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Key Points:

- The sprinkling trigger temperature is the dominant design parameter for the rainwater harvesting and roof sprinkling system
- Increasing rainwater tank size diminishes marginal benefits for reducing air conditioning energy consumption
- The sprinkling system reduces the intensity, total days, and frequency of consecutive heatwave events and mitigates extreme runoff

Supporting Information:

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

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Optimizing the Rainwater Harvesting and Roof Sprinkling System to Adapt to Urban Extreme Heat

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Abstract Roof watering is a novel strategy for reducing air conditioning energy consumption and mitigating excess urban heat, yet its application is often constrained by water availability. To address this challenge, we propose an adaptation strategy that integrates rainwater harvesting tank with roof sprinkling to strengthen urban heat resilience. We develop a new module implemented in the Community Land Model Urban (CLMU) to evaluate the efficacy of the proposed strategy, whose parameters were further determined by a framework using multi-objective optimization combined with a transformer-based tabular foundation model. This integrated modeling framework enables the optimization of the proposed strategy and provides insights into its impacts on air conditioning energy consumption and its co-benefits on the urban thermal environment. Results show that the temperature threshold for triggering sprinkling is a more important parameter than rainwater tank size or sprinkling intensity. The optimal strategies effectively reduce cooling energy demand, lower extreme temperatures, and decrease heatwave days. However, a trade-off exists between rainwater tank size and the reduction in cooling energy consumption and heatwave days. Additionally, the energy saving is more pronounced under higher atmospheric temperatures. The implementation of the rainwater harvesting and roof sprinkling system in CLMU provides valuable insights for improving urban resilience and can be further coupled into Earth system model for large-scale studies.

Plain Language Summary Urban watering technologies are becoming important ways for reducing extreme heat in cities, but their use is often limited by the availability of water. In this study, we propose a rainwater harvesting and roof sprinkling strategy, supported by a framework that combines urban climate modeling, machine learning, and optimization to address both water constraints and heat risks. Using Tokyo, Japan, as a case study, we find that this strategy can reduce the energy demand for air conditioning with the co-benefit of lowering extreme urban temperatures, reducing the number of heatwave days, and reducing extreme urban surface runoff. However, there is a trade-off between the size of the rainwater tank and the benefits achieved in reducing extreme heat and cooling energy use. Our results also suggest that the effectiveness of this strategy will increase with a warming atmosphere. This framework can support local governments in identifying the best ways to apply urban watering technologies in their cities.

1. Introduction

Urban areas are increasingly facing extreme heat, posing threats to urban infrastructures (Lola et al., 2020; Zheng et al., 2024), public health (X. Yang et al., 2024; Masselot et al., 2025; García-León et al., 2024; W. T. K. Huang et al., 2023), and energies (X. Li, Zhao, Qin, et al., 2024; X. Li, Zhao, Oleson, et al., 2024). According to the World Health Organization (WHO), the population exposed to extreme heatwaves increased by around 125 million from 2000 to 2016 (World Health Organization, 2023), leading to a decline in societal productivity (Takakura et al., 2017). This excessive heat in urban areas will also increase cooling demand, with global energy consumption for air conditioning (AC) projected to rise by 300% by 2050, equivalent to the total electricity consumption of the United States, Europe, and Japan (based on the 2019 annual electricity consumption) (United Nations Environment Programme, 2021). Due to the urban climate-energy biophysical feedback, AC demand is likely to increase dramatically with global warming (X. Li, Zhao, Qin, et al., 2024). The heat produced by AC

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systems will also exacerbate the urban thermal environment, underscoring the importance of adaptation strategies to reduce AC demand and alleviate urban heat (Z. Zhang et al., 2025).

Roof watering has emerged as a cooling strategy to mitigate the excess heat in urban areas (ketan Nayak et al., 2020; Chaumont et al., 2025; Mao et al., 2021). Compared to road watering and soil irrigation, the roof sprinkling is expected to reduce AC energy consumption as it increases the roof evaporation, thereby cooling the roof surface and decreasing the heat transferred into buildings (Chaumont et al., 2025). According to Chaumont et al. (2025), such a system can cool the roof surface by 5.5°C–19.5°C. However, the effectiveness of sprinkling is inherently constrained by the availability and allocation of water resources. Drawing on the concept of rainwater harvesting, coupling roof sprinkler cooling with a rainwater collection system represents a viable strategy to mitigate water expenses and strengthen the sustainability of such interventions. Given that roofs account for a substantial portion of urban surface area and possess inherently high water-draining capacity, they also offer potential as catchment areas for rainwater harvesting (Campisano et al., 2017). In many countries, roof rainwater harvesting has been promoted or already employed to address water scarcity (Campisano et al., 2017). Extending this practice to serve as a water source for roof sprinkling highlights the dual roles of rainwater harvesting in alleviating urban water stress while providing a strategy for reducing AC energy consumption and cooling urban environments (Courtts et al., 2013).

A roof rainwater tank and sprinkling system (RWTSP) directly and immediately alters the building's surface energy balance and reduces indoor heat gains. The cooling of the urban outdoor thermal environment is subsequently driven by both roof evaporation and reduction in anthropogenic heat emissions, which acts as a critical co-benefit. Consequently, RWTSP can be designed to reduce AC energy consumption and/or building temperatures. However, the design of RWTSP involves a trade-off between water consumption and energy savings. This trade-off arises from the design of operational parameters, including the size of the rainwater tank, the intensity of water sprinkling, and the temperature threshold for triggering sprinkling. For example, Chaumont et al. (2025) investigated the optimal sprinkling intensity for the effect of sprinkling cooling by laboratory experiments, and found that the optimal watering rate relies on the roof structure. Unfortunately, optimizing the proposed RWTSP requires a sophisticated laboratory experimental setup capable of simultaneously supporting rainwater collection and sprinkling trials. Moreover, before implementing such a novel strategy, it is important to evaluate not only its impact on energy use but also its influence on local climate, as well as how background climate conditions may affect its effectiveness. Nonetheless, such an evaluation framework is not yet available, particularly when integrated with process-based urban climate models.

To address these challenges, we develop a numerical module of RWTSP within an urban climate model. Such a framework facilitates the evaluation of impacts on building energy consumption and urban thermal environment (K. Oleson et al., 2010), as well as the assessment of the role of background climates in shaping the effectiveness of the novel RWTSP strategies. Furthermore, to design the optimal operational parameters through process-based simulations, a large number of simulations are still required, demanding substantial computational resources and time (Gong et al., 2015; R. Sun et al., 2023). To improve computational efficiency, machine learning-based surrogate modeling techniques are employed to accelerate the parameter optimization process (Sun et al., 2022; R. Sun et al., 2023; P. Li et al., 2022). Taken together, this framework provides a cost-effective and robust approach for evaluating and optimizing the proposed system.

This study aims to develop the RWTSP module to investigate its efficacy in reducing AC energy consumption and its co-benefits on cooling urban thermal environment. To achieve this, we integrate machine learning and an optimization algorithm to construct an operational workflow. The optimization workflow is designed to identify solutions that minimize AC energy consumption while requiring the smallest possible rainwater tank size. The parameter importance analysis of RWTSP and the identification of the optimal solution are further conducted, followed by an evaluation of the impacts of the optimal strategies on urban thermal environment.

2. Methods and Data

The workflow of this study is described in Figure 1. The urban climate model and the design of RWTSP are firstly introduced, followed by the parameter optimization of RWTSP. The details of the simulation experiment that include the study area and data are presented in the last subsection.

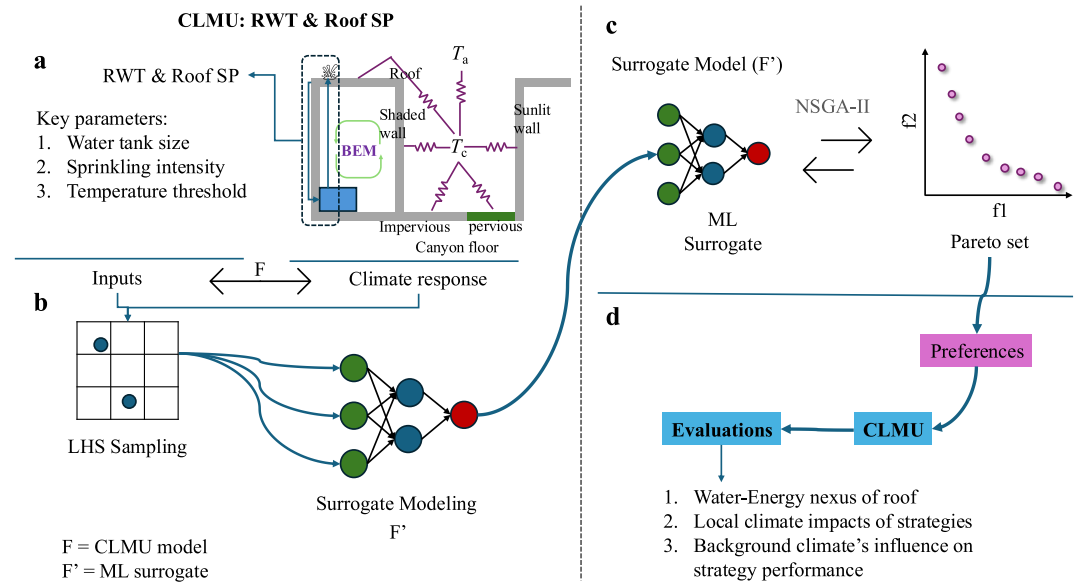


Figure 1. Overview of the workflow. (a) Schematic of Community Land Model Urban (CLMU) and RWTSP system. (b) Schematic of sampling and surrogate modeling. (c) Multi-objective optimization of RWTSP using surrogate and (d) evaluation of Pareto set. RWT: Rainwater tank; Roof SP: Roof sprinkling; BEM: Building energy model; T_a : atmospheric air temperature; T_c : Urban canopy temperature; LHS: Latin hypercube sampling; ML: Machine learning; NSGA-II: Non-Dominated Sorting Genetic Algorithm 2.

2.1. Model Development of Rainwater Tank and Roof Sprinkling

The Community Land Model Urban (CLMU) is an urban climate model that describes the interaction between the atmosphere and urban land surfaces, using the concept of “urban canyon” (Figure 1a). In a canyon, urban areas are represented by five surfaces, including roof, sunlit wall, shaded wall, impervious canyon floor, and pervious canyon floor (K. Oleson et al., 2010). CLMU can simulate the surface turbulence flux (sensible and latent heat), canopy climate, hydrology, and building energy (Y. Sun et al., 2024; K. W. Oleson et al., 2010; Yu et al., 2025). Furthermore, CLMU has been used to evaluate the effects of roof adaptation strategies on the urban thermal environment (Y. Sun et al., 2024; K. W. Oleson et al., 2010; K. Zhang et al., 2025; L. Wang et al., 2021, 2020). In this study, the Fortran-based rainwater tank (RWT) module was further implemented to investigate the impacts of the rainwater tank and roof sprinkling system on reducing AC energy consumption (Figure 1a). The surface water balance for roofs is described in Equation S2 in Supporting Information S1.

In the original CLMU, rainfall on roofs is partitioned into evaporation, ponding, and runoff. Within the CLMU-RWTSP framework, the roof runoff is further routed into RWT until the maximum storage capacity is reached. When specific sprinkling conditions are triggered (in this study, defined as the roof surface temperature exceeding a predefined threshold), a controlled volume of water from RWT is sprinkled onto roofs, thereby enhancing the evaporation of roofs. The implementation of the RWTSP module does not alter the physical processes represented in CLMU, such as convection, evaporation, and heat conduction. Instead, it only modifies the routing of roof runoff.

Here, we incorporated the water balance of RWT into CLMU's roof surface balance. Tank volume is represented as proportional to roof area ($N \times \text{roofarea}$) (Demuzere et al., 2014). Thus, the water storage capacity of the tank can be represented by the parameter N ($\text{kg}\cdot\text{m}^{-2}$ or mm). The water balance of the rainwater tank is expressed as follows:

$$\Delta n = (q_{\text{in}} - q_{\text{out}}) \times \Delta t, \quad (1)$$

where n is the actual water stored in the tank ($\text{kg}\cdot\text{m}^{-2}$ or mm), and Δn is the change in water storage due to harvesting and sprinkling. q_{in} and q_{out} are the water fluxes into the tank and taken out of the tank ($\text{kg}\cdot\text{m}^{-2} \cdot \text{s}^{-1}$ or $\text{mm}\cdot\text{s}^{-1}$), respectively. q_{out} is determined by water usage. q_{in} is calculated by

$$q_{in} = \begin{cases} q_{over}, & \text{if } N - n \geq q_{over} \cdot \Delta t \\ \frac{N - n}{\Delta t}, & \text{if } N - n < q_{over} \cdot \Delta t \end{cases} \quad (2)$$

q_{over} is the roof surface runoff in CLMU, and q_{over} is given by

$$q_{over} = \begin{cases} \frac{w_{liq}}{\Delta t} + q_{liq} - q_{seva} - \frac{w_{pond,max}}{\Delta t} \geq 0, & \text{if } snl = 0 \\ q_{liq}, & \text{if } snl < 0 \end{cases} \quad (3)$$

where w_{liq} is the liquid water content of top roof layer ($\text{kg} \cdot \text{m}^{-2}$), q_{liq} is the water reaching the roof, and q_{seva} is the evaporation of liquid water ($\text{kg} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$). sml is the layer of packed snow (K. Oleson et al., 2010). $w_{pond,max}$ is the roof surface ponding limit ($1 \text{ kg} \cdot \text{m}^{-2}$).

The $w_{liq,1}$ is adjusted by

$$w_{liq} = \begin{cases} w_{pond,max}, & \text{if } q_{over} > 0 \\ w_{liq} + (q_{liq} - q_{seva}) \times \Delta t, & \text{if } q_{over} = 0 \end{cases} \quad (4)$$

Since this study aims to explore the potential of RWT in cooling and AC energy savings, it is assumed that the water used for roof sprinkling is always sourced from RWT, indicating the maximum potential of RWT in sprinkling. Other water demands, such as toilet flushing, car washing, and household use, require higher water quality than roof sprinkling. Therefore, this study focuses solely on roof sprinkling. The water used for the roof cooling is derived from

$$q_{out} = \begin{cases} \frac{\alpha}{100} \times \frac{w_{pond,max}}{\Delta t}, & \text{if } \frac{\alpha}{100} \times \frac{w_{pond,max}}{\Delta t} \leq \frac{n}{\Delta t} \\ \frac{n}{\Delta t}, & \text{if } \frac{\alpha}{100} \times \frac{w_{pond,max}}{\Delta t} > \frac{n}{\Delta t} \end{cases} \quad (5)$$

where α is the prescribed sprinkling intensity coefficient (0–100). In simulation experiments, the roof sprinkling is triggered when the temperature of the first (top) layer of roof surface (T_{roof}) is higher than the threshold (T_{max}):

$$\alpha = \begin{cases} \alpha, & \text{if } T_{roof} \geq T_{max} \\ 0, & \text{if } T_{roof} < T_{max} \end{cases} \quad (6)$$

The roof surface runoff in RWTSP module ($q_{over,rwt}$) is then given by

$$q_{over,rwt} = q_{over} - q_{in} \quad (7)$$

The q_{out} is then directly added as the external source of the water flux revived by roof surface (q_{rain}). The $q_{rain,rwt}$ is updated by $q_{rain,rwt} = q_{rain} + q_{out}$. Finally, the updated water balance of the roof with rainwater tank implementation is expressed as follows:

$$\Delta W_{sno} + \Delta w_{liq} + \Delta w_{ice} = (q_{rain,rwt} + q_{sno} - E_{roof} - q_{over,rwt} - q_{in} - q_{rgwl} - q_{snwep,ice}) \Delta t, \quad (8)$$

where ΔW_{sno} , Δw_{liq} and Δw_{ice} are the snow, liquid water, and ice stored on the top of the roof surface ($\text{kg} \cdot \text{m}^{-2}$). q_{rain} and q_{sno} are the precipitation from atmosphere ($\text{kg} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$). E_{roof} , q_{over} , q_{rgwl} , and $q_{snwep,ice}$ are the roof surface evaporation, surface runoff, liquid runoff due to snow capping and the solid runoff due to snow capping ($\text{kg} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$), respectively.

2.2. Problem Formulation and Parameters Optimization Workflow

The RWTSP has three critical parameters: tank size, sprinkling intensity, and temperature threshold (Figure 1a). The temperature threshold and sprinkling intensity represent when and how to sprinkle under a specific tank size. Thus, these parameters collectively determine the efficiency of RWTSP for temperature cooling and energy consumption. This study proposes an RWTSP system, which is designed to utilize rainwater as a cooling resource for buildings during extreme heat events. By cooling the roof, this system aims to reduce air conditioning usage, thereby achieving energy savings.

The integration of RWTSP system into CLMU and the calculation of AC energy consumption (E_{AC}) can be summarized as follows:

$$E_{AC} = F_{CLMU}(urb, \mathbf{AF}), \quad (9)$$

where urb represents urban-related parameters (including the parameters of RWTSP system), and $\mathbf{AF}$ denotes atmospheric forcing. In this study, the $\mathbf{AF}$ remains unchanged throughout the parameter optimization process (using the same atmospheric forcing for running CLMU). Additionally, all urban parameters remain static except for the RWT size (N), sprinkling intensity (α), and sprinkling temperature threshold (T_{max}). Therefore, Equation 9 can be rewritten as

$$E_{AC} = F(N, \alpha, T_{max}), \quad (10)$$

where the function F captures the relationship between the RWTSP system parameters and the response from CLMU in the specific urban parameters and $\mathbf{AF}$.

The climate model simulations are usually time-consuming, thereby extending the convergence time of optimization algorithms when directly using F as part of the objective function. To address this, a data-driven approach was adopted to approximate F (Figure 1b). While this approximation may degrade accuracy, it can enhance the feasibility and scalability of the optimization algorithm by improving computational efficiency. The surrogate is given by

$$E_{AC} \approx F'(N, \alpha, T_{max}), \quad (11)$$

where the function F' is the surrogate of F .

Due to the area and resource limitations, the size of RWT will be limited. Thus, finding the optimal solutions of the parameters that lead to lower E_{AC} and smaller N is desirable, which is a two-objective optimization problem (Figure 1c). The optimal solutions of the parameters are formulated as follows:

$$P^* = \arg \min_{N, \alpha, T_{max}} [F'(N, \alpha, T_{max}), N], \quad \text{s.t.} \quad \mathbf{x}_l \leq (N, \alpha, T_{max}) \leq \mathbf{x}_u, \quad (12)$$

where P^* is the optimal solutions of the parameters, and $F'(N, \alpha, T_{max})$ and N are the objective functions. In this study, $\mathbf{x}_l$ denotes the lower bounds of N , α , and T_{max} , which are 0.01 mm, 1.0, and 35°C, respectively. The lower bound of T_{max} corresponds to the upper quartile of simulated roof surface temperature from June to September in 2010–2019 and also the extreme air temperature in Japan (Anadolu Agency, 2025). $\mathbf{x}_u$ is the upper bounds, corresponding to 20.0 mm, 20.0, and 65°C, respectively.

The optimization of parameters is based on a surrogate modeling and multi-objective framework. The samples for surrogate modeling were created by Latin hypercube sampling (LHS), and surrogate models were constructed using Transformer-based tabular foundation model (TabPFN) and Automated machine learning (AutoML) (Hollmann et al., 2025; Wang et al., 2021). The multi-objective optimization algorithm is the non-dominated sorting genetic algorithm II (NSGA-II) (K. Deb et al., 2002), and the parameter importance analysis employs the Shapley Additive exPlanations (SHAP) (Lundberg et al., 2018; Lundberg & Lee, 2017). Details of above methods are described in Supporting Information S1.

2.3. Experimental Design

2.3.1. Simulation Details

Tokyo, Japan, was selected as the study area. The climate in Tokyo is warm and temperate, which is a subtropical monsoon climate with distinct seasonal variations. Tokyo experiences hot and humid summers and cold winters, and receives abundant rainfall throughout the year. Moreover, Japan is one of the most successful countries in Asia in promoting RWT (Campisano et al., 2017). Therefore, Tokyo serves as a potential site for evaluating RWTSP strategies due to its hot climate and experience in RWT.

The atmospheric forcing data were retrieved from a roof flux tower (52 m above ground and 25 m above the roof), which is located in a compact, mid-rise residential neighborhood in Yoyogi, Tokyo, Japan (35.66°N, 139.68°E) (Hirano et al., 2015). The average building height around the site is 9 m, and the instruments are above the roughness sublayer within the building canopy layer. The atmospheric forcing data from observational and gap-filling data were further produced by Lipson et al. (2022b). The period of atmospheric forcing ranges from 2006 to 2020. The time series of atmospheric forcing variables is shown in Figure S1 in Supporting Information S1. The urban surface parameters used in this study are described in Table S1 in Supporting Information S1. Based on Lipson et al. (2022b), the study area covers a 500 m radius, with the 170°–260° wind sector excluded, resulting in an effective area of approximately 0.589 km² and a roof fraction of 0.41 (Figure S2 in Supporting Information S1). A total of 1996 roofs are located within the study area (Figure S2 in Supporting Information S1). We calculated the AC energy consumption across the study area with a coefficient of performance of 3.6 (K. W. Oleson & Feddema, 2020). The simulations run for 15 years, with the first 5 years dedicated to the spin-up phase and the remaining years used for analysis with cold spin-up initial conditions (K. Oleson et al., 2010). The sprinkling system is activated in hot months (June to September in this study), a period of higher atmospheric temperatures (Figure S1 in Supporting Information S1). Such a restriction to the hot months reduces maintenance and operating costs, which is expected to prolong the lifespan of the system.

2.3.2. CLMU Validation

CLMU simulations were compared with the observations from a flux tower in Tokyo. The mean absolute errors (MAE) and Pearson correlation coefficient (R) between simulation and observation were calculated. The results show that the MAE for upward short-wave radiation (SWup), upward long-wave radiation (LWup), latent heat flux (Qle), and sensible heat flux (Qh) are 5.16 W/m², 12.43 W/m², 22.15 W/m², and 31.35 W/m², respectively, and the R for SWup, LWup, Qle, and Qh are 0.97, 0.97, 0.47, and 0.81, respectively (Figures S3–S6 in Supporting Information S1). These results indicate the capacity of CLMU to capture the pattern of the local urban climates of Yoyogi site. Further, CLMU presents a similar performance with other urban climate models in Urban-PLUMBER project (<https://urban-plumber.github.io/sites>). The diurnal profiles of the simulations and observations show that CLMU can reproduce the diurnal distribution of these variables (Figures S3–S6 in Supporting Information S1).

3. Results and Discussion

3.1. Influence of Design Parameters on RWTSP Performance

The parameters of RWTSP are RWT size, the temperature threshold for triggering sprinkling, and sprinkling intensity, which corresponds to N , $T_{\max}$, and α in the equations. Here, we sampled the parameters using LHS to generate 400 cases of CLMU simulations. The result shows that annual total AC energy consumption across the study areas (E_{AC}) is largely affected by $T_{\max}$, with the higher thresholds leading to the higher E_{AC} (Figure 2a). When $T_{\max}$ is set to a lower value, α will markedly influence the roof sprinkling performance on decreasing E_{AC} . This demonstrates the interaction effect among the parameters of RWTSP.

To probe how the parameters of RWTSP affect the strategy's effectiveness, we built the TabPFN and AutoML surrogate models and then applied SHAP method to assess the importance of parameters. The result shows that TabPFN performs better than AutoML with a lower mean absolute error (MAE) and root mean squared error (RMSE) (Figure S7 in Supporting Information S1). The outperformance of TabPFN indicates that the advancing foundation model is more adaptive for surrogate modeling with small data sets. Since TabPFN demonstrated superior modeling performance, the feature importance analysis focuses on the results of TabPFN.

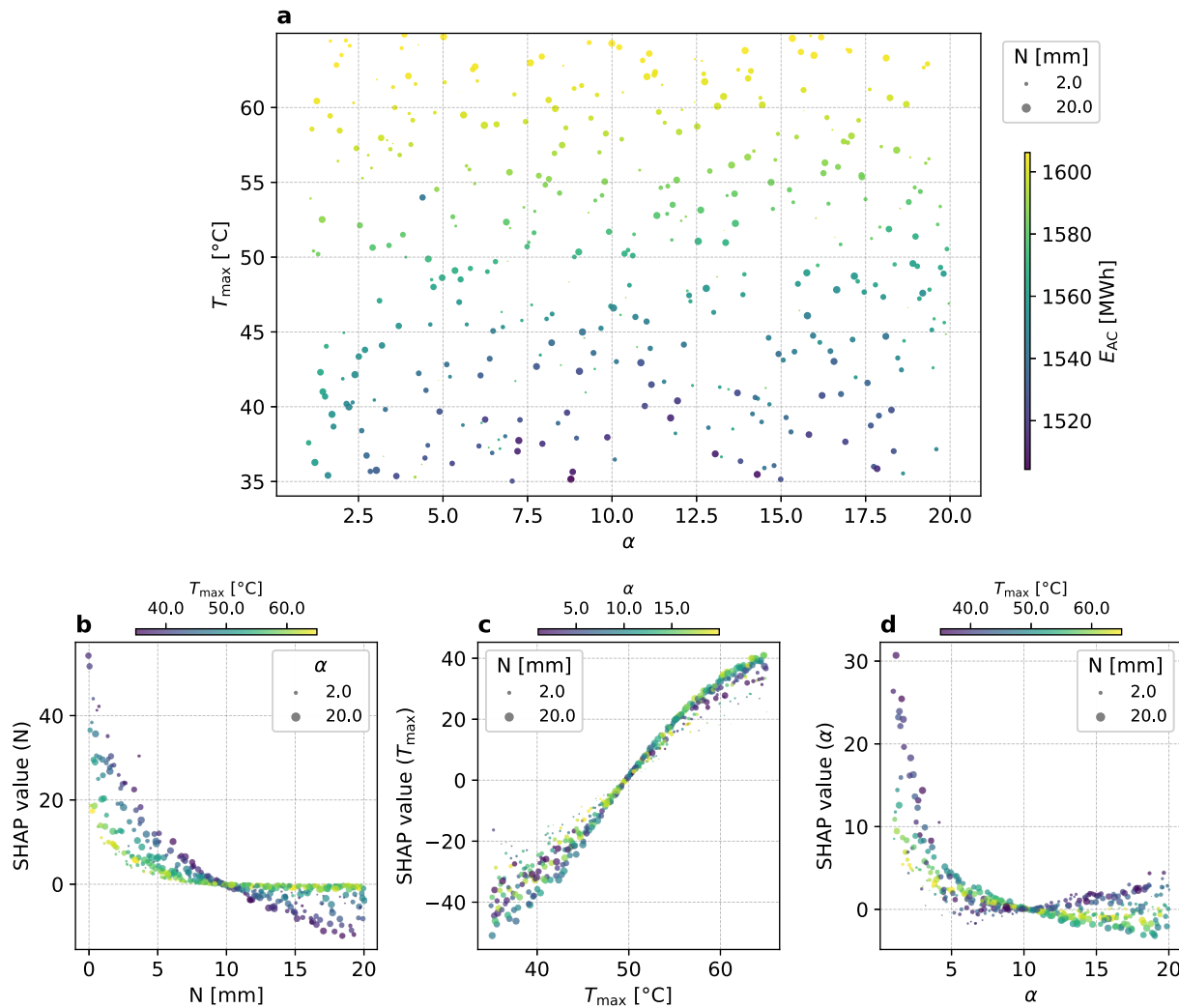


Figure 2. The impacts of different RWTSP parameters on the annual total AC energy consumption. (a) Performance of RWTSP system with different parameters sampled by LHS. (b) SHAP dependence scatter plot of RWT size (N). (c) SHAP dependence scatter plot of temperature threshold for triggering sprinkling (T_{max}). (d) SHAP dependence scatter plot of sprinkling intensity (α). Annual total AC energy consumption (E_{AC}) aggregated over the entire study area. MWh: megawatt-hour.

The impact of RWT size on the reduction of E_{AC} is considered, as RWT size is a critical factor in practical applications, considering equipment cost and area constraints. The SHAP values of RWT size in response to RWT size indicate that, in general, larger RWT sizes correspond to smaller SHAP values, meaning less contribution to E_{AC} (Figure 2b). This can be explained by the fact that a larger water tank provides greater water storage capacity to fight against extreme heat situations. However, it is important to note that the SHAP values of RWT size are influenced by α and T_{max} , especially T_{max} . When both T_{max} and RWT size are at low values, the SHAP value is positive and relatively high, indicating a higher contribution to E_{AC} (i.e., less of a reduction in E_{AC}). Conversely, when T_{max} is low but RWT size is large, the benefits of RWT size are amplified (SHAP values become negative), reflecting a stronger impact on reducing E_{AC} . Similarly, the influence of T_{max} was examined (Figure 2c). The impact of T_{max} on its SHAP value exhibits a positive correlation. At a lower T_{max} region, the α and RWT size largely influence the T_{max} SHAP values. As α increases, the α SHAP value generally shows a decreasing trend (Figure 2d). To provide an overview, the mean absolute SHAP values for all samples were calculated (Figure S8 in Supporting Information S1). The results indicate that T_{max} has the highest SHAP value in the designed regions of parameter spaces, surpassing those of α and RWT size. This pattern was observed consistently in both the TabPFN and AutoML models. These findings highlight the importance of T_{max} selection in roof sprinkling cooling strategies, demonstrating that its influence outweighs the other two parameters. However, the lower relative importance of α does not imply that the applied water amount is physically irrelevant. It reflects the

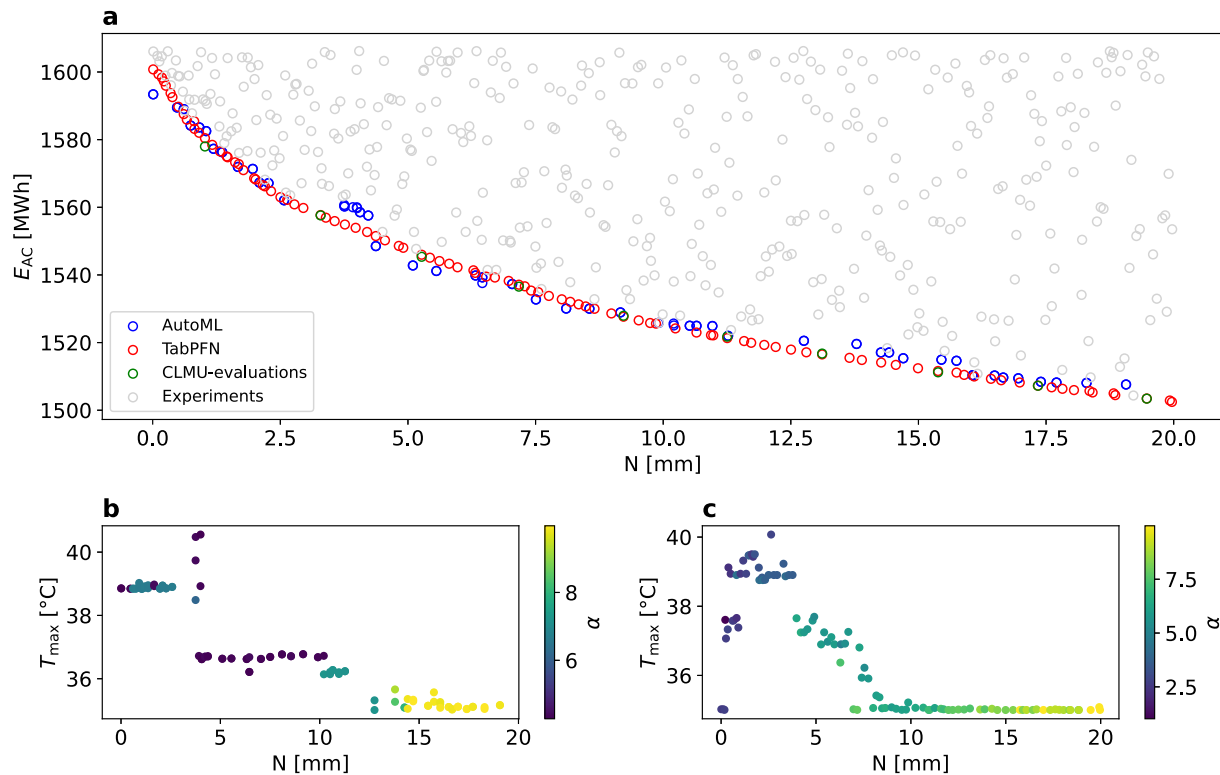


Figure 3. Results analysis of NSAG-II optimization. (a) Pareto front and the evaluations. Each evaluation point was selected from the Pareto front generated using TabPFN surrogate model. (b) The Pareto solutions generated using AutoML surrogate model. (c) The Pareto solutions generated using TabPFN surrogate model.

diminishing returns of evaporative cooling within the tested parameter range. As the roof surface becomes increasingly wet, the excess water may remain on the roof without being effectively used for evaporation. Further, under limited water availability, a longer sprinkling duration with an appropriate intensity may sustainably wet the roofs and reduce total AC energy consumption more than short, high-intensity sprinkling. Therefore, the activation timing (T_{max}) is more influential for the system's performance.

3.2. Parameter Optimization

Although we described the impacts of design parameters on the performance of RWTSP, manual selection of the parameters is still challenging due to the intricate interactions among the parameters. Consequently, an optimization approach was employed to identify the optimal parameter combinations. The Non-Dominated Sorting Genetic Algorithm 2 (NSGA-II) was applied to optimize E_{AC} and RWT size using the surrogates. The Pareto front obtained by the optimization algorithm is shown in Figure 3a. Any solution from the Pareto front ensures that E_{AC} cannot be further reduced without increasing RWT size, and vice versa. This helps decision-makers better understand the trade-off between RWT size and E_{AC} . Results based on TabPFN produced a denser and smoother Pareto front, which dominates the most solutions from the front generated using AutoML as the surrogate model. This can be attributed to the better performance of TabPFN and its superior extrapolation capability compared to tree-based models. As a result, the corresponding Pareto front from TabPFN is also more continuous than that from AutoML.

To evaluate the effectiveness of the surrogate in optimization, nine solutions were selected from the Pareto solutions generated by TabPFN and used as inputs to run CLMU simulations. The results show that the Pareto front estimated by TabPFN closely matches the ground truth from CLMU (Figure 3a), indicating the feasibility of using TabPFN surrogate for parameter optimization and highlighting the advantages of TabPFN in this case study. However, while TabPFN performs better than tree-based models on small data sets, its performance may decline when applied to larger data sets (Hollmann et al., 2025). Moreover, the inference speed of TabPFN is much slower than that of tree-based models in this study due to the sophisticated architecture of TabPFN. Therefore, when

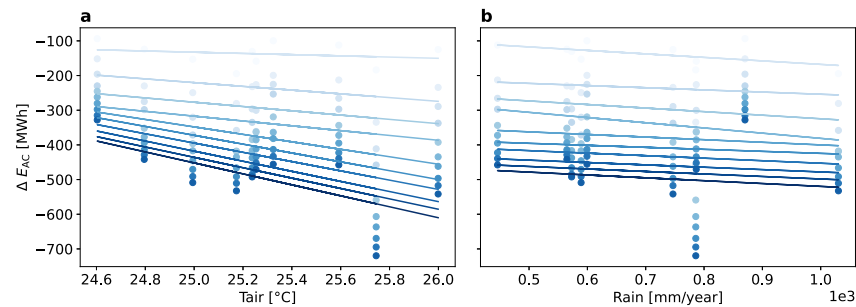


Figure 4. Relationship between the atmospheric forcing variables and reduction in E_{AC} with different parameter configurations of RWTSP. (a) Atmospheric air temperatures. (b) Atmospheric rain. The blue lines represent the cases with RWTSP and the darker blue indicates a bigger RWT size. Each point represents a yearly average of the atmospheric forcing variable with different parameter configurations of RWTSP from Figure 3.

using this framework for parameter optimization, both TabPFN and AutoML should be considered for comparison to identify the suitable surrogate for optimization.

The Pareto front from TabPFN shows that the decrease rate of E_{AC} decreases slowly with RWT size increasing, and increasing RWT size will benefit more when RWT is on a small scale. For instance, decreasing E_{AC} from 1600.76 (the maximum of the solutions) MWh to 1551.49 MWh (the average of maximum and minimum of the solutions) can be achieved with an RWT size of only 4.37 mm. However, a further reduction to 1502.45 MWh requires a size of 19.99 mm, approximately 4.6 times larger, indicating the diminishing marginal benefit of increasing RWT size.

In contrast to the AutoML group, which exhibited no clear patterns (Figure 3b), the TabPFN experimental group displayed clear trends (Figure 3c). The optimal solutions of TabPFN experimental group show that the T_{max} is more affected at a smaller RWT size, and the α increases with a larger RWT. This complex relationship highlights the importance of T_{max} selection, emphasizing the importance of optimization. The daily mean profile of sprinkling flow indicates that the sprinkling began at 9:00 a.m. and ended at 7:00 p.m., with the mean flow rate increasing with larger RWT sizes (Figure S9 in Supporting Information S1). This suggests that the optimal operating strategy is typically active during the daytime, particularly around noon when extreme temperatures most frequently occur.

3.3. Background Climate Impacts on the Efficacy of RWTSP

The influence of background climate on urban climate adaptation strategies is crucial. For example, the effectiveness of cool roofs and urban greening has been shown to depend on the urban background climate (L. Wang et al., 2020; J. Zhao et al., 2023). Similarly, the strong correlation between urban heat island and background climate is proposed (L. Zhao et al., 2014; Manoli et al., 2019). In this study, the impact of varying annual climate conditions on reducing E_{AC} was investigated. Air temperature is negatively correlated with the reduction in E_{AC} (Figure 4), with the Spearman rank-order correlation coefficient increasing with RWT size from -0.18 to -0.59 . This indicates that the strategy yields greater benefits during warmer years. Thus, this cooling strategy may play a more positive role in mitigating the rise in E_{AC} under the backdrop of global warming. By reducing the dependency on air conditioning, the strategy can contribute to energy savings and enhanced urban climate resilience in a warming world. The sensitivity of E_{AC} reduction to atmospheric air temperatures increases with the rise in RWT size (indicated by the increasing absolute value of the slope). This indicates that a larger RWT size provides greater benefits during hot climate conditions, amplifying the cooling effects of the strategy under higher air temperatures. This highlights the importance of optimizing RWT size to maximize the strategy's effectiveness in mitigating the impacts of extreme heat. Interestingly, rainfall levels did not show a strong correlation with the reduction in E_{AC} (Figure 4), with the Spearman rank-order correlation coefficient ranging from -0.16 to -0.37 .

3.4. The Impacts of RWTSP on Urban Thermal Environment

The roof surface temperature, canyon air temperature, canyon Humidex (a human heat stress index combining the effect of temperature and humidity), and surface runoff from CLMU simulations were output to analyze the

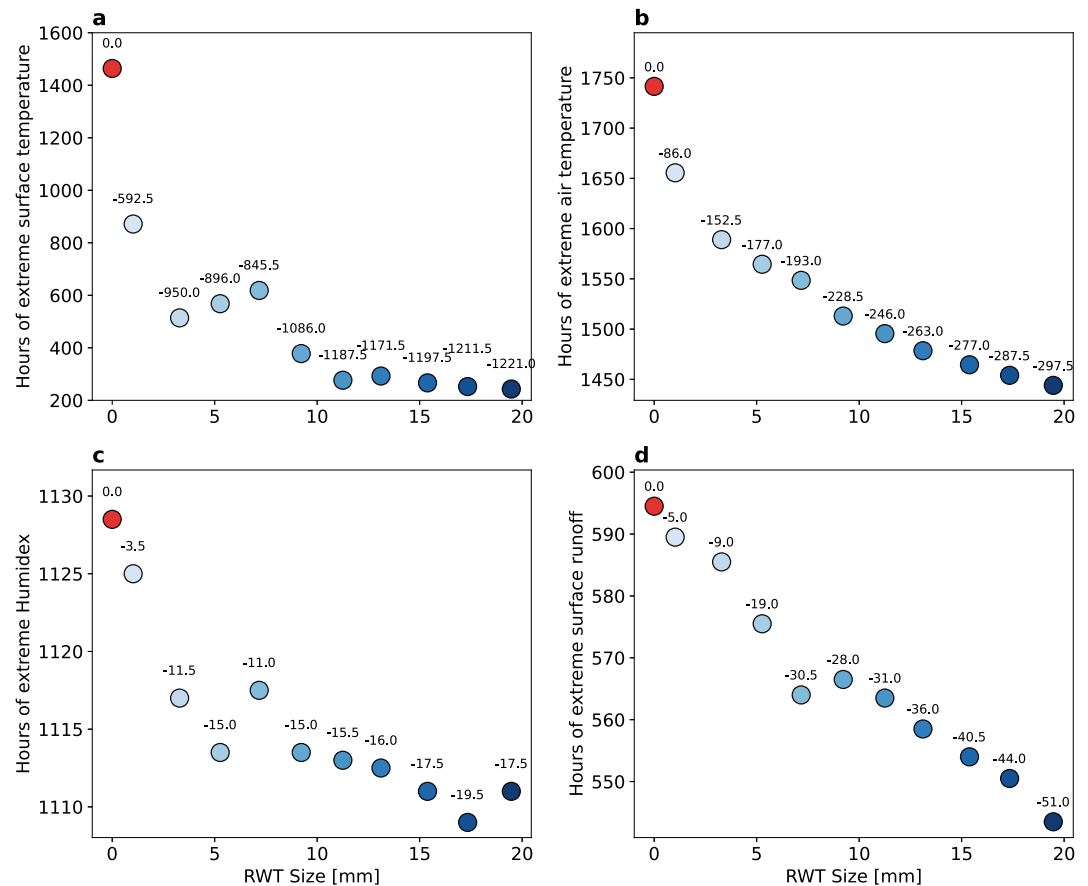


Figure 5. Hours of extremes in different parameter configurations of RWTSP from June to September. (a) Roof surface temperature. (b) Urban canyon air temperature. (c) Humidex. (d) Surface runoff. The red color is the reference case without RWTSP. The blue lines represent the cases with RWTSP, and the darker blue indicates a bigger RWT size from the optimized configurations. Texts above the markers show the decrease in extreme hours compared to the reference case. The analysis period is 2010–2019 (10 years).

impact of RWTSP on urban thermal environment. The parameter configurations are obtained from the optimal solutions of Figure 3. As the sprinkling system is activated between June and September, the following analysis is focused on this period. The diurnal variation reveals that the strategy's impact on roof surface temperatures and canyon air temperatures is primarily during the daytime, with the effects persisting into the evening, while the impact is minimal during the early morning (Figure S10 in Supporting Information S1). The impact on Humidex shows a clear diurnal variation: from morning to noon, Humidex increases slightly, likely due to higher humidity levels, but after reaching its peak during the day, Humidex decreases in the afternoon. The effect on runoff is consistently a reduction throughout the day. In summary, this strategy generates greater benefits during the daytime.

The probability density function (PDF) distribution shows that the RWTSP strategy effectively reduces the likelihood of extreme roof and canyon air temperatures (Figure S11 in Supporting Information S1). We further analyzed the exposure hours under extreme conditions (Figure 5). The 95th percentile of the reference case was adopted as the threshold for extremes in roof surface temperature and surface runoff, while thresholds of 35°C for air temperature and 46°C for the Humidex were applied. The 35°C represents extreme air temperature in Tokyo (Anadolu Agency, 2025), and a Humidex of 46°C corresponds to the level of great discomfort for humans (Buzan et al., 2015). The results indicate that the RWTSP strategy effectively reduces the exposure hours of extreme roof surface temperature and extreme air temperature. The exposure hours of roof surface temperature/extreme air temperature decline with increasing RWT size, ranging from −592.5/−86.0 to −1221.0/−297.5 hr. For the Humidex, the reduction in exposure time is smaller than for air temperature (−3.5 to −19.5 hr), likely due to increased humidity caused by the sprinkling. The exposure hours to extreme Humidex initially decrease but

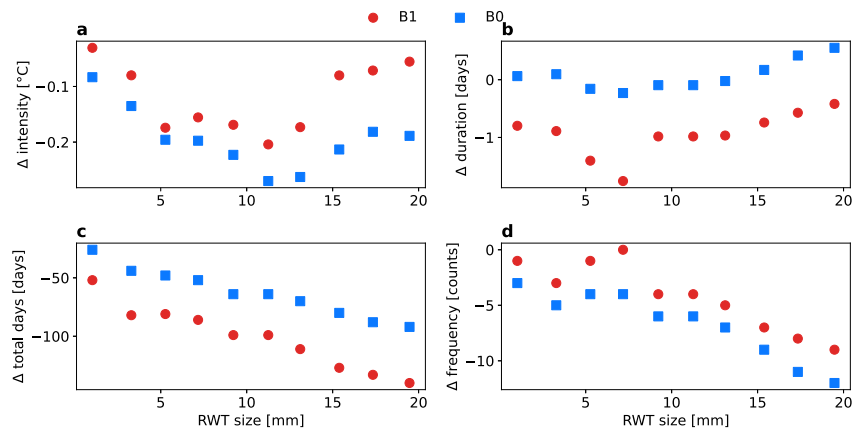


Figure 6. Heatwave responses to different optimized configurations of RWTSP. (a) Intensity (average maximum temperature during the events). (b) Duration (number of days per event). (c) Total days (days of events). (d) Frequency (number of events). The analysis period of heatwave events is 2010–2019 (10 years). B0: Each heatwave event does not include a breaking day, which is not the extreme hot day. B1: The heatwave event can include a breaking day.

subsequently increase with larger RWT sizes, indicating a potential risk associated with excess water usage on sprinkling. Additionally, the installation of RWT mitigates extreme surface runoff, exhibiting a linear reduction trend with increasing tank size. Overall, these findings suggest that the RWTSP strategy can play an effective role in alleviating local urban heat extreme events by lowering roof surface temperatures, reducing air temperature and heat stress, and mitigating extreme surface runoff.

The benefits of mitigating extreme heatwave events were further analyzed. It should be noted that there is more than one definition of a heatwave event across different fields and studies (Chen et al., 2015; Mohammad Harmay & Choi, 2022; Ramallo-González et al., 2020). Here, the definition derived from an absolute temperature threshold was adopted (Hu et al., 2024; Tan et al., 2007) in this study. We further used two other definitions to test the robustness of our results. Two definitions of heatwaves were described: (a) B1: the maximum temperature is greater than or equal to 35°C for three consecutive days, allowing for one breaking day within the event. This definition is more lenient and effectively captures the dispersed impact of heat events, assuming that a single non-extreme breaking day does not provide sufficient recovery from the cumulative effects of prior extreme heat days. (b) B0: the maximum temperature is greater than or equal to 35°C for three consecutive days without a breaking day. This definition is more conventional and widely applied (Hu et al., 2024; Tan et al., 2007). These definitions can be used to comprehensively evaluate the strategy's effectiveness in mitigating different types of heatwaves. The intensity (average maximum temperature during the events), frequency (number of events), duration (number of days per event), and total days (days of events) were used to represent the heatwave characteristics.

The results indicate that the intensity of heatwave events decreases with the implementation of the strategy, demonstrating its effectiveness in alleviating extreme heatwave events (Figure 6). Under the B0 definition, the reduction in heatwave intensity is more significant, suggesting that the strategy is particularly effective in reducing the intensity of heatwaves when stricter criteria are applied. However, the reduction in heatwave intensity does not continue to increase with increasing the RWT scale. The duration of heatwaves tends to increase slightly under B0 definition. This might be attributed to the strategy effectively breaking shorter heatwave events, leading to fewer short-duration heatwaves overall, which increases the proportion of longer-lasting events. The duration of heatwaves shows a decreasing trend under B1 definition. This is likely because the strategy can suppress the onset or conclusion of heatwave days, reducing the total duration of such events. Under both definitions, the total number of heatwave days decreases, with a greater reduction as the RWT size increases. The frequency of heatwave events also decreases after implementing the strategy, with a more noticeable reduction under B0 definition, indicating the strong capacity of RWTSP for breaking the consecutive heatwave days. These findings underscore the strategy's ability to mitigate heatwaves, especially in terms of reducing their frequency and total days.

4. Conclusions and Limitations

This study proposes a roof rainwater harvesting tank and a roof sprinkling cooling system. By restructuring the water-energy nexus of urban roofs, this system can better utilize natural resources to reduce air conditioning usage and fight against extreme heat. This study implemented an RWTSP module in CLMU to explore the efficacy. Three key parameters that determine the system performance, including the rainwater tank size, sprinkling intensity, and sprinkling temperature threshold, are non-linear to the AC energy consumption. With the temperature threshold set to a lower value, the sprinkling intensity will be more important for the roof sprinkling performance on decreasing AC energy consumption. In addition, the temperature threshold is the most important parameter for this system. To find the optimal solutions for this system with the objectives of smaller rainwater tank size and lower AC energy consumption, multi-objective optimization with a surrogate model framework was employed to optimize the parameters. The transformer-based tabular foundation model is more suitable as a surrogate for optimization. The generated solutions using surrogate closely match the ground truth from the CLMU model, showing the feasibility of this framework for optimizing urban climate adaptation strategies.

The impacts of the RWTSP strategy on local urban climate and extreme heatwaves were investigated, demonstrating its capability to decrease the extreme roof surface temperature and urban canyon air temperature. Moreover, the strategy can markedly decrease the total number of heatwave days, with a greater reduction by increasing the RWT size. However, there is a trade-off between increasing RWT size and reducing heatwave days. Background climate also impacts the efficacy of the strategy, with a higher background air temperature and a greater AC usage reduction.

The feasibility of RWTSP in a given region will depend on local climatic, regulatory, and economic conditions (Campisano et al., 2017). In general, RWTSP is likely to be more favorable in regions with both substantial cooling demand and sufficient rainfall, while its applicability may be more limited in arid regions with insufficient rainfall. Additional constraints may arise from the local regulations on rainwater harvesting (Loper & Anderson, 2019), the moisture risks such as mold growth and roof material deterioration due to sprinkling (U.S. Environmental Protection Agency, 2013), and the cost of system installation and maintenance. The suitable and optimal designs require balancing these multifaceted constraints, making traditional, intuition-based design inefficient. This highlights the contribution of our framework, which integrates process-based simulations, surrogate modeling, and optimization to find the optimal solutions. By navigating these complex trade-offs, our approach evaluates the performance and rapidly identifies optimal operational parameters, providing feasibility analysis and adaptable solutions for RWTSP implementation. Furthermore, there are many innovations in applying blue infrastructures to control the extreme heat in urban areas, such as misting (X. Huang et al., 2025), road sprinkling (Lee et al., 2018), and urban irrigation (J. Yang & Wang, 2015; P. Li et al., 2024). This framework can be adaptable to such strategies. By leveraging the power of global Earth system modeling, this framework can also be seamlessly scaled to cities worldwide.

This study is subject to limitations associated with the urban canopy model formulation and the evaluation of the strategy. In the urban canopy concept, the flow above the roof is partially decoupled from that in the canyons (Oke et al., 2017). While some urban canopy models explicitly decouple heat and moisture exchange between the roof and canyon air (Demuzere et al., 2013; Joshi et al., 2025), CLMU couples the roof with canyon (K. Oleson et al., 2010) and considers that the heights of urban roofs are heterogeneous. When wind flows over heterogeneous urban rooftops, it may generate wakes and downdrafts that can enhance exchange between roof-level air and street-canyon air (Oke et al., 2017). However, the strength of this exchange likely varies with urban morphology and atmospheric conditions (Demuzere et al., 2013), so the CLMU representation may not be universally applicable. In models with weaker roof-canyon coupling, the impacts on canyon air may be smaller, and any canyon impact may occur through reduced anthropogenic heat due to lower AC use. Therefore, the simulated canyon cooling effect of RWTSP in this study should be interpreted within the CLMU framework and may be more representative of urban settings where the exchange between the roof and canyon air is relatively strong. Another limitation of this study is the lack of observational data to directly validate the RWTSP strategies. Our framework is indirectly validated, meaning the results should be interpreted as process-based model estimations. Nevertheless, the core physical processes of CLMU remain unchanged, and only the routing of roof runoff was modified. By preserving the default model processes, our framework remains physically consistent with the original CLMU.

Conflict of Interest

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

Availability Statement

Scripts and data to reproduce the results and figures are preserved in the author's GitHub repository (Yu & Zheng, 2026). The default input data for pyclmuapp simulations was generated by Dr. Keith W. Oleson using the “mksurfdata_map” tool in Community Terrestrial Systems Model (CTSM) (CTSM Development Team, 2020). Observation data from the Urban-PLUMBER project is available at Lipson et al. (2022a).

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