Optimizing Groundwater's Role in Enhancing Water Infrastructure Resilience

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1. Abstract

The impacts of global warming, urbanization, and extreme climate events are presenting unprecedented challenges to water resource systems. Groundwater reserves play a critical role in enhancing water infrastructure resilience, yet they are often oversimplified or overlooked in modeling and planning efforts. This study aims to develop a comprehensive water resource management model by coupling the Community Water Model (CWatM) with the MODFLOW groundwater model. The primary objective is to strengthen the resilience of water supply systems under extreme climatic conditions, such as droughts and floods, through multi-objective optimization. By optimizing groundwater management, including strategies such as Managed Aquifer Recharge (MAR), the research aims to improve water supply reliability, reduce economic costs, and maximize social welfare, particularly for vulnerable communities. The study will evaluate the model's performance under various climate scenarios and provide actionable policy recommendations based on cost-benefit analyses. The expected outcomes include a more accurate assessment of groundwater's role in integrated water management, cost-effective solutions for water resource systems, and resilient infrastructure planning that ensures sustainability and equity in the face of climate-induced risks.

2. Research Background

In the Anthropocene, global warming, the melting of polar ice caps, rising sea levels, and the increasing frequency of extreme climate events highlight the profound impact of human activities on terrestrial water cycle processes, which in turn significantly affect global water resources (Haddeland et al., 2014). Human interventions alter watershed characteristics (e.g., urbanization, land use/land cover changes), modify river network structures (e.g., reservoir construction), and influence global and regional climates (e.g., greenhouse gas emissions, consumptive water use). More than 50% of the world's population reside in cities, and this is expected to increase by a further 2.5 billion by 2050 (UN, 2014). Rising demand for food and energy, driven by population growth and urbanization, is intensifying pressure on water resources, which are becoming increasingly unpredictable due to climate change and shifting hydrological cycles (Dadson et al., 2020).

A water resources system (see Fig. 1), composed of "connected hydrologic, infrastructure, ecologic, and human processes that involve water," serves as a fundamental cornerstone for our utilization of water resources. Progress to improve water availability is most challenging in contexts where water resources are threatened by acute (e.g., floods, cyclones and droughts) and chronic (e.g., groundwater contamination) threats (Brozović et al., 2007; Roman et al., 2021). Floods can cause direct damage to critical water supply infrastructure, such as pumping stations and treatment facilities, resulting in disruptions to water supply. Similarly, extreme winds from cyclones can damage water infrastructure and related systems, such as power lines, upon which water services rely (Becher et al., 2023). Urban heat waves exacerbate water stress by driving excessive water consumption, particularly during drought conditions (Hatvani-Kovacs et al., 2016).

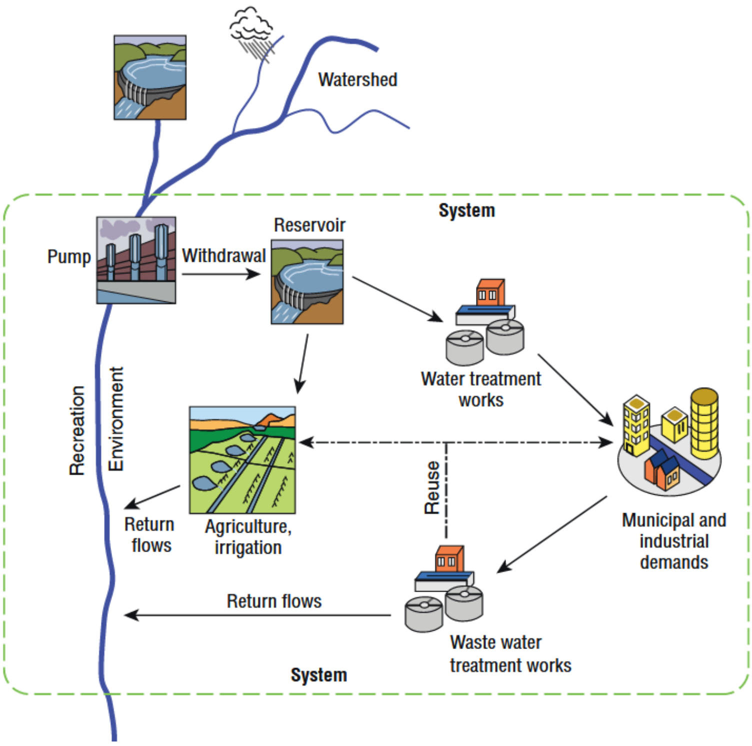

Fig 1. Schematic of the water resource system, including diversions for human uses and return flows (Dadson et al., 2020).

There are lots of examples, such as Hurricane Katrina in 2005 (Pielke Jr et al. 2008), Amazon Drought in 2010 (Lewis et al. 2011), Heavy Rain Event of July 2018 in Japan (Tsuguti et al. 2019), Thai Floods in 2011 (Komori et al. 2012), and Kyushu's flash floods in 2014 (Duan et al. 2014). All these disasters have resulted in significant water supply shortages and severe damage to water infrastructure, presenting a major obstacle to achieving water availability and sustainable socio-economic development (Jongman et al. 2014; Jonkman 2005; Smith and Katz 2013). The statistic obtained from the Global Emergency Disaster Database (EM-DAT) showed that there were 11,707 hydrological disasters from 1970 to 2013, killing more than 3,525,166 people, affecting more than 6.6 billion, and inflicting more than US$ 2,600 billion in damage. According to a World Bank report, annual economic losses caused by natural disasters have risen from $50 billion in the 1980s to $180 billion in the most recent decade (Jha et al., 2012). Over the past 30 years, natural disasters have resulted in approximately $4 trillion in global economic losses, with 75% of these losses attributed to major hydrometeorological extreme weather events, of which urban flooding constitutes a significant proportion (Lee et al., 2020). The report 'Natural Hazards， UnNatural Disasters: The Economics of Effective Prevention' published by the World Bank and the United Nations highlights that urbanization will increase the risk of cities being exposed to disasters (Sanghi et al., 2010).

Also, these events caused the second disaster. For example, floods can generally cause serious environmental damage and pollution (Duan et al. 2013). In addition, certain regions, such as Bangladesh, face multiple overlapping risks. As one of the world's most vulnerable and biophysically dynamic regions, coastal Bangladesh faces multiple water-related hazards, including cyclones, tidal and river flooding, salinization and waterlogging. With the potential for multiple coinciding hazards to increase in the future, the impact of hydroclimatic risks is likely to be magnified (Barbour et al., 2022).

Resilient water supply infrastructure is fundamental for human life and wellbeing (Hallegatte et al., 2019). Water resilience refers to the capacity of water systems—including natural hydrological systems and human-made infrastructure—to absorb, adapt to, and recover from disturbances caused by factors such as climate change, extreme weather events (e.g., floods, droughts, storms), or human activities, while maintaining their core functions (Rockström et al., 2014). It involves the ability to ensure sustainable water availability and quality in the face of such challenges and is often linked to broader efforts in sustainability and disaster risk management. In light of these escalating risks, the need for resilient water supply infrastructure is increasingly important if several SDG targets including clean water and sanitation (SDG 6) are to be met by 2030 (Krueger et al., 2020).

Groundwater is a vital freshwater resource on Earth, providing 25% of the water used by humans, with 70% of the extracted groundwater being utilized for agricultural irrigation. Groundwater resource management is pivotal in strengthening water resilience, especially as climate change and increasing water demands exacerbate the pressures on water systems. Groundwater acts as a vital buffer during droughts and periods of water scarcity, providing a stable water supply when surface water is insufficient. Apart from hard infrastructure options such as leakage reduction, reservoir storage, and desalination, soft options like managed aquifer recharge also represent a critical approach to enhancing the resilience of water infrastructure (Becher et al., 2024). Integrating groundwater management with broader water resource planning, considering both surface and subsurface water systems, enhances the adaptive capacity of communities to respond to hydrological extremes. By improving groundwater governance and adopting sustainable management practices, societies can enhance their resilience to climate-induced water stress and ensure reliable water availability under challenging conditions.

Ensuring the reliability and sustainability of water systems requires proactive measures to safeguard against both acute and chronic threats. Resilience can be achieved by developing a diverse portfolio of solutions, such as increasing supplies, reducing demands, nature-based solutions, and storing and transporting water, to address multipronged issues, including water scarcity and excess, and water quality degradation (Scanlon et al., 2023). Conjunctive management of surface water and groundwater is an increasingly critical component of water management, where both are available, to holistically address climate and human stressors on water resources. Additionally, resilience will require multiple approaches with redundancies as backup, and therefore the most resilient systems will probably not be the most efficient systems. Only through coordinated efforts and investment in resilience can we hope to mitigate the impacts of climate-related disasters and achieve sustainable water resource management for future generations.

Global hydrological models that account for human water use, along with physically-based groundwater models, offer new insights into the reliability and sustainability of water systems. Compared to traditional hydrological models that simulate only natural hydrological processes, global hydrological models such as CWatM (Lee et al., 2020), H08 (Hanasaki et al., 2008), PCR-GLOBWB (Wada et al., 2014) and WGHM (Döll & Fiedler, 2008), consider the impacts of human water withdrawals on the terrestrial water cycle. These models simulate water usage across sectors such as domestic, industrial, agricultural irrigation, and livestock, and describe the interaction between available water resources and water demands by calculating the amounts of surface water (from rivers, lakes, reservoirs) and groundwater that can be used to meet water needs. Meanwhile, groundwater models (such as MODFLOW (McDonald & Harbaugh, 2003) and FEFLOW (Diersch, 2013)) are built based on hydrogeological data (such as aquifer thickness, porosity, and permeability), allowing for a more accurate representation of aquifer properties and enabling simulations of groundwater storage changes.

In conclusion, integrating surface and groundwater management is essential to enhance water system resilience in the face of climate change and increasing demands. By leveraging advanced hydrological models and improving groundwater governance, we can ensure reliable water availability and support global sustainability goals. Proactive management and investment in resilient infrastructure are crucial to secure water resources for future generations.

3. Research Aim

This study aims to develop and optimize a water resource management model, CWatM-MODFLOW, with a focus on evaluating the resilience of water infrastructure under extreme climate conditions and gaining a deeper understanding of groundwater's role in integrated water resource management. The primary objective is to enhance the reliability and sustainability of water supply systems through multi-objective optimization, reducing economic costs while improving social welfare, particularly in the context of extreme events such as droughts and floods driven by climate change. The research will optimize groundwater management, managed aquifer recharge (MAR), and water allocation strategies to offer future-oriented water resource management solutions that strengthen the resilience and equity of water supply systems under extreme climate conditions. The potential research content is as follows:

a. Model Development and Integration:

A coupled CWatM (Community Water Model) and MODFLOW model will be constructed to assess the interactions between groundwater and surface water and simulate water resource management under different climate scenarios.

b. Development of a Multi-Objective Optimization Framework:

A multi-objective optimization framework will be developed based on the study's optimization goals, such as operational rules, extreme hazard contingency plans, investment portfolios, and social welfare. Appropriate optimization algorithms, such as genetic algorithm (NSGA-II) or particle swarm optimization, will be employed to explore the optimal combination of water management strategies.

c. Simulation of Extreme Climate Scenarios:

Future climate conditions, including droughts and floods, will be simulated under various climate change scenarios. The performance of the water supply system under these conditions will be evaluated, particularly focusing on changes in aquifers and the balance between water supply and demand.

d. Evaluation of Managed Aquifer Recharge (MAR) Strategies:

The study will evaluate MAR as a key strategy to enhance system resilience. Different MAR strategies will be simulated to assess their impact on groundwater levels and the role of MAR in improving water resource availability and system resilience. The long-term benefits of MAR, especially in the context of extreme events, will also be examined.

e. Economic and Social Impact Analysis:

A cost-benefit analysis will be conducted to assess the economic feasibility of the optimized water supply system strategies. The study will explore ways to improve the reliability and sustainability of the water supply system without significantly increasing costs. Additionally, the analysis will focus on how the optimized system ensures equitable access to water and social welfare, particularly for vulnerable groups during extreme events.

f. Policy and Management Recommendations:

The policy recommendations derived from the model's optimization results will provide decision-makers with adaptive water resource management strategies tailored to different climate scenarios and social contexts, ensuring long-term water resource resilience and equity, particularly in urban areas vulnerable to climate-induced risks.

4. Literature Review

4.1 Groundwater Storage

In the context of climate change, maximizing the use of groundwater storage will be crucial for ensuring water supply security. Groundwater offers a sustainable, decentralized, and cost-effective solution for climate change adaptation, particularly at the scale of individual cities and their surrounding catchments (Foster et al., 2018). Understanding the impact of climate change and human activities (such as water supply and demand) on groundwater storage variations is crucial for groundwater management and protection, as well as the construction of resilient water infrastructure. Due to its large storage capacity and long retention times—ranging from decades to centuries—groundwater provides a natural buffer against variability in surface water sources, such as rivers and reservoirs. Additionally, groundwater is naturally shielded from evapotranspiration and surface-level pollution, making it a more reliable and secure resource in times of drought. Groundwater development is typically characterized by relatively low capital and operational costs, which can be expanded in line with increasing demand. This is largely because groundwater is generally of high quality and requires minimal treatment (Foster et al., 2012; Foster & Varaivamoorty, 2013). Furthermore, in many urban settings, the widespread availability of groundwater makes it possible to quickly and cost-effectively develop decentralized water systems.

For example, there is a growing interest in managed aquifer recharge (MAR)—a process that involves artificially infiltrating or injecting water into the ground for storage and later recovery. In many cases, both in developed and developing countries, soft options (e.g., MAR) are often preferred over hard infrastructure (e.g., reservoirs) due to lower costs and feasibility, especially in lower-income countries. High-income countries, with advanced water supply systems, extensive storage, and access to desalination, may have reached the point where further hard infrastructure investments are no longer cost-effective. Social acceptance also limits infrastructure development, particularly for large reservoirs that displace communities. Managed aquifer recharge and other nature-based solutions present alternatives for future applications. The global volume of water stored through MAR reached approximately 10 km^3 in 2015 (Dillon et al., 2018). While this is small compared to surface reservoirs, MAR provides a vital local-scale strategy for reducing regional water stress. For instance, in Orange County, California, MAR plays a crucial role in supplying water to 850,000 people, with added benefits such as seawater intrusion prevention and improved water quality (District, 2018). By integrating MAR with traditional surface reservoirs, cities can expand their storage capacity and enhance the resilience of their water supply systems.

However, existing research has rarely considered the role of aquifers in risk assessments of urban resilient water infrastructure (Becher et al., 2024). Moreover, the representation of the impact of water usage on surface and groundwater resources in current models remains overly simplified, requiring further refinement to enable more accurate evaluations.

4.2 Community Water Model coupled with MODFLOW

Water resource modelling and simulation is the best approach available to address water resource problems and to optimize planning solutions. Water system models are tools that can be used to analyse risk and resilience of water systems and to identify infrastructure options that are robust to plausible future conditions of the world (Hall et al. 2019). Large-scale hydrological models are often used to assess water resource trajectories under different scenarios for climate change, socioeconomic development, and water management. Despite extensive work, at least three challenges persist: appropriately representing groundwater dynamics and flow, including human impact and improving spatial resolution (Guillaumot et al., 2022).

Several large-scale hydrological models include representations of groundwater flow between grid cells and interactions among groundwater, soils, and surface water bodies, such as CWatM (Burek et al., 2020), LISFLOOD (Trichakis et al., 2017), ORCHIDEE (Verbeke et al., 2019), ParFlow-CLM (Keune et al., 2016; Maxwell et al., 2015), PCR-GLOBWB (Sutanudjaja et al., 2018), ISBA-CTRIP (Decharme et al., 2019), VIC (Scheidegger et al., 2021), LEAFHYDRO (Martínez-de la Torre and Miguez-Macho, 2019), and WaterGAP (Reinecke et al., 2019). These models differ somewhat in their implementation, including the physical representation and parametrization of the groundwater. Currently, developments are oriented towards hyper-resolution models (less than or around a 1 km grid) and representing water management (Hanasaki et al., 2022). However, large-scale model resolutions (∼10–50 km) remain much coarser than the hillslope-scale controlling hydrologic processes, as hypothesized by Fan et al. (2019) and Swenson et al. (2019). In addition, coarse resolutions of groundwater representation tend to smooth hydraulic gradients, leading to unrealistic aquifer properties (Shrestha et al., 2018), and potentially to underestimate water table depth drawdowns due to groundwater pumping because withdrawals are applied to entire grid cells instead of applied to punctual boreholes.

A proper representation of groundwater is essential to consider lateral groundwater exchanges between grid cells; otherwise, they remain connected only through the river or drainage network. Darcy’s law links hydraulic head gradient, hydraulic conductivity, and aquifer thickness and can describe this lateral groundwater flow. Some studies have already highlighted the contribution of lateral groundwater flow to regions and basins (Krakauer et al., 2014).

The impact of the depth of the groundwater level on evapotranspiration and consequently on net groundwater recharge (recharge minus capillary flux) has also been demonstrated by Szilagyi et al. (2013) based on observed depth to groundwater and evapotranspiration estimated from MODIS data and by Koirala et al. (2017) based on simulated depth to groundwater and remote sensing data. Finally, reproducing soil moisture drainage, capillary rise, and baseflow more accurately depends on properly representing groundwater depth and time fluctuation.

Recent studies based on different models (Fan et al., 2013; Martínez-de la Torre and MiguezMacho, 2019; Maxwell et al., 2015) have compared simulated and observed water tables at continental and regional scales; these studies have argued that the main spatial trends were well reproduced. However, some of these studies have acknowledged that water table depth is not well reproduced, given the coarse spatial resolution (including problems of the spatial representativity of the boreholes and potential bias sampling) and the lack of representation of water management within the models (Fan et al., 2013; Maxwell et al., 2015; Reinecke et al., 2020). This raises the question of the reliability of such models in terms of parametrization and application (Gleeson et al., 2021). For example, regional- and continental-scale models often assume very simple groundwater pumping schemes or no pumping at all, and they consider these withdrawals to simply leave the system (Vergnes et al., 2020).

To predict future water resources, it is necessary to decipher climate and human contributions contained within the space and time variability of hydrological signals. Large-scale hydrological models have been developed to estimate water availability and water use from surface water bodies and groundwater at a global scale (Döll et al., 2014; Wada et al., 2014). Recently, Hanasaki et al. (2018) improved the representation of human interventions in the H08 model and showed more realistic river discharges and terrestrial water storage anomalies for several huge basins. Sadki et al. (2022) explored the possibility of improving dam representation in the ISBACTRIP model applied over Spain. Long et al. (2020) studied the impact of the south-to-north water diversion in China on groundwater pumping using CWatM. Using a global-scale hydrological model coupled with MODFLOW, de Graaf et al. (2019) reproduced the water table drawdown dynamic caused by pumping and its impact on rivers. The latest study employed a large-scale hydrological model, the Community Water Model (CWatM) (Burek et al., 2020), in conjunction with the groundwater flow model MODFLOW, to investigate groundwater exchanges, recharge processes, and the impacts of water extraction and irrigation (Guillaumot et al., 2022).

Studying and simulating regions with significant use of ground and surface waters requires accounting for the management and linkages between the two sources of water. Surface water management and groundwater management are fundamentally connected. Water demand that is satisfied with surface water stored in reservoirs and delivered through pipes or canals may be supplemented with groundwater when the timing or volume of delivery does not coincide with the need. Distribution networks, including urban pipes and agricultural canals, may encourage groundwater recharge through aging and leaking infrastructure.

We applied the model at finer spatial resolutions, incorporating water management practices, and compared the simulations with observed water table fluctuations and depths. To achieve this, we coupled a high-resolution version of CWatM (approximately 1 km resolution) with MODFLOW, implemented at high resolutions of 100 and 250 meters.

4.3 Multi-objective optimization

There are different types of uncertainty, of which deep or severe uncertainty is particularly challenging to handle because it is not amenable to conventional statistical analysis (Hall et al., 2012). This uncertainty about future climate change is described as “deep uncertainty” because the planning for secure urban water supply involves “parties to a decision [who] do not know or do not agree on the system models relating actions to consequences or the prior probability distributions for the key input parameters to those models” (Hall et al., 2012). Urban areas typically possess a complex infrastructure network that draws water from multiple surface and groundwater sources, stores it in reservoirs, and treats and transfers it to consumption zones. The decision-making landscape is intricate and nonlinear, often involving multiple conflicting objectives that must be balanced.

Optimization models have been extensively applied in engineering and infrastructure planning to assess adaptation costs and determine optimal solutions for fundamental planning problems. In water resources planning, multi-objective optimization serves as a critical decision-making tool, ensuring that the objectives and risk tolerances of various users within headworks systems are met (Cui & Kuczera, 2005). Multi-objective optimization is a method used to evaluate feasible solutions to a water supply-demand problem by considering two or more objectives simultaneously. It can be defined as “a vector of objective functions and a feasible region defined by a set of constraints”. Deb (2001) outlines two main objectives of multi-objective optimization: (i) to find a set of feasible solutions that are as close as possible to the Pareto-optimal front, and (ii) to achieve a set of feasible solutions that are as diverse as possible within the decision variable space.

Mortazavi et al. (2012) demonstrated that combining a Monte Carlo simulation model based on network flow programming with multi-objective evolutionary optimization could help identify practical optimal solutions for complex urban bulk water systems. They calibrated a stochastic model using historical data to generate long time series, ensuring the system was exposed to extreme drought conditions. Notably, they found that the cost of optimal future investment portfolios is highly sensitive to the return period of the design drought (i.e., the most severe drought the system can withstand without failing) and that the bulk water system is particularly vulnerable to droughts with return periods exceeding the design threshold. However, a key limitation of the Monte Carlo approach used by Mortazavi et al. (2012) was the assumption that the historical hydrological record would be representative of future conditions. With the potential for human-induced climate change affecting water availability, basing the optimization of the urban bulk water system on the assumption of a stable, unchanging climate risks leaving the system vulnerable if the actual climate during the planning period turns out to be less favorable than anticipated.

Considering the frequent occurrence of "broken assumptions" (Weaver et al., 2013) in water resource management, multi-objective optimization serves as a powerful tool to assist decision-makers in identifying operational rules, extreme hazard contingency plans, and investment portfolios that balance the trade-offs between sensitivity to uncertain future climate change and expected economic efficiency. This approach helps mitigate the risks associated with reliance on potentially flawed assumptions while optimizing resource allocation under uncertainty. This study integrates the multi-objective optimization approach with simulation models to identify robust optimal solutions that safeguard urban water infrastructure against extreme hazards, despite deep uncertainties surrounding future climate change. By doing so, the framework enhances the resilience of water systems in the face of unpredictable environmental conditions.

5. Research Method

5.1 CWatM

5.1.1 Introduction of CWatM

The spatiotemporal distribution of global precipitation may change under the influence of climate change, which in turn affects the availability of global water resources. Additionally, extreme climate events such as droughts and floods may impact water use behavior (e.g., increased agricultural irrigation during droughts), indirectly influencing the amount of available water resources. At the same time, with socioeconomic development and population growth, future human water demand is expected to rise significantly.

To analyze the relationship between water supply and demand in the context of population growth and socioeconomic development, the response of available water resources to climate change, and changes in human water demand, the International Institute for Applied Systems Analysis (IIASA) has developed the Community Water Model (CWatM) (Figure 2). This model is open-source, flexible, and user-friendly. It operates in Python, allowing for flexible development and model coupling. The model's configuration is straightforward, with settings directly adjustable via configuration files. Input data are in NetCDF format, facilitating standardized processing, and users can customize output variables and types of results (e.g., monthly/annual averages, monthly/annual cumulative values). Output data can be presented as time series on daily, monthly, or annual scales, or as spatial distribution maps. The model accounts for water usage impacts on the water cycle across four sectors: domestic, industrial, agricultural, and livestock. It also describes the effects of other human activities (e.g., reservoir operations, groundwater extraction, irrigation) on surface and groundwater systems. Consequently, CWatM can serve as a valuable tool for future water resource management, providing insights into the impacts of climate change and human activities.

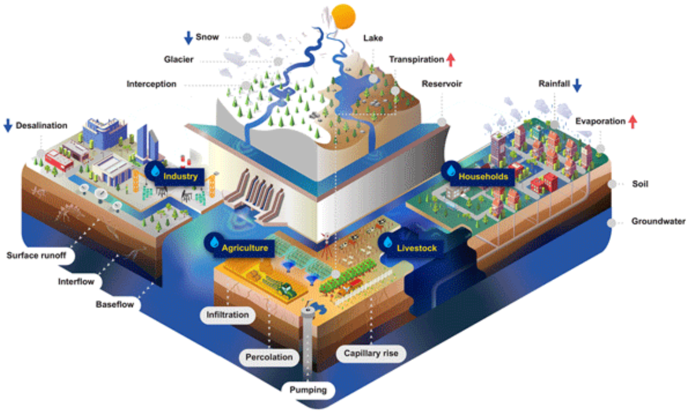

Fig.2 Diagram of the Community Water Model (CWatM)

CWatM is a grid-based global distributed hydrological model capable of simulating water processes on daily, monthly, and annual time scales at spatial resolutions of 0.5° (~50 km) and 5' (~10 km) globally, as well as at higher spatial resolutions (~1 km) at regional scales. The model is based on the water balance equation, with key computational modules including interception, evapotranspiration, snow cover/permafrost, land cover, soil, groundwater, runoff, lakes and reservoirs, and water withdrawals (domestic, industrial, agricultural, and livestock water use). Sub-grid spatial variability is described by distinguishing different land use types, soils, and topography within each grid cell.

Land cover is classified into six main types: forest, grassland, paddy fields, general crops (non-paddy), impervious surfaces, and water bodies. The simulation of interception, evapotranspiration, and soil hydrological processes (infiltration, percolation, etc.) within each grid cell is based on the different land cover types. The fluxes within a single grid cell are calculated by integrating the simulated fluxes from the six land use types, weighted by their respective area proportions. The model includes a three-layer soil system, with the topsoil layer having a depth of 5 cm to facilitate comparison with remote sensing soil moisture products (which measure soil moisture at 5 cm depth). A groundwater layer is placed beneath the soil layers, and vertical water exchange processes are simulated through processes such as infiltration, percolation, and capillary rise.

5.1.2 The principles of the main modules of the model

The principles of the main modules of the model are as follows: interception is calculated based on the interception capacity of different surface crops. The potential evapotranspiration can be calculated using the Penman–Monteith equation (based on daily mean temperature, net radiation, wind speed, and vapor pressure deficit) (Allen et al., 1998), the Hargreaves method (Hargreaves & Samani, 1985), or the Hamon method (both based on daily mean temperature) (Hamon, 1963). The snow cover/permafrost module includes the division between rain and snow and simulates snowmelt and glacier melt processes, with snowmelt calculated using the degree-day factor method and permafrost simulated using a dynamic threshold method. The model is configured with a three-layer soil system, with soil water retention characteristics and hydraulic conductivity calculated using the Van Genuchten model. Groundwater storage and outflow are calculated using a linear reservoir approach, where groundwater outflow is determined by a specified groundwater recession coefficient. The reservoir/lake module dynamically simulates inflow, outflow, and storage changes in reservoirs/lakes based on water balance. Reservoir inflow is equal to upstream river flow, and outflow is calculated using empirical formulas based on the current storage level. For lakes, inflow is set to the long-term average outflow, and outflow is calculated based on water balance, the lake stage-discharge relationship, and the lake stage-storage relationship. Runoff generation is calculated using the Improved Arno Scheme (Hagemann & Gates, 2003), which considers the spatial heterogeneity of soil water-holding capacity as influenced by terrain, soil type, and vegetation. Runoff can be generated when part of the grid area becomes saturated. Flow routing is computed using the kinematic wave method. The water demand module simulates four components: domestic water use, industrial water use, agricultural irrigation water use, and livestock water use.

5.2 CWatM coupled with MODFLOW-NWT

The original groundwater module of CWatM is simplified as a linear reservoir, where groundwater outflow is calculated based on the outflow coefficient of the linear reservoir, but it cannot simulate lateral groundwater flow. To further simulate groundwater storage changes at an urban scale and to account for the effects of lateral groundwater flow on groundwater storage, this study integrates CWatM with the groundwater model MODFLOW-NWT (Newton formulation of MODFLOW-2005). The coupled model, CWatM-MODFLOW, is then used to simulate changes in groundwater storage (Figure 3). The coupling of hydrological and groundwater models can be categorized as either one-way or two-way coupling. In one-way coupling, the model first runs according to the standard groundwater module (only vertical fluxes), generating time series of net groundwater recharge and surface water levels. These simulated fluxes are then used to drive the groundwater model. In two-way coupling, the groundwater model fully replaces the original groundwater module in the hydrological model. In this case, the fluxes simulated at each time step are directly exchanged between the groundwater model and surface water modules, as well as between the groundwater model and surface runoff modules.

In this study, the coupling of CWatM with MODFLOW-NWT is performed in a one-way manner, where MODFLOW-NWT is constructed based on aquifer property parameters and can incorporate additional hydrogeological parameters to describe changes in groundwater storage. Additionally, MODFLOW-NWT includes inputs for groundwater extraction. After coupling CWatM with MODFLOW-NWT, the model can simulate the impact of groundwater extraction on groundwater storage. During the coupling process, the groundwater recharge simulated by CWatM (including infiltration and preferential flow) is used as input data for MODFLOW-NWT. The drainage module of MODFLOW-NWT further simulates groundwater capillary rise and baseflow, which are then fed back to CWatM.

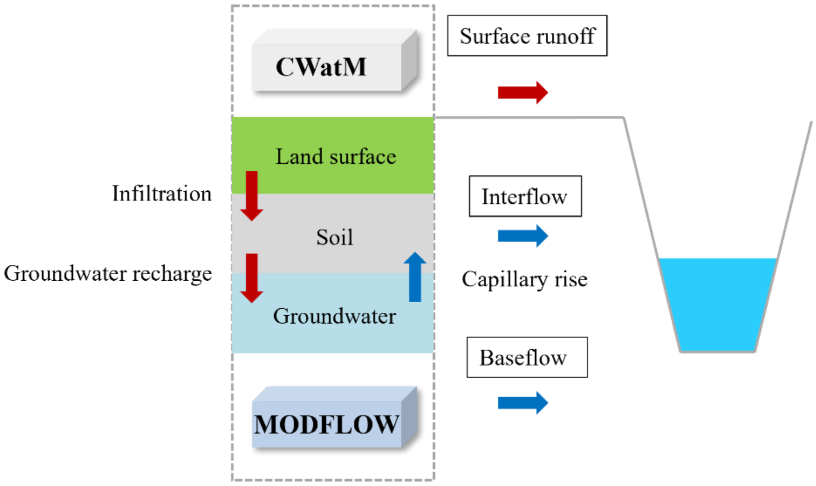

Fig.3 Coupling mechanism between CWatM and MODFLOW. The blue boxes and flow indication arrows represent groundwater-related hydrological processes simulated by MODFLOW, while the gray boxes and red indication arrows represent hydrological processes simulated by the modules of CWatM.

5.3 Data

The integration of climate model outputs into water systems planning enables water managers to estimate the impacts of climate change on critical decision variables within the water system. By quantifying climate-related risks in this manner, communication with key stakeholders, who may not be familiar with climate science principles, is significantly enhanced.

Meteorological driving data: The meteorological driving data for the CWatM model during the historical period are planned to be sourced from the CMADS, ERA-Interim, and NCEP/NCAR Reanalysis datasets. For the future period, the meteorological driving data for CWatM will be derived from the CMIP6 (Coupled Model Intercomparison Project Phase 6) climate model data. Under different climate scenarios—SSP1-2.6 (low-emission scenario), SSP2-4.5 (medium-emission scenario), and SSP5-8.5 (high-emission scenario)—the model will be used to assess climate uncertainty.

Topography Data: DEM data with appropriate resolution for the study area will be used. Slope calculations will be performed based on elevation data using the Slope tool in ArcGIS, and the results will serve as the topographic input for the model.

Land Cover Data: The FROM-GLC dataset, with a spatial resolution of 30 m, is planned to be used. This dataset represents global land use/land cover spatial distribution for 2010, generated from LandSat TM (Thematic Mapper) and ETM+ (Enhanced Thematic Mapper Plus) imagery.

5.4 NSGA-II

In addressing multi-objective optimization problems, it is often to analyze complex issues and convert them into mathematical expressions, including decision variables, constraints, and optimization objectives. Typically, the objective functions involve either maximization or minimization. For the purposes of this section, we focus primarily on the minimization of objective functions. The corresponding mathematical expression is outlined as follows:

$$(MOP)Min: y = f(x) = (f_l(x), f_2(x), \dots \dots, f_k(x))^T \quad (1)$$

$$s.t. \quad g_i(x) = 0, i = 1,2, \dots \dots, m \quad (2)$$

$$h_j(x) = 0, j = 1,2, \dots \dots, n \quad (3)$$

Here, $x = (x_l, x_2, \dots \dots, x_p) \in X$, where, x represents the decision variables in multi-objective optimization; $y = (y_1, y_2, \dots \dots, y_q) \in Y$, with Y representing the set of possible outcomes of the objective functions, and X denoting the set of feasible decision variables for the multi-objective problem. The function $f_w(x)(w = 1, \dots, k)$ refers to the value of the objective function in the w-th dimension. The constraints are expressed as $g_i(x)(i = 1,2, \dots \dots, m)$ and $h_j(x)(j = 1,2, \dots \dots, n)$, representing the conditions that must be satisfied. Together, these constraints define the feasible region of the objective function.

Drawing inspiration from natural selection and evolution principles, multi-objective optimization evolutionary algorithms (MOEA) (Seshadri, 2006) and genetic algorithms (MOGA) (Murata & Ishibuchi, 1995) are commonly applied to produce a diverse and well-distributed set of solutions. This study intends to employ multi-objective optimization algorithms, such as NSGA-II (Hojjati et al., 2018), to simultaneously consider multiple conflicting objectives. The optimization goals may include operational rules, extreme hazard contingency plans, investment portfolios, and ensuring equity for vulnerable communities.

a. Water Supply Reliability: To ensure that water supply systems maintain stable service during extreme climatic events, such as droughts and floods, by optimizing aquifer management and employing strategies such as Managed Aquifer Recharge (MAR).

b. Optimizing Investment Portfolios: To reduce the costs associated with the construction, operation, and maintenance of water resource infrastructure, including treatment facilities, pumping stations, and groundwater recharge systems.

c. Maximizing Social Welfare: To improve water accessibility and equity for different social groups, particularly protecting the water security of vulnerable communities during extreme climatic events.

By addressing these objectives concurrently, the approach aims to develop a more comprehensive and balanced framework for decision-making in urban water management.

6. Expected Results

1. Enhanced Water System Resilience and Model Accuracy

The coupled CWatM-MODFLOW model will provide a comprehensive understanding of the interactions between groundwater and surface water, particularly under extreme climate scenarios such as droughts and floods. By refining groundwater dynamics, including lateral flow, the model will set a new benchmark for integrating surface and groundwater systems. This improved accuracy will enhance the evaluation of water infrastructure resilience, optimizing groundwater's role in stabilizing water supply during extreme events, and informing future infrastructure planning.

2. Optimized Groundwater Management and MAR Strategies

The multi-objective optimization framework will yield strategies that optimize groundwater management and Managed Aquifer Recharge (MAR) to enhance system resilience. The expected result is the identification of cost-effective and socially equitable solutions for water management under varying climate conditions.

3. Economic Feasibility and Policy Guidance

The cost-benefit analysis will identify economically viable water management strategies that ensure supply reliability and promote equity, particularly for vulnerable communities during extreme climatic events. The optimized model will translate these findings into actionable policy recommendations, providing decision-makers with adaptive strategies to manage both acute and chronic water-related threats. These strategies will enhance long-term water system sustainability and resilience, offering a balanced approach to economic feasibility and social equity.

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