed to any single intervention component, but rather to their collective impact.

Agricultural-to-urban water transfer represents the intervention where peri-urban farmers are incentivized to sell their groundwater to the urban residents as an additional tanker water source instead of using it for crop irrigation. It contributes to increased per capita water use and greater equality by providing additional supply, but this supply is still insufficient under the multi-year drought. As a key component of comprehensive action, agricultural-to-urban water transfer is the single most effective intervention in reducing overall water expenditure for all income groups. However, low-income groups' water use remains financially constrained. This intervention also effectively reduces vulnerability and shortage duration for high- and middle-income residents who can afford tanker water but provides limited benefits to low-income residents. In the second drought year, agricultural-to-urban water transfer reduces vulnerability and shortage duration by 42% and 46% respectively for high-income residents, but only by 11% for low-income residents.

Enhanced piped water supply consists of water transfer from Tata (private) dams and reduction in non-revenue water in the piped supply system (reducing leaks and unauthorized uses) from 35% to 20%. It significantly benefits urban residents in reducing their vulnerability and shortage duration by providing additional inexpensive piped water supply. However, the most significant benefits accrue to high-income and smallest to low-income residents due to the positive income elasticity of water demand (Klassert et al., 2018). In the second drought year, vulnerability reduction is 12% for low-, 28% for middle-, and 46% for high-income residents. Similarly, shortage duration decreases by 15%, 31%, and 50% over income groups, respectively. The effectiveness of this intervention portfolio in reducing water use inequality is limited due to the insufficient additional piped supply. Enhanced piped water supply also has a minor impact on reducing water expenditure. This is because a high tanker water price is the most significant contributor to water expenditure. An increase in piped water supply is insufficient to notably reduce tanker water price, hence the overall water expenditure.

Infrastructure management combines capping groundwater pumping at 40 LPCD when groundwater depletion exceeds 80% of the aquifer saturated thickness and an increase in irrigation efficiency from 60% to 80% for all crops. As a demand management intervention portfolio, infrastructure management has a moderate impact on reducing water insecurity. Capping excessive groundwater pumping slows down groundwater depletion, which enables more sustained groundwater use throughout the drought years, benefiting all income groups in getting

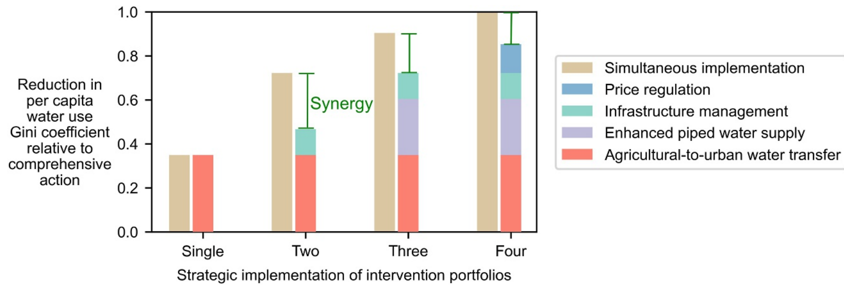

Figure 6. For year 2 of a mid-century multi-year drought, strategic subsets of intervention portfolios to reduce inequality (measured by the water use Gini coefficient) under extreme climate change and high urbanization. The left bars represent the effectiveness of simultaneously implementing all intervention portfolios, with the model automatically accounting for synergies among the portfolios. The right groupings show the sum of effectiveness when each intervention is implemented individually, without considering their simultaneous interactions. The difference in height between the combined intervention portfolios (left) and the sum of individual interventions (right) represents the complex nonlinear interactions among portfolios, in this case, generating synergies.

more water for their basic needs (40 LPCD). Improving irrigation efficiency reduces agricultural water demand, ultimately making more reservoir water available for urban use. Together public and private infrastructure management lowers the cost of water from 18% to 7% of income for low-income residents, and from 10% to 5% for middle-income residents in the second drought year, with high-income residents lowered to around 1%. However, infrastructure management is ineffective in reducing inequality because capping groundwater pumping is only triggered when groundwater depletion exceeds 80% of the aquifer saturated thickness, when only 15% of users deplete groundwater in their wells to that extent. Agricultural water savings from reservoirs are also limited due to limited remaining storage in the second drought year (Figure 3).

Price regulation doubles municipal piped water tariff for the high price tier and reduces electricity subsidies for groundwater pumping which results in doubling the electricity cost of pumping. As a demand management intervention portfolio, price regulation has a marginal impact on reducing inequality in water use due to the modest price increase and low price-elasticity of demand for water. Price regulation has a minimal impact on mitigating vulnerability, and even slightly increases vulnerability mainly among low-income residents. This aligns with the finding by Savelli et al. (2023) that low-income groups tend to be less resilient as they cannot easily afford price increases, especially during a drought when alternative supplies are particularly expensive. Similarly, price regulation exacerbates the duration of reduced supply for low-income groups by making water unaffordable (Savelli et al., 2023).

We summarize the effectiveness of each intervention portfolio compared to business-as-usual across all well-being metrics in Figure 5f. It is clearly shown that comprehensive action is the most effective intervention portfolio in reducing water use inequality. Comprehensive action is also the most effective in increasing water use, decreasing vulnerability and shortage duration for all income groups. Agricultural-to-urban water transfer is the most effective in reducing unaffordability across high- and middle-income residents, with pronounced impact on low-income residents. Enhanced piped supply is mainly effective in increasing water use and decreasing vulnerability and shortage duration, with benefits increasing with income level. Infrastructure management only has significant impact on reducing unaffordability for low-income residents, while the impact of price regulation across all metrics is minimal.

4.5. Strategic Intervention Subsets Leveraging Synergies

One key advantage of the systems modeling framework is that it enables us to evaluate simultaneous implementation of multiple policy interventions and capture their synergistic effects. Such effects are an emergent property. They stem from complex interactions within the coupled human-natural-engineered system. Our results show that only implementing a strategic subset of intervention portfolios can effectively reduce water insecurity by leveraging synergies (Figure 6). We define synergy in our study as the extent to which the effectiveness of simultaneously implemented intervention portfolios is attributed to positively interactive effects among their components, exceeding the sum of their individual effects.

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For example, consider inequality reduction, reflected in the Gini coefficient for per capita water use. The strategic implementation of intervention portfolios would start with agricultural-to-urban water transfer, the single most effective intervention for reducing inequality in water use.

For the case of simultaneously implementing two intervention portfolios, without a systems perspective, water managers might tend to prioritize interventions based solely on their individual effectiveness. This would result in the top two choices: agricultural-to-urban water transfer and enhanced piped water supply. However, our analysis reveals that pairing agricultural-to-urban water transfer with infrastructure management is 16% more effective. This improvement is attributed to the synergy between these two intervention portfolios. Together, the redistributive effect from capping excessive groundwater pumping, which preserves water to meet basic needs (40LPCD), and subsequent additional tanker water supply, collectively amplifies the reduction in inequality.

When three intervention portfolios are implemented together, the combined effectiveness of agricultural-to-urban water transfer, infrastructure management, and enhanced piped supply still outperforms the sum of each individual intervention effectiveness. This is due to synergistic interactions among interventions.

Comprehensive action, which incorporates price regulation, leads to the greatest reduction in water use inequality. However, it also produces the least incremental benefit. This suggests that strategically implementing fewer interventions can be a wiser strategy—achieving benefits very close to comprehensive action but with a lower implementation burden. Additional synergistic benefits across other metrics, including per capita water use, vulnerability, and shortage duration, are presented in Supporting Information, Figure S12.

5. Discussions

We develop a coupled multi-agent systems model that captures the dynamic interactions among the natural and built environment, social and economic systems, and water resources use and management. The model successfully replicates historical system-level observations, including sectoral water use and reservoir releases in the Bhima basin and the Pune agglomeration. Using the coupled agent model, we systematically assess the effectiveness of interventions in reducing urban water insecurity among socioeconomic groups, expressed through a suite of well-being metrics under future climate and urbanization scenarios. This addresses a critical gap in urban water security research: the lack of systems analysis on access inequalities, particularly the distributional impacts of policy interventions on low-income households under future conditions. Together, this study advances an integrated framework for urban water security, and improves the policy relevance of urban water security research, providing decision-relevant insights for local policymakers and water managers.

5.1. Water Access Inequalities in the Pune Agglomeration

Our model results show progressive declines of water storage and river flows during a mid-century multi-year drought in the Bhima basin. Without decisive actions, major reservoirs upstream of the Pune agglomeration experience marked storage decreases. Aquifers are depleted in the urban, peri-urban, and agricultural areas. Analysis of human well-being metrics shows that while all urban residents in the Pune agglomeration suffer from extensive water insecurity during the multi-year drought, low-income urban residents are severely affected. Our results reveal widespread inequalities in urban water access which exacerbate water security challenges posed by mid-century climate change and urbanization. Comparison across scenarios shows that while both climate change and urban population growth threaten water security, water security is more sensitive to urbanization.

5.2. Decision-Ready Insights for Policymakers

Our policy analysis results suggest that addressing complex water security challenges under mid-century urbanization and climate change in the Pune agglomeration will require comprehensive action, which integrates both supply- and demand-side measures. Specifically, Comprehensive action is the most effective in reducing water use inequality, and increasing water use, reducing vulnerability and shortage duration for all income populations during the multi-year drought. It is also the most effective in reducing unaffordability for the low-income population. In contrast, single interventions provide only limited improvements across the full suite of well-being metrics. For instance, infrastructure management and agricultural-to-urban transfer mainly show pronounced impacts on reducing unaffordability, and enhanced piped supply on increasing water use, reducing vulnerability and shortage duration. Moreover, policy makers can achieve the greatest synergy by only

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implementing agricultural-to-urban water transfer and infrastructure management simultaneously. This result demonstrate that policy makers can achieve substantial practical benefits by strategically implementing a smaller set of intervention portfolios that leverage their synergistic effects.

Although 90% of urban population benefits significantly from implementing all-inclusive measures, the 10% low-income residents remain under-served. Therefore, we suggest that policy makers consider a further safety net to ensure that low-income urban residents, largely in informal settlements, do not suffer during a mid-century, multi-year drought. With comprehensive action implemented, ensuring all low-income residents reach 40 LPCD requires only an additional ∼1% of the total water supplied compared to that of business-as-usual conditions, which can be achieved by policy measures targeting at low-income residents (Supporting Information, Table S9). Additionally, increasing public awareness of potential future drought impacts is crucial, as is mitigating negative impacts by securing equal water access, particularly for low-income residents.

5.3. Transferability to Other Regions

While we focus on the Pune agglomeration, the critical water access inequalities identified in this study results from complex system interactions that are not unique to Pune. Similar conditions exist in many drought-prone, rapidly developing municipalities where income disparities, wide-spreading informal settlements, and inadequate infrastructure interact to shape urban water security. By 2050, an estimated 46% of global cities are expected to face water security issues (Krueger et al., 2019). Our coupled multi-agent systems model not only reveals how water access inequalities exacerbate water security challenges within the Pune context, but further quantifies them and evaluates policy interventions via a suite of well-being metrics under future climate and urbanization scenarios. Therefore, our modeling framework provides a transferable way to represent and evaluate complex water security challenges and identify viable policy solutions across many other urban socio-hydrologic contexts similar to Pune.

To study water security challenges in other emerging megacities, different elements of our model should be parameterized and calibrated to the local context. This includes updating and calibrating surface water and groundwater models to represent local dynamics, applying an agriculture module to represent local cropping patterns and water use. It also requires updating the human module to represent local human agents and their decision-making. Finally, the climate change and socioeconomic development scenarios need to be downscaled to the region of interest. Policy intervention options are also context-specific, such as those related to sectoral water transfer, tariff structures, and infrastructure improvement.

Although specific parameter values and governance settings differ across regions, the policy insights identified in this study are also transferable. Based on our model results and similar findings from other studies (e.g., Klassert et al., 2023; Yoon et al., 2021), we suggest that when studying other regions with similar challenges, one should take into consideration that no single intervention is likely to achieve the necessary improvements. Instead, coordinated intervention portfolios leveraging synergies among supply- and demand-side measures need to be identified.

5.4. Model Limitations and Future Work

However, there are limitations in our model. Our study area represents conditions in many Indian cities and basins, where detailed, complete, and consistently reported water use data sets are scarce. Therefore, for system-level model validation, we rely on limited basin-wise water use data. Future work can benefit from collecting additional data. Second, the model does not perform policy optimization which demands substantial computational resources. Instead, it focuses on evaluating interventions that emerged from stakeholder workshops and identifying inequalities among different socioeconomic groups. In future work, this policy-evaluation model framework can be integrated with multi-objective optimization algorithms capable of searching policy options through a broader set of combinations and uncertainties. Third is the simplifications of the government agent's behaviors. We did not model endogenous institutional responses or adaptive governance responses to a water crisis. Instead, the government agent implements defined policies and we only simulate urban and farmer agents' response to these regulatory changes. Further work can include institutional evolutionary response to better represent the multi-level systems dynamics and how it shapes urban water security outcomes. Despite these limitations, the model provides useful insights on water access inequalities and synergies among policy interventions that emerge from system interactions.

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5.5. Broader Policy Implications

In addition to these model limitations, it is also important to consider the broader implications of the proposed policy interventions, especially their potential social and economic trade-offs. Our study shows that agricultural-to-urban water transfer is very effective in reducing urban water insecurity from the supply perspective during future prolonged droughts. This finding aligns with previous studies that have emphasized its value in meeting growing urban water demands and their potential for broader implementation in the future (e.g., Amaya et al., 2025; Marston & Cai, 2016). Although effective, this intervention may also generate negative impacts on rural agricultural production and food security, which would further lead to unemployment (Amaya et al., 2025), commodity prices fluctuations, and environmental impacts (Molle & Berkoff, 2009). Nevertheless, the policy intervention we proposed can be regarded as an emergency response based on incentives to cope with urban water crises, as an alternative to unregulated transfers or long-term land use change from irrigated cropland to urban areas (Garrick et al., 2019). Another key message is that future research should focus on how the resilience could be strengthened before such a crisis happens, to better prepare for future water shortages. Moreover, in Maharashtra, electricity for groundwater pumping is provided at highly subsidized flat rates. Increase in pumping cost may have significant societal and political implications, such as affecting farmers profit particularly from low-value crops, increasing social resistance, and influencing political economy of agricultural policies (Badiani et al., 2012; Lee et al., 2020).

Regarding the relative costs, benefits, and likelihood of the proposed interventions being implemented, non-revenue water reduction from 35% to 20% is effective for improving utility cost recovery (National Institute of Urban Affairs, 2021). This policy intervention is highly likely to be implemented as Pune has already taken positive actions including installation of water meters under the 24/7 water supply project, replacing leaky pipelines, and disconnecting illegal connections (P. Kulkarni, 2025; PMC, 2026). Similarly, the ongoing meter installation program provides the foundation for price regulation, which has the potential to improve revenue recovery. However, any urban water pricing increase must be accompanied by better service delivery as highlighted by local stakeholders during the stakeholder workshops (Küblböck et al., 2022).

Two other interventions are most likely to be implemented. The Tata dam transfer has been approved to divert some water from Mulshi Dam to Pune that currently goes to Mumbai, while ensuring hydropower generation for Mumbai (Hindustan Times, 2025). It is reasonable to expect agricultural-to-urban water transfer to occur as it is a logical extension of the existing tanker water market. This intervention is designed to offer farmers the opportunity to benefit economically by selling their water to urban users. Farmers receive a price for tanker water set to be the higher of the profitability of their marginal crop production (reservation price) and the urban agents' willingness-to-pay for tanker water. Moreover, Pune is now implementing a licensing policy for tanker trucks, which increases the acceptance of regulated water transfers from farmers to urban users (Punekar News, 2025).

Some interventions require a tracking and regulatory capacity that is currently limited but that we assume will be strengthened by our mid-century implementation target. Specifically, increases in groundwater pumping cost and pumping caps require metering, monitoring, and enforcement and face societal and political barriers, which have constrained near-term implementation, but could be resolved by mid-century.

6. Conclusions

This study demonstrates the importance of evaluating regional water scarcity within the context of local poverty and inequality using coupled multi-agent systems analysis. Such analysis shows how drought impacts and policy interventions affect different socioeconomic groups, revealing critical inequalities in urban water access that would otherwise remain hidden. Using this coupled multi-agent modeling framework, we systematically evaluate strategic combinations of policy interventions that emerged from stakeholder workshops. We find that comprehensive action combining supply- and demand-side measures effectively addresses water security challenges, yet remains insufficient to ensure water access for the low-income population. Through this novel multifaceted framework, we for the first time, identify synergies among policy interventions—information critical to policy makers and water managers. More broadly, we provide a transferable analytic approach to target viable policy interventions that are valuable to other rapidly urbanizing regions facing similar challenges, largely in the Global South.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The coupled multi-agent systems model code, including all the input data required to run the model, as well as code to process output data and to reproduce the figures are available at the Stanford Digital Repository (Wang et al., 2026). Climate projections are available from the NASA NEX-GDDP-CMIP6 data set (Rama Nemani/NASA, 2021), and downscaled socioeconomic projections under Shared Socioeconomic Pathways are from Karutz et al. (2023). Figures were generated using ArcGIS Pro version 3.2.0 (Esri, 2023), Excel, and Matplotlib version 3.5.1 (Hunter, 2007).

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