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Distributional outcomes of urban heat island reduction pathways under climate extremes

Ali Eyni[1]✉, Benjamin F. Zaitchik[1], Benjamin F. Hobbs[2], Antonia Hadjimichael[3,4] & Rui Shi[2]

Global warming and the rise in extreme heat days elevate the risk of heat-related mortalities, particularly in cities due to the Urban Heat Island (UHI) effect and vulnerabilities tied to housing, exposure, and health conditions. City planners can mitigate these effects through urban adaptive actions. UHI mitigation, however, needs to balance several goals: strategies that maximize temperature reduction or minimize their impacts may not be best for cost effectiveness, carbon emissions, environmental amenities, health impacts, or distributional outcomes. Here, we implement a multi-objective robust decision-making tool for heat mitigation—the City-Heat Equity Adaptation Tool (City-HEAT)—to identify potential heat mitigation pathways at neighborhood scales. We find that more expensive pathways tend to have larger benefits in reducing heat-related deaths, but that these pathways sometimes underperform against other alternatives on reducing inequality in mortality outcomes. Pathways that focus on tree planting, a popular and powerful tool for UHI reduction, were found to be expensive and less effective at reducing health disparities than more diversified pathways, if no specific measures are taken to target tree distribution for distributional benefit. The generated pathways can reduce Baltimore's heat related mortality by 81–670 deaths in the next 50 years, considering different investment plans in the city's neighborhoods. We also find that these results are relatively insensitive to expectations for future warming: pathways designed for high warming rates are similar to those designed for low warming rates, suggesting that general strategies for UHI mitigation can be robust to climate uncertainties.

Heat exposure significantly impacts human health, leading to increased morbidity and mortality[1,2]. Studies have documented these effects globally, highlighting the vulnerability of certain populations. For instance, heat waves and high temperatures are linked to elevated mortality rates, particularly affecting the elderly, women, and individuals in low socioeconomic brackets[3,4]. A study analyzing data from 732 locations in 43 countries found that 37% of warm-season heat-related deaths between 1991 and 2018 could be attributed to anthropogenic climate change, with increases in mortality observed globally[1]. Research shows that heat sensitivity varies across regions due to differences in socioeconomic conditions and adaptation efforts. In developed areas, improved warning systems and living conditions have reduced vulnerability[5,6]. However, low- and middle-income countries continue to face significant health burdens, exacerbated by limited resources[6]. Urbanization and global warming amplify risks, particularly in urban areas where heat exposure is intensified[7,8]. Localized studies reveal that some regions are adapting, with shifts in minimum mortality temperatures reflecting long-term acclimatization to heat stress[9,10].In urban environments, the impacts of heat are exacerbated by the Urban Heat Island (UHI) effect, where urban areas experience elevated temperatures due to human activities and land surface modifications. UHI intensity can vary significantly based on factors such as urban density, contiguity of dense development, vegetation cover, and the extent of impervious surfaces[11]. Studies show significant warming trends in urban areas compared to rural areas. This intensification of the urban heat island effect leads to increased energy consumption for cooling and worsens indoor thermal environments, exacerbating heat stress among urban populations[12,13]. Factors such as land cover changes and urbanization patterns further amplify these effects, with research showing that local and regional warming is strongly influenced by urban development[14,15].

These patterns and trends have drawn significant attention to the necessity of heat adaptation, particularly in urban contexts where vulnerable communities face heightened risks. Effective urban heat adaptation strategies

[1]Department of Earth and Planetary Sciences, Johns Hopkins University, Baltimore, MD, USA. [2]Department of Environmental Health and Engineering, Johns Hopkins University, Baltimore, MD, USA. [3]Department of Geosciences, The Pennsylvania State University, University Park, PA, USA. [4]Earth and Environmental Systems Institute (EESI), The Pennsylvania State University, University Park, PA, USA. ✉email: aeyni1@jhu.edu

must address the complex interplay of urban elements, such as land cover, infrastructure, and resident behaviors, which collectively influence heat exposure and health outcomes[14,16,17]. Additionally, these strategies should incorporate a nuanced understanding of vulnerability factors, including socioeconomic status, demographics, and geographic disparities, to ensure fully-informed measures that protect the most at-risk populations[18,19]. Spatial and temporal assessments of urban heat island effects further highlight the importance of integrating green infrastructure and urban planning innovations to mitigate localized heat impacts and promote sustainable urban development[20,21].

Confronting the multifaceted impacts of heat on human well-being, which varies significantly across communities and demographic groups, poses a complex challenge. This complexity is rooted in the need to balance diverse goals such as improving public health, economic implications, and environmental sustainability. These criteria often conflict, reflecting differing priorities and interests among stakeholders. Meanwhile, evaluating these impacts involves significant uncertainties, such as predicting the future frequency and intensity of heat events, understanding the long-term health effects across various populations, and anticipating the socio-economic consequences of adaptive actions. These challenges are compounded by Deep Uncertainty (DU), where there is disagreement or a lack of knowledge regarding the appropriate models, probability distributions, or value systems needed to accurately assess these complex factors[22].

To manage the profound uncertainties associated with urban heat adaptation effectively, decision-makers are increasingly relying on sophisticated methodologies such as Exploratory Modeling and Analysis[23,24]. These kinds of approaches offer structured frameworks to evaluate various adaptation strategies under multiple plausible future state of the worlds (SOW), facilitating the identification of robust solutions amidst uncertainty. They employ models as "thinking tools" to capture key uncertainties by exploring a range of assumptions through numerous computational experiments[24].

In this context, dynamic adaptive policy pathways (DAPP) have emerged as a powerful framework for managing deep uncertainty in climate adaptation, enabling the design of flexible and robust strategies that can evolve over time in response to new information and changing conditions[25]. The DAPP framework was initially conceptualized to manage pre-defined policy options and their corresponding triggers[25]. This concept was later expanded through the integration of multi-objective evolutionary algorithms (MOEAs) to search for and combine adaptive pathways, thereby enhancing the capacity to navigate complex decision landscapes[26]. Subsequent studies have further refined the DAPP framework by optimizing state-aware triggers and incorporating ensembles of uncertain future conditions into the search phase[27,28]. However, UHI problems still challenge DAPP approaches as they currently exist, and there is need for a comprehensive study in this framework for UHI interventions.

These advances underscore the critical role of adaptability and resilience in managing uncertain climate futures, especially in complex urban environments where multiple stakeholders and diverse hazards converge. This paper investigates how integrating data-driven models, participatory planning processes, and cross-sectoral collaboration can enhance urban heat adaptation strategies, addressing gaps in traditional approaches that often overlook distributional outcomes and inclusivity. For instance, resilience is explored through the lens of flexible infrastructure development whose adaptability enables them to be capable of withstanding a range of climate impacts, ensuring that vulnerable communities are protected[18,29]. Inclusivity is examined by evaluating participatory approaches that involve marginalized groups in the decision-making process, aiming to address their unique needs and vulnerabilities. Additionally, this study emphasizes distributional effects by analyzing how resources and interventions can be prioritized in areas disproportionately affected by climate change, ensuring that adaptive strategies reduce inequality in outcomes at community level.

By bridging these gaps, this paper extends traditional planning methods, proposing pathways for urban adaptation that are not only sustainable and robust but also responsive to the diverse needs of urban populations. In doing so, it highlights innovative frameworks that can serve as models for future urban resilience and adaptation efforts.

The rest of the paper is structured as follows: the remainder of the introduction describes Baltimore's UHI and introduces the City-HEAT modeling framework; results and discussion are presented in Sect. "Results and discussion"; and Sect. "Conclusion" offers conclusions. Methods are described in detail in Sect. "Methods and data".

Baltimore

Baltimore, a city located in the Mid-Atlantic region of the United States, experiences a humid subtropical climate with hot and humid summers. Average high temperatures during the summer months range from 29–32°C (85–90°F)[30], though heatwaves can drive temperatures even higher, intensifying the urban heat island (UHI) effect. The city experiences pronounced disparities in temperature due to the UHI[31]. This phenomenon is particularly severe in densely populated and industrial parts of the city where green spaces are limited. The UHI effect in Baltimore not only elevates temperatures but also exacerbates public health issues, particularly affecting the elderly, children, and economically disadvantaged populations who may lack adequate access to cooling resources. Studies indicate that during heat waves, these populations exhibit higher rates of heat-related illnesses and mortality[32]. Neighborhoods characterized by poor socio-economic conditions and higher density of buildings experience significantly higher incidences of heat-related hospital admissions. These same neighborhoods are often characterized by lack of access to indoor air conditioning and by aging building stock and infrastructure.

Figure 1 shows the variability of various metrics relevant to our study in different Baltimore Community Statistical Areas (CSAs). Here we highlight the percentage of the population living below the poverty line and percentage of the population over age 65 as two indicators of heat-related vulnerability. The spatial distributions of poor and elderly populations are quite different, indicating that the way in which decision-makers frame the heat vulnerability problem can have a substantial impact on heat mitigation strategies. Figure 1 also shows the

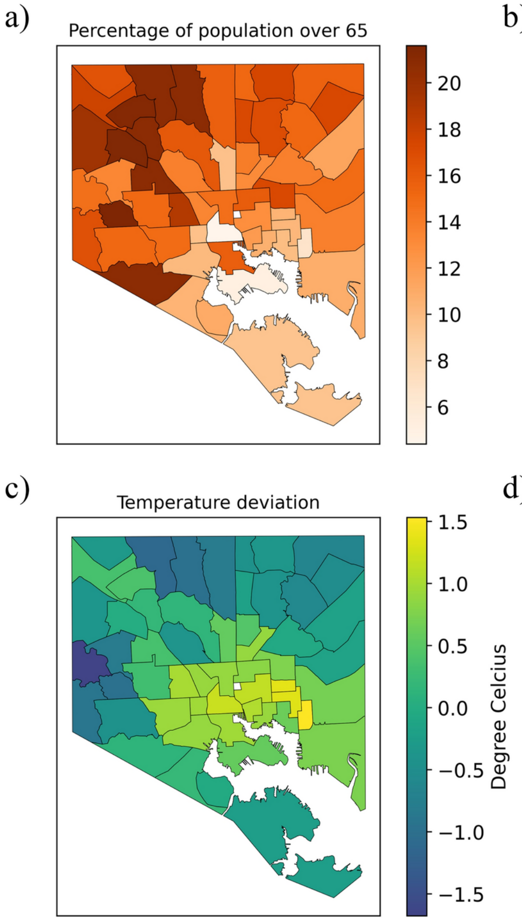

Fig. 1. Characteristics of Baltimore Community Statistical Areas (CSAs) relevant to heat vulnerability and mitigation potential. (**a**) and (**b**) show the variations in demographic characteristics among CSAs. Panel (**c**) shows the value of temperature deviation from the city average. (**d**) shows the percent canopy cover in each CSA. The maps were generated using the matplotlib python package version 3.7.1[69,70], https://doi.ieeecomputersociety.org/10.1109/MCSE.2007.55.

current summer temperature difference between different CSAs versus the city average and current tree canopy cover, as an indicator of unequal access to heat-mitigating green infrastructure.

City-HEAT

Urban heat mitigation is a clear case of many-objective adaptation involving diverse stakeholders. Recognizing this, we utilize the City Heat Equity Adaptation Tool (City-HEAT)[33]. Initially presented as a software framework in a simplified demonstration, written in C++programming language, City-HEAT offers a tool that can be customized and has a potential for participatory heat mitigation planning in a wide range of settings. Here, we present the first application of City-HEAT to a realistically constrained heat mitigation case, using best-available climate projections, high resolution urban heat island maps, and a distribution-oriented, neighborhood-scale objective space informed by Baltimore City's 2019 Sustainability Plan[34] and 2023 Climate Action Plan update[35]. In doing so, we highlight the significance of City-HEAT as a tool for urban climate adaptation. Our approach contributes to the ongoing discourse in the climate impacts and adaptation community and offers new insights into the design of adaptive strategies that can navigate the deep uncertainties and complexities of urban systems. This paper aims to study dynamic adaptive pathways in complex systems, thereby advancing the field of urban climate resilience.

The adaptive learning process in City-HEAT enables the tool to be robust under conditions of uncertainty, providing a comprehensive approach to urban heat management. By optimizing plans based on the type, location, timing, and magnitude of adaptation actions, City-HEAT balances objectives such as reducing total heat-health impacts and reducing inequality in heat-health burden. It evaluates the long-term costs and benefits and accounts for spatial variability within cities, ensuring that adaptation actions are tailored to specific vulnerabilities and opportunities, and considering the distribution of costs and benefits across different sub-city areas.

The model tackles DMDU by evaluating a wide range of future SOWs and allowing for the flexibility to adapt plans based on new information. This dynamic approach incorporates a Direct Policy Search method, which systematically optimizes decision rules through simulation, adjusting decisions at each stage based on observed system changes and prior decisions[36,37]. DPS facilitates the identification of strategies that are not only effective under expected conditions but also robust, meaning they maintain satisfactory performance across a variety of uncertain futures[38]. Adaptability is defined as the model's capacity to adjust strategies in response to evolving conditions, ensuring continuous alignment with system objectives. By explicitly considering both robustness and adaptability, City-HEAT helps mitigate risks associated with deep uncertainties, such as those related to climate change and socio-economic developments. This makes it a powerful tool for city planners and researchers aiming to develop resilient and broadly beneficial urban heat adaptation strategies.

In this study, we customize City-HEAT to find policies at the neighborhood level in the city of Baltimore, focusing on cost-reasonable investment plans. The policies are optimized for reducing the city's heat-related mortality, minimizing the cost of adaptation, reducing inequality in heat-related deaths across neighborhoods, and achieving greenhouse gas benefits through CO2 uptake. The model also optimizes to increase reliability which here is defined as reducing the worst-case mortality. In this application, we presently utilized mitigation strategies such as reflective pavements and roofs; and greenery-based solutions, especially tree-planting; and vulnerability reduction through cooling centers. Reflective surfaces, for instance, work by increasing the albedo (surface reflectivity), which reduces the absorption of solar heat and lowers surface temperatures. Greenery based solutions, such as urban tree canopies, leverages evapotranspiration—the process by which plants release water to cool the surrounding air—to reduce local heating, and can also provide shade. These measures not only lower localized temperatures but also enhance thermal comfort and reduce the energy demands for cooling. We limited our simulations to the use of the current mitigation strategies for two reasons: we wanted to focus on techniques that have well-defined performance characteristics that can be implemented immediately, and we want for the results of the tradeoff analysis to be intuitive to community members and decision-makers who are already familiar with white roofs, standard cool pavements, tree planting, etc. Further information about the model customization and how metrics are calculated is provided in the methods section and supplementary table 1.

Results and discussion

Figure 2 illustrates the Pareto-approximate adaptation pathways and their corresponding objective values discovered through multi-objective optimization. The solution set comprises 630 policies, each representing a distinct configuration of adaptation strategies tailored to different neighborhoods. The pathways are optimized to address five key objectives: reducing the overall cost, minimizing heat-related mortality, lowering CO2 emissions, improving reliability by decreasing the worst-case mortality year, and reducing inequality by reducing the maximum mortality rate difference between neighborhoods, a set of objectives that encompass conventional health goals, that recognize economic constraints on adaptation investments, and that address concerns related to greenhouse gas mitigation, disaster reduction, and vulnerability distributions prioritized in the City's Climate Action Plan, Disaster Preparedness and Planning Project, and Sustainability Plan, respectively[34,35,39]. Over the 50 years of the simulation period and averaged over all SOWs, the pathways cost between 18 million and 1.023 billion dollars; and reduce heat related mortality by 81–670 deaths, considering different investment plans in the city's neighborhoods.

Four pathways are color-coded in Fig. 2(a) to highlight solutions with different combinations of strategies. Specifically, we examine four contrasting representative pathways: high investment in multiple strategies (blue; "all strategies"), moderate investment in multiple strategies (purple), focus on tree planting (green; "greening focused"), and focus on cool roofs and pavements (orange; "infrastructure focused"). These are only four of many Pareto-approximate solutions. We focus on them as representatives of different ways in which the city could approach heat mitigation. These representative pathways were defined based on specific distinguishing metrics (see Methods). We present results for one example of each type of pathway and find that results are similar for all Pareto-approximate solutions that share those characteristics (Supplementary Fig. 1). In this figure, each y-axis measures performance with respect to one of the five optimization objectives, with movement down the axis indicative of better performance—a "perfect" solution would yield a flat line along the x-axis. The slope of the lines between axes, then, reveals the degree of tradeoff between objectives: a steeper slope suggests a more significant tradeoff between two competing goals.

Focusing on the highlighted example pathways, we see that in this formulation of the model, a greening-focused pathway that invests heavily in tree planting can achieve substantial reductions in total heat-related mortality and CO2 emissions, compared to not using any adaptation, but that it fails to perform well in terms of reducing inequality in heat-related mortality. This outcome indicates that while the indicative tree planting pathway we have highlighted is effective for environmental and health benefits, it does not equally distribute these benefits across neighborhoods, leading to disparities. In contrast, the pathways representative of a more balanced or infrastructure-focused approach, which emphasize cool pavements and cool roofs, exhibit superior performance in reducing the mortality rate difference between neighborhoods, thereby better meeting the equality criterion, and doing so at lower total cost. Their performance on carbon sequestration is not as good as the tree-focused pathway, and they do not reduce total mortality as much as the tree planting pathway or the "all strategies" option (blue).

Figures 2(b) and 2(c) further illustrate the tradeoffs between pairs of objectives for all solutions, as well as the representative pathways. Overall, as more is spent on a heat mitigation pathway, more lives are saved (Fig. 2(b)), and the unit cost of saving a life increases (colors in Fig. 2(b) and 2(c)); i.e., the marginal benefits for mortality reduction diminish with increasing investment. There is a tendency for higher unit cost, more expensive and mortality-reducing pathways to reduce disparities between neighborhoods—the general negative association in Fig. 2(c)—but there is considerable scatter, with different strategies yielding different inequality outcomes at a common level of mortality reduction. In fact, the most expensive and mortality-reducing pathways do not yield the smallest differences in mortality between neighborhoods (the slight upward tendency at high mortality

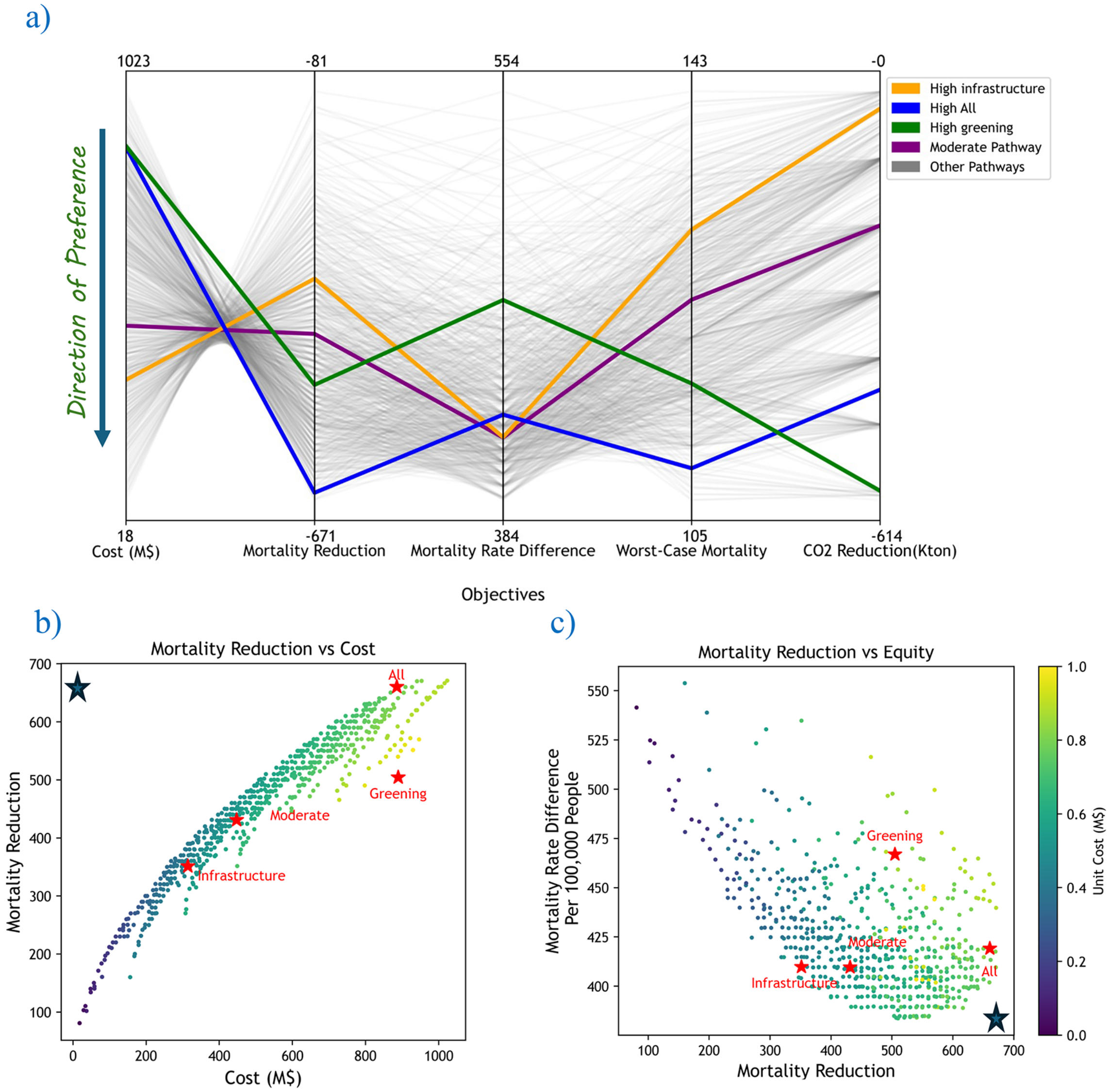

Fig. 2. (**a**) Parallel coordinate plot of different objectives, showing all Pareto optimal solutions (gray) and pathways representative of different cooling strategies (colors). (**b, c**) Tradeoff between pairs of objectives of the generated adaptive pathways: total cost and mortality reduction in (**b**) and mortality reduction and equity (difference in heat-related deaths between CSAs) in (**c**).

reduction values in Fig. 2(c)). Interestingly, for a given level of mortality reduction, it is not necessarily true that the more expensive pathways most effectively reduce mortality disparities. At each mortality reduction level, lower-cost pathways frequently outperform higher-cost pathways with respect to the mortality difference between neighborhoods; i.e., they result in reduced inequality in outcomes.

Why doesn't higher spending consistently reduce inequality? And, specifically, why is it that pathways focused on tree planting perform relatively poorly with respect to inequality? This is initially surprising, given the emphasis placed on urban greening to address the urban heat island in so many cities. The proximal reason is that the tree-dominated strategy invests less in underserved neighborhoods (Fig. 3). Where infrastructure focused (cool roofs and pavements) and moderate balanced strategies weight investment towards inner city neighborhoods and the poorer neighborhoods towards the northwest of the city, the "all strategies" and greening dominated pathways have different geographic distributions. Even though reduced inequality is one of the optimization criteria, these expensive paths do not aggressively favor spatial patterns that would achieve it.

One contributing explanation for this is the lack of tree planting sites in the urban core (Supplementary Fig. 2). This implementation of City-HEAT calculates the number of planting sites in each CSA using the USGS Chesapeake land cover maps[40]. The landcover map indicates that it is not possible to plant large numbers of trees in the hot and vulnerable neighborhoods that might need them most. Is this true? Not in a literal sense, but to some extent it is accurate, since it is considerably more expensive and riskier to create a space for a tree by removing concrete, rehabilitating tree pits, or demolishing vacant buildings than it is to plant a tree in an open space. Indeed, one of the community concerns about current government-supported tree initiatives in Maryland

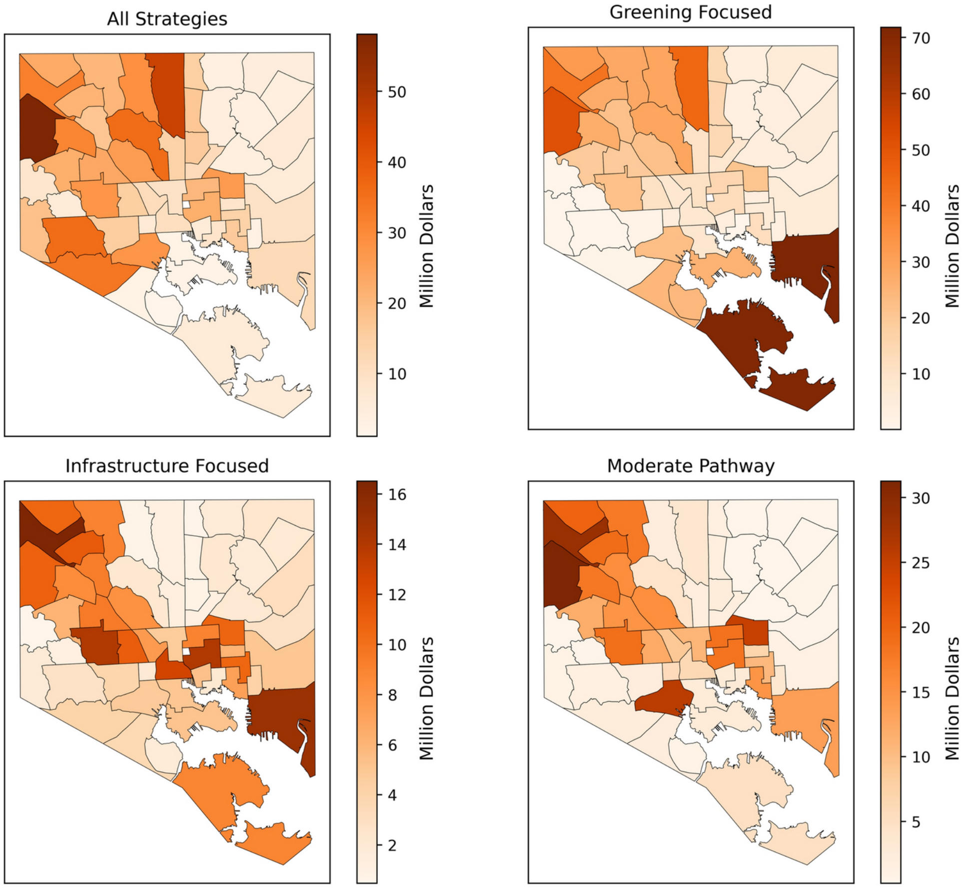

Fig. 3. Map of total investment (Million $) per community statistical area (CSA) for representative pathways focused on all strategies, greening, infrastructure and moderate development of each strategy. The maps were generated using the matplotlib python package version 3.7.1[69,70], https://doi.ieeecomputersociety.org/10.1109/MCSE.2007.55.

is that contracts are awarded on a cost-per-tree basis, which encourages planting in easily greened areas that tend to be more affluent. But it is not strictly true that there are not enough places to plant trees in urbanized, low-income neighborhoods. It simply requires more investment. In this respect, the model's adherence to the stated availability of tree planting sites forces ambitious greening pathways to favor less urban, lower impervious surface neighborhoods, when a committed approach to greening underserved communities might, in fact, be favorable, even if it comes at higher cost. It should also be noted that our distributional results focus on only one way in which one might define a fair, equal, or equitable outcome; evaluating strategies on the basis of distributional outcomes, as is done in City-HEAT, doesn't capture all aspects of equity and can miss context-specific nuances relevant to local outcomes[41].

But lack of planting sites alone does not explain the result: in simulations that apply uniform planting site availability to the entire city, we still see tree-dominated pathways perform relatively well on mortality reduction but poorly on distributional outcomes. A complementary reason is the way in which heat vulnerability is defined in the model. The neighborhoods with relatively low impervious surface and high percentage of easily plantable land covers also tend to be demographically older. Age is a significant risk factor for acute heat-related mortality. City-HEAT considers both age and income when calculating mortality risk, so neighborhoods that are relatively well-off but also relatively older are, for the optimization algorithm, good targets for mortality reduction, even if the baseline heat-related mortality rate is relatively low.

These findings highlight the complexity of urban heat adaptation planning. It is important to consider multiple, often competing, objectives and to interrogate assumptions and constraints. For instance, while tree planting initiatives are valuable for environmental sustainability and public health, they do not ensure optimal distribution of benefits across all neighborhoods; for the distributional outcomes metric used in City-HEAT, for example, tree-oriented pathways performed poorly even as they performed well for other objectives. Such strategies might need to be placed in a diverse package of adaptation techniques that include infrastructure solutions that are more easily applied in a dense urban matrix, or they might need to emphasize relatively expensive planting strategies that yield healthy trees in difficult urban environments. This multifaceted approach is essential for developing robust adaptation policies that not only mitigate the impacts of urban heat but also promote inclusive benefits.

To further illustrate the four representative pathways, Fig. 4 shows the performance of each pathway through time, averaged for all SOWs. In analyzing the performance of our four distinct heat adaptation pathways, our results highlight significant improvements across all strategies in reducing heatwave days (HWD) and heat-related mortality. Benefits for both are greatest in the "all measures" pathway, which offers about a 25% improvement relative to the lower cost "infrastructure" pathway by the end of the simulation period. However, both the 'all measures' pathway, integrating a high concentration of cooling techniques, and the 'greening' pathway, which emphasizes planting trees, require substantial upfront investments. These investments result in a steeper financial trajectory over time, suggesting the need for significant initial funding but promising potentially greater long-term benefits in reducing urban heat and enhancing environmental health. Such comprehensive strategies, while effective, pose challenges in scalability and immediate cost burden, which might limit their applicability in financially constrained urban settings.

The implications of these pathways for distributional outcomes are shown in Fig. 4 by applying a Gini index calculation to heat-related deaths across CSAs. The Gini index is a measure of statistical dispersion that represents the inequality in a distribution, commonly used to quantify income or wealth disparities. In this context, it quantifies inequality in heat-related deaths. A Gini index of 0 indicates perfect equality, while a Gini index of 1 indicates maximum inequality[42]. Throughout the simulation period the 4 representative pathways result in Gini index of between 0.2 and 0.4 on average. Pathways that reduce inequality in heat-related mortality in a highly economically stratified city like Baltimore are considered to be distributionally effective, in that they are defined by investments that reduce the disparity between vulnerable and less-vulnerable neighborhoods.

Consistent with the results shown in Fig. 2, there is a divergence in Gini index between the representative pathways. The paucity of available tree planting sites in marginalized neighborhoods and the prevalence of older adults in some of the more affluent neighborhoods with abundant planting spaces leads the model to generate greening pathways that direct investment towards less urbanized parts of the city, thus not benefiting all city residents equally and possibly exacerbating socio-economic disparities. The "all measures" approach tends in the same direction largely because those pathways also include large amounts of tree planting. For both of these pathways, investment in non-tree strategies is distributed to neighborhoods with relatively high socio-economic vulnerability; it is the tree investments that drive the balance of investment towards less economically vulnerable neighborhoods (Supplementary Fig. 3). In contrast, the moderate pathway distributes its benefits more uniformly, since tree planting does not dominate the approach, and marginalized neighborhoods have ample

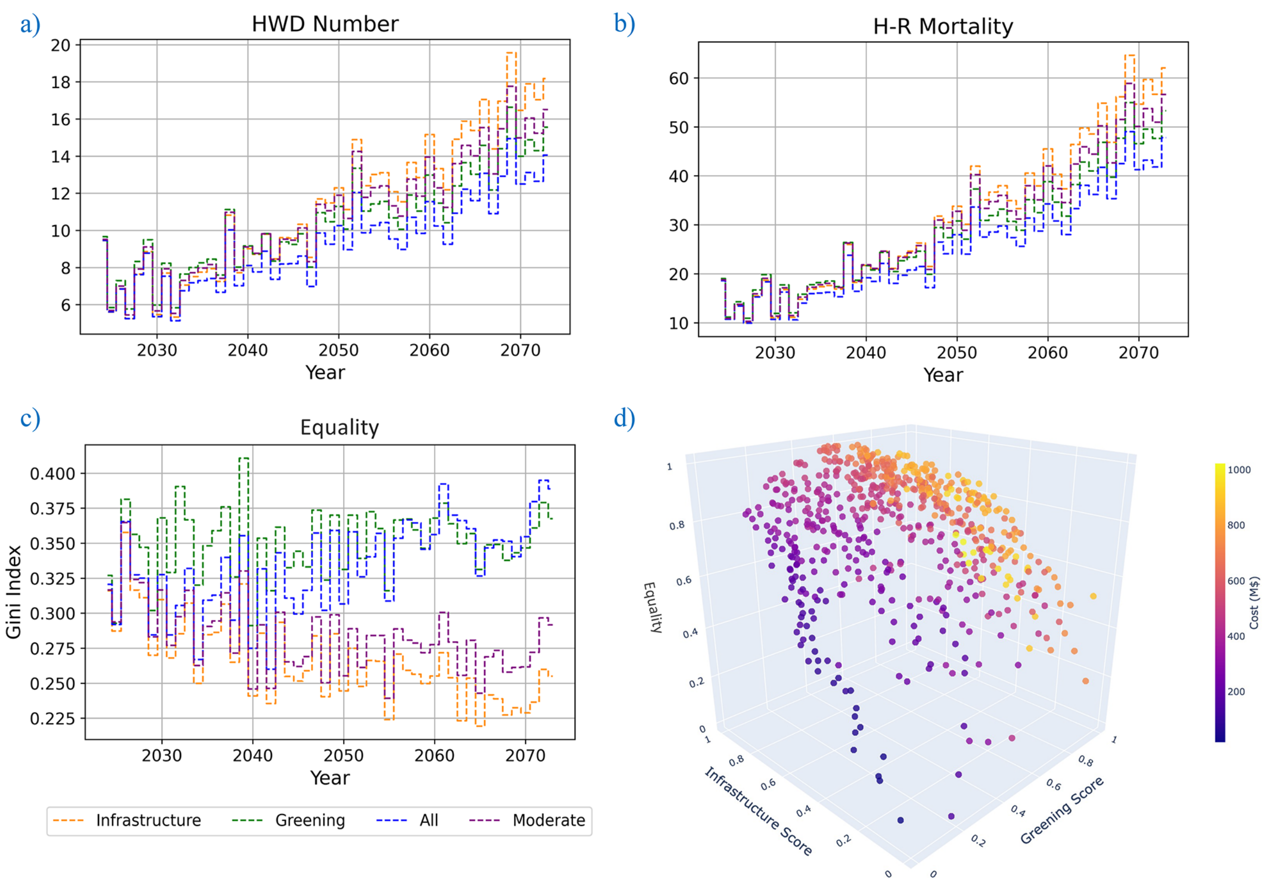

Fig. 4. Change in the number of heatwave days (**a**), heat related mortality (**b**), equality (Gini index method) (**c**) throughout the simulation period for the four representative pathways. The values are averaged across all training SOWs. (**d**) shows the relationship between developing greening or infrastructure with equality. The values are standardized for all three metrics, with 1 showing the highest and 0 showing the lowest.

sites available for white roofs and cool pavements relative to wealthier neighborhoods. This indicative pattern is also clear when we look at the relationships between infrastructure, greening, and distributional outcomes across all Pareto-approximate solutions (Fig. 4d). As spending on infrastructure (cool roofs and pavements) increases, the equality score rises. But as spending on green infrastructure rises there is no systematic reduction in inequality.

These results highlight several considerations in heat mitigation planning: (1) the use of mitigation strategies that are most easily implemented in vulnerable neighborhoods can lead to pathways that reduce distributional inequality at relatively low cost; (2) assumptions about what kinds of mitigation actions are possible—e.g., tree planting in soil vs. in areas that are currently paved—will have a major influence on estimated benefits and distributional implications of different cooling strategies; (3) the most expensive pathways tend to save the most lives, but they do not necessarily minimize inequalities in heat burden.

Distributional outcomes in neighborhood investment

Baltimore, like many cities, is strongly rooted in its neighborhoods. As a highly segregated and economically divided city, Baltimore is also a place where disparity is very much perceived and discussed at neighborhood scale. A global metric such as the mortality rate difference or Gini index, may be indicative of a form of distributional effects, but if a proposed adaptation pathway fails to invest and improve conditions in historically marginalized neighborhoods then it will not be viewed as acceptable in the terms most frequently discussed in the City and embodied in City plans like the 2019 Sustainability Plan, which defined sustainability through a lens of racial equity[34].

To understand the distributional outcomes of representative pathways in these terms, we examine heatwave outcomes and investment patterns across the 55 CSAs of Baltimore. Each CSA is an aggregation of neighborhoods, as colloquially defined (there are over 200 commonly used neighborhood designations in Baltimore City), but the CSAs capture the pattern of economic and social conditions across the City. When the CSAs are ranked by median household income, we see that investments over time in the representative greening-oriented pathway (Fig. 5a) show no particular pattern with respect to the economic status of the CSA. The poorest neighborhoods receive relatively little investment, while very large investments are made in some middle- and high-income CSAs. Averaged over all SOWs, the yearly investment in each CSA peaks at 3 million dollars for the greening pathway and at 0.8 million dollars for the infrastructure pathway.

In the infrastructure-oriented pathway, there is a stronger tendency to weight investment to some of the poorest CSAs (Fig. 5b). There is still considerable scatter in investments across the economic gradient, as these pathways are shaped by multiple objectives and constraints, and they do not explicitly optimize for progressive investment patterns. Community perspectives emphasize the importance of aligning such pathways with the distribution of health outcomes, particularly in neighborhoods with the highest heat burden[43].

Viewed in terms of distributional effects by race, all four representative pathways invest most heavily in the top quartile of percent African-American CSAs (Fig. 5c), a consideration that is not represented in the model but that is a City priority and something that correlates with mortality differences between neighborhoods. Baltimore's historical patterns of disinvestment and redlining continue to influence contemporary inequalities in urban heat vulnerability, underscoring the need for more targeted and intentional investments[41]. But the infrastructure-oriented and moderate pathways, which scored well in the aggregate mortality-based distributional outcomes objective (Fig. 2), direct a much higher percentage of total investment to those CSAs, in contrast to the greening-oriented and all measures pathways, which spread spending more evenly across CSAs. Race is not directly considered in City-HEAT, but pathways that perform better on the model's defined mortality-based equality metric also tend to invest more heavily in African-American neighborhoods, reflecting the health burden patterns that motivated the City to frame its Sustainability Plan in terms of racial equity.

Sensitivity to climate trajectory

City-HEAT optimizes its decision rules over all SOWs it is provided. For the analyses presented so far, we trained the model using the full range of future climate trajectories included in our family of climate scenarios (see Methods section). Since City-HEAT pathways are dynamic adaptive policy pathways (DAPP), decision rules trained using all future climate scenarios should be able to produce high performing pathways even for very different climate trajectories: the same decision rules should succeed for both high and low warming rates.

It is not obvious that this dynamic characteristic will also apply when the model is trained with one set of climate scenarios (e.g., low warming rates) and then applied to other climate realizations (e.g., unexpectedly high warming rates). This is of interest, since planning for low warming rates may result in adaptation measures that are inadequate, should warming turn out to be higher than expected, but planning for high warming rates might incur unnecessary costs if warming turns out to be more gradual. From the perspective of policy formulation, actors inclined towards risk-averse planning that focuses on high-end warming events might be at odds with actors who view climate change as a low concern and prefer to plan for low warming estimates. To examine the influence of climate expectation, we optimized City-HEAT using only high warming scenarios and again using only low warming scenarios. Then we examined distributional outcomes and robustness scores when strategies optimized for one anticipated warming rate were confronted with out-of-sample realizations from the warming rate they optimized for (e.g., high warming training, high warming scenarios) or with the opposite (e.g., high warming training, low warming scenarios).

To quantify robustness in this analysis, we use the satisficing method[38,44]. Satisficing is used in decision-making theory to describe a strategy that aims for acceptable results rather than optimizing a specific criterion. In this context, we assess the robustness of various solutions based on two primary criteria: the Gini index as an indication of distributional outcomes in heat-related mortality and a Reliability index as an indication for worst case heat-related mortality numbers. These metrics help us understand the distributional outcomes and

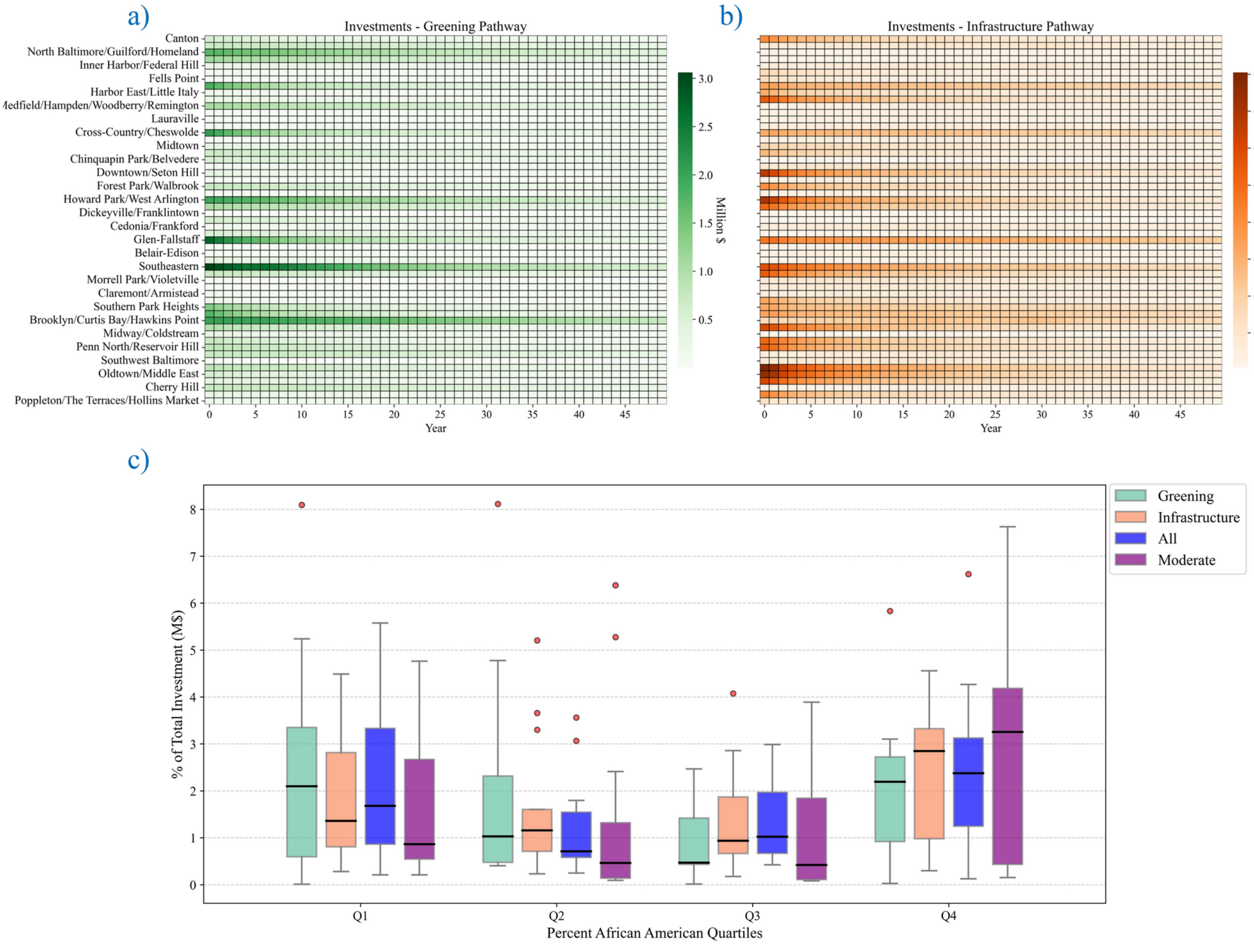

Fig. 5. Investment patterns across CSAs, ordered bottom to top by median household income, for greening pathway (**a**), Infrastructure pathway (**b**) through time and for four representative pathways for quartiles of percent African-American residents (**c**).

consistency of outcomes across different SOWs. To ensure the rigor of our robustness analysis, we employed out-of-sample SOWs to evaluate the performance of the proposed adaptation pathways. This approach allowed us to test the strategies under conditions not previously considered in the initial modeling phase, thereby assessing their generalizability. Details of this analysis are provided in the Methods section.

Our climate crossover analysis yields several notable results (Fig. 6). First, the costs of optimal pathways do not differ dramatically between the four considered training and application SOWs. Here, costs of investments have been determined as the sum of discounted costs of implementation and maintenance for all mitigation strategies throughout the 50 year simulation period, averaged across scenarios. Total costs rise to a somewhat higher maximum for solutions trained on high warming rates—the slightly brighter pink dots in the top right panel of Fig. 6, for example—but this is a small difference, and there is no systematic difference between the pathways produced using high warming or low warming training data in the unit cost of saving a life (the x-axis values; compare the values in top right to bottom left panels and top left to bottom right panels). For this implementation of City-HEAT, then, planning for the worst does *not* result in overspending relative to more optimistic approaches.

A second notable result is that the pathways trained on low warming projections produce robustness scores under high warming rates (bottom left panel, Fig. 6) that are comparable to the scores of pathways trained with high warming rates and confronted with high warming rates (top right panel). There is no evidence that failing to train pathways for high warming leads to markedly poorer performance in terms of those objectives if high warming rates are encountered.

Taken together, the relative similarity of cost and performance for the two differently trained sets of pathways suggests that the climate projection—and uncertainty in that climate projection—does not have a major impact on the selection of optimal adaptation strategies. This is in part due to the constraints on the solution space (spending restrictions, available sites for interventions, multiple competing objectives) and in part due to the fact that a trained "pathway" is a set of decision rules rather than a fixed set of investments. The investment pattern for any given pathway emerges over time and is responsive to realized conditions—e.g., more spending on interventions as impacts of heat grow. Insomuch as a local government can adopt such a decision rule approach, as opposed to a fixed long-term heat mitigation spending plan, there is significant opportunity for "no regrets"

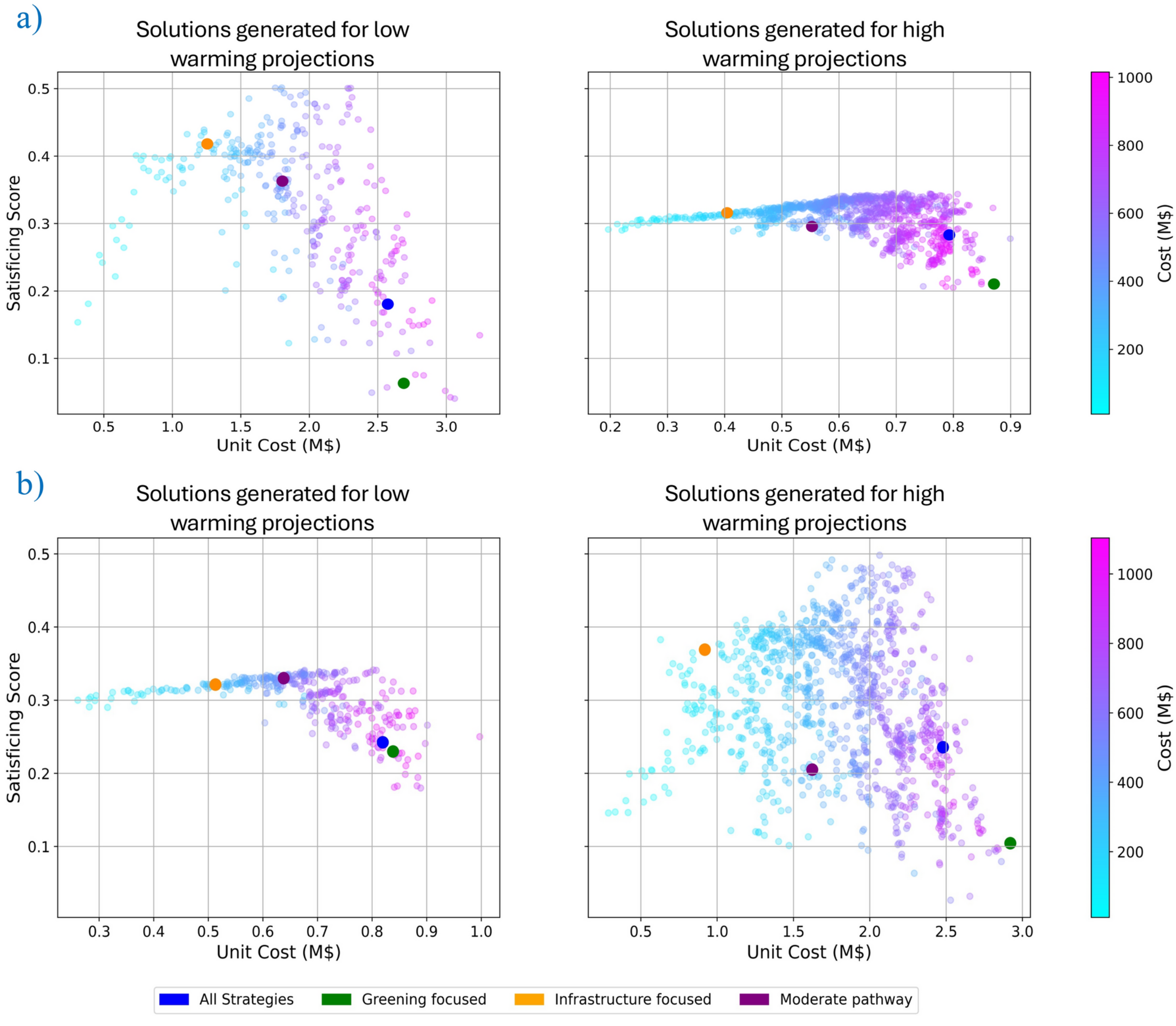

Fig. 6. Satisficing scores for all solutions generated for low warming and high warming projections. The scores are calculated for out of sample projections drawn from (**a**) consistent scenarios (low warming for low warming and high warming for high warming) and (**b**) cross examination of scenarios (low warming for high warming and high warming for low warming).

adaptation investments, and perhaps for agreement on decision rules across groups with different views on the risk of future climate change.

That said, the unit cost of saving a life is much higher for low warming trajectories (top left panel and bottom right panel), regardless of how the pathways were trained. This is a logical result of the fact that fewer lives are at risk, and thus fewer lives are saved, if warming occurs at a low rate. In this sense, there *is* the potential for regret. While the total cost of a heat mitigation portfolio is lower for the lower warming rate, decision-makers might regret expenditures on mitigation if it turns out that the amount and impacts of warming are smaller than feared, so that the investments result in saving a relatively small number of lives.

When looking at the representative pathways, we see no systematic changes in pathway behavior for the various warming training and realization tests. The “greening-focused” and “all strategies” pathways tend to be more expensive and satisfice less when compared to the infrastructure-focused and moderate pathways. At higher warming rates the gap in satisficing does close, but it does not disappear. There is some variability in the details of representative pathways performance for the different tests shown in Fig. 6. But this variability is to be expected, since these are representative pathways that are not identical realizations for all four tests. These results are in accordance with previous studies applying DPS in similar settings; as by applying DPS to find adaptive pathways, the models could perform well even while only trained using one SOW, when tested against other SOWs[45,46].

Conclusion

The purpose of the work presented in this paper is to take the concept of a MORDM for urban heat adaptation, as presented in the documentation of the initial version of City-HEAT[33], and move it closer to being a practically implementable plan by better UHI data, meaningful spatial resolution, realistic budget constraints, best-available climate projections, and other data and structure improvements. The model produced 630 urban adaptation pathways, costing between 18 million dollars and 1 billion dollars (discounted, averaged over SOWs) for the next 50 years. These pathways yielded some findings we had failed to anticipate (e.g., greening pathways that do not reduce disparities, low sensitivity to future climate conditions) and that have already led to highly engaged conversations with our partners in local government and the Baltimore community.

City-HEAT has a number of significant limitations as an exploratory model. As a MORDM framework for urban climate adaptation, City-HEAT is subjective in the selection of objectives and intervention options, relies on direct policy search (DPS) functions and climate projections that have both practical and inherent uncertainties, and is incomplete in its portrayal of heat mitigation priorities. In the urban context, City-HEAT is also idealized, applying general relationships between heat, interventions, and outcomes that are grounded in best-available data but that do not resolve the microvariabilities in urban environments that can affect the success of any given project in a specific neighborhood. So, while our use of MORDM in climate decision-making is supported by successful applications in other contexts[25,47,48], the complexity of urban adaptation questions—diverse and distributed stakeholders, fine scale environmental variability, evolving technologies—forces us to ask whether decision-makers can really make use of this type of tool.

At this juncture, we have decided, cautiously, that the answer is yes. The findings presented here, including the risk of uneven distribution of benefits of current tree planting programs, the relative insensitivity of UHI mitigation strategies to future climate projections, and the presentation of credible heat mitigation pathways at neighborhood scale over multiple decades, are powerful conversation starters that can inform a process of deliberation with analysis[49]. Given the realities of city-scale policy making and the simplifications in City-HEAT, we would never expect to see a specific pathway output by the model adopted in all of its details. Rather, the pathways offer data and physics informed narratives that stakeholders can gather around to review tradeoffs and debate priorities and actions.

Our results are still not actionable. The next step in this work is to bring this model into dialog with a broader group of decision-makers and stakeholders in an iterative participatory process to refine City-HEAT objectives and assumptions and, ultimately, to produce potential pathways for heat adaptation that are a product of knowledge co-generation. Such co-generated pathways have the potential to be robust politically, and not just robust in their technical performance metrics.

Methods and data

The initial presentation of City-HEAT[33] introduced a software framework for applying multi-objective robust decision making (MORDM) to the problem of urban heat mitigation. In its initial implementation, this framework was introduced as a proof of concept, demonstrated at the relatively coarse scale of planning districts and not yet considering budget constraints, UHI details, or climate projection characteristics relevant to the actual decision-making context. Here, we have enhanced City-HEAT in support of ongoing climate adaptation efforts in the City of Baltimore[34,35,39].

City-HEAT utilizes a sophisticated multi-objective optimization model to determine the most effective urban heat adaptation strategies. This model leverages the Borg Many-Objective Evolutionary Algorithm (MOEA)[50], a state-of-the-art optimization technique known for handling complex, many-objective problems under uncertainty. Borg MOEA is adept at identifying a set of Pareto-optimal solutions, meaning it finds the best trade-offs among conflicting objectives without one solution being superior in all aspects.

Direct policy search (DPS)

This study employs Direct Policy Search (DPS)[36,37] to facilitate adaptive decision making, enabling the model to adjust strategies dynamically in response to observed changes in the system. Unlike static policies, which remain unchanged once implemented, DPS defines policies as a set of rules or guidelines dictating adaptation actions based on the current state of the system. This adaptive approach is essential for managing the deep uncertainties inherent in climate change and urban dynamics. Comparatively, functions with more parameters could lead to problems such as overfitting and increased computational burden[51].

The DPS function monitors several state variables, including current temperature, the rate of temperature change, demographics, and economic conditions. These variables provide a real-time snapshot of the urban system's state, informing decision-making processes. Policies within the DPS framework are defined by a set of decision rules that specify actions based on the state variables. For instance, if the temperature exceeds a certain threshold, the policy might mandate the implementation of additional cooling measures or increased tree planting. The DPS function incorporates learning mechanisms through the MOEA search which would allow it to update decision rules based on observed outcomes. This ensures that the policy evolves over time, becoming more effective as new information becomes available during the many-objective search. Based on this method, the strategy development (SD) in our model is determined by the following logistic growth function:

$$SD = Cap_{i,j} * \left(\frac{L}{1 + \exp\left(-k * (x_i - x_0)\right)}\right) \tag{1}$$

where, $Cap_{i,j}$ is the capacity of region i for installing the strategy j. L, k, and x_0 are the maximum range, curvature, and inflection point of the DPS curve, respectively. And x represents the system state for region i. We chose this formulation of the DPS function, as it allows for a more gradual increase in adaptation development.

In this setting of City-HEAT, the investment decisions are in the form of fractional increment of trees planted on available lands as well as pavements and roofs converted to cool pavements and roofs. These factions are expected to monotonically increase with the number of heat waves and are bounded between 0 and 1[33].

The implementation of DPS begins with the design of an initial set of policies based on historical air temperature data. These policies serve as a starting point for the DPS function. The model then simulates the urban system's response to different policies under a range of SOWs, evaluating each policy's performance based on predefined criteria. Based on these evaluation results, the DPS function adjusts the decision rules, informing the selection of adaptation strategies.

The DPS function generates adaptive response curves that illustrate how the policy responds to changes in state variables over time. These curves provide valuable insights into the policy's adaptability and effectiveness, facilitating stakeholder engagement by providing clearer insights into the system's adaptive responses. This transparency helps stakeholders understand the implications of different policies and make more informed decisions. Supplementary Fig. 4 shows several examples of the shape of the logistic function used in this study.

Problem formulation

During the problem formulation phase, we systematically identify and mathematically define several key elements: regional performance objectives, candidate policy actions, pertinent deep uncertainties, and sampling strategies for creating deep uncertainty SOWs specific to our study area[33]. Our approach to problem formulation places a strong emphasis on regional outcomes, ensuring that we disaggregate regional performance across the urban landscape. This allows us to prioritize and enhance the performance outcomes for the region's most vulnerable populations during the optimization process.

Once the problem is formulated, we undertake Deep Uncertainty Optimization. This involves employing a many-objective evolutionary search[52] across all formulated SOWs. The goal is to identify robust greening and infrastructure investment policies that can withstand the variability and uncertainty inherent in the SOWs. The optimization process generates a suite of candidate policies, which we then analyze to explore tradeoffs between conflicting objectives. This analysis helps us evaluate how regional performance evolves over time, providing insights into the dynamic interplay between various policy choices and their impacts.

Many-objective optimization

We employ the Borg Multi-Objective Evolutionary Algorithm (MOEA)[50] to identify an approximate Pareto set of nondominated solutions for the many-objective optimization problem outlined in the Problem Formulation section. In this context, "non-dominated" policies are those that outperform all other policies in at least one of the objectives defined above. The Borg MOEA is a global, population-based evolutionary algorithm that uses multiple evolutionary search operators, which are adaptively selected based on their effectiveness in finding optimal solutions. Additionally, the Borg MOEA incorporates epsilon dominance archiving[53], stagnation detection, and randomized restarts to avoid local optima and overcome dominance resistance[50]. These features enable the Borg MOEA to excel in exploring and optimizing complex, high-dimensional problems with nonlinear, discontinuous decision spaces[54–56].

In Eq. 1, L, k, and x_0 for each region are selected as the decision variables of our optimization model. The optimization is performed to obtain the five following objectives[33]:

1. Mortality Reduction: Maximize the reduction in heat-related mortality.
2. Cost Minimization: Minimize the total net present value of all costs associated with adaptation strategies.
3. Distributional Equality: Minimize disparities in heat-related mortality rates across different urban sub-regions.
4. Reliability Improvement: Minimize the worst-case, single-year, city-wide heat-related mortality.
5. Carbon Reduction Co-benefit: Maximize the cumulative CO2 mitigation achieved as a byproduct of adaptation actions.

The distributional equality objective, a critical component of our model, has been redefined to better capture disparities in impact across different regions. One way to illustrate the spatial inequality of heat-related health risks within a city is by comparing the maximum and minimum mortality rates across sub-city regions[41]. Since inequality is a serious social concern, options with a smaller maximum mortality difference between sub-city regions might be more desirable. Specifically, here, the inequality objective is now quantified as the area under the curve (AUC) of the maximum mortality rate difference between regions over time. The mathematical formulation of this objective is given by:

$$Distributional\,Outcomes\,Value = \int_{t=0}^{t=T} \max(MR\,(t)) - \min(MR\,(t))dt \qquad (2)$$

where $MR\,(t)$ is the vector of mortality rates of all regions at time t, and T is the total time horizon. This definition ensures a nuanced assessment of distributional outcomes of heat mitigation strategies, emphasizing temporal dynamics and highlighting periods of significant disparity.

The five objectives used in the current implementation of City-HEAT are a product of our review of the literature, read of the City of Baltimore's 2019 Sustainability Plan[34], and informal consultations with decision-makers. They are subject to change in future implementations of the models, as broader consultation informs the selection of objectives and additional data on heat impacts become available.

Model operation and data collection

Our model operates at both fine temporal (annual) and spatial (CSA) resolutions. This allows the model to tailor adaptation actions to specific sub-city regions and to adjust plans dynamically based on evolving conditions. This high resolution ensures that the model can address local vulnerabilities and variations in temperature and population demographics, providing a comprehensive assessment of long-term cost and benefits. For each CSA, data is collected using the census demographics and the land cover and high-resolution temperature maps[40]. Data collected from Chesapeake land cover maps include the canopy cover, road, roof and impervious surface percentage. Census demographic data includes total population, percentage of population over 65 years old and percentage of population under poverty.

The temporal scope of our model spans 50 years, allowing for long-term evaluation of adaptation strategies. Given the potential for significant early investments, particularly in strategies such as extensive tree planting, we incorporated a dynamic yearly constraint within the model, using the new DPS function (Eq. 1) and an upfront cost limit of 50 million dollars. This form of constraint allows for changing investment over time, making it possible to invest in upfront costs for ambitious adaptation initiatives and to adjust spending in response to realized outcomes, but it prevents unrealistically rapid budget changes and spending beyond a realistic threshold. The cost constraint also encourages the development of policies that can be realistically implemented by local governments and organizations, facilitating smoother transitions from planning to execution.

Urban heat island representation

To accurately represent the Urban Heat Island (UHI) effect in our model, we employed high-resolution 1-m maximum air temperature maps of Baltimore[31]. These maps provided detailed temperature data across the city, allowing for a precise depiction of the UHI phenomenon at a granular level.

The temperature values from these maps were aggregated to the Baltimore CSAs, which serve as the spatial units for our analysis. This aggregation process involved averaging the temperature readings within each CSA, ensuring that our model captures the localized temperature variations effectively. We then calculated the deviation of each CSA's temperature value from the city's weighted mean temperature. This deviation value was then used as a key parameter in our model, representing the relative temperature difference for each CSA. By focusing on deviations from the mean, we account for the uneven distribution of heat across different neighborhoods, highlighting areas that experience more intense UHI effects.

During the simulation, the temperature deviation values are dynamic and subject to change based on adaptation strategy implementation. This adaptability is crucial for accurately modeling the impact of various adaptation strategies. As different adaptation measures are implemented, such as increased vegetation or reflective roofing materials, the local temperature deviations adjust accordingly. Additionally, the model considers temperature changes in neighboring CSAs, acknowledging the interconnected nature of urban environments. This means that a cooling strategy in one CSA can influence the temperature deviations in adjacent areas, creating a more comprehensive and realistic simulation of UHI mitigation efforts.

By integrating these detailed temperature maps and dynamic deviation values, our model provides a robust representation of the UHI effect in Baltimore. This approach enables us to assess the effectiveness of different adaptation strategies and understand their spatial impacts, ultimately guiding more informed and broadly beneficial urban planning decisions.

Scenario development

To ensure that the identified policies maintain robust performance across various DU futures, we integrate DU into the many-objective search process through DU Optimization[28]. DU Optimization has proven effective in producing robust policies with acceptable performance across a large ensemble of SOWs[57]. During this process, each candidate policy is evaluated against 6,000 DU SOWs, which consist of random pairings of one DU sample with a set of temperature projection with a time horizon of 50 years and other uncertain variables. The SOWs are combinations of different realizations of uncertain parameters that describe future climate, demographics, and action effectiveness. Realizations are drawn using Latin Hypercubic Sampling (LHS)[58]. The detail of each SOW is built either with a selection of a certain criteria such as specific temperature projection or heat wave definition, or as a specific value in a range for relationships between different variables[33,59–63], such as temperature and mortality. These samples are represented in a comprehensive matrix, that captures a vast ensemble of potential future SOWs, including those with extreme events. The objective is to efficiently explore the impacts of global warming and other socio-economic uncertainties on the performance of specific policies.

The uncertainties in the model are incorporated in several aspects:

1. Climate Projections: Different climate models and emission scenarios are used to represent possible future temperature changes. Future air temperature projections are obtained from the NEX-GDDP-CMIP6 global downscaled climate scenarios[64] and are bias corrected for the city of Baltimore. The bias correction is performed based on air temperature observations from the station located at Maryland Science Center[65].
2. Adaptation Action Effectiveness: There is uncertainty in how effective different adaptation actions (e.g., urban afforestation, cool roofs) will be in reducing temperatures.
3. Heat Wave Definitions: Multiple definitions of heat waves are considered to capture scientific uncertainty in how heat waves are characterized.
4. Demographic Changes: The model projects future population sizes and demographics, which can vary significantly.
5. Mortality Relationships: The relationship between temperature and mortality is uncertain, and the model uses various mortality risk factors to estimate the impact of temperature changes on human health.

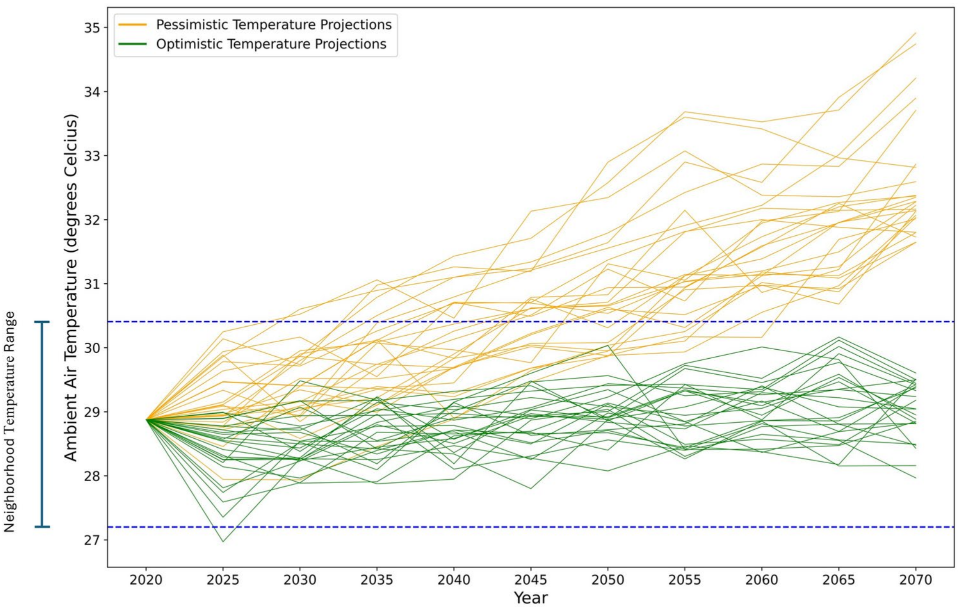

Fig. 7. Pessimistic and Optimistic air temperature projection used to train the rival framings.

The model addresses these uncertainties by evaluating a wide range of future states of the world. This approach ensures that the adaptation strategies it recommends are robust, meaning they perform well across different possible futures.

Sensitivity analysis

For evaluating the sensitivity of the model to climate trajectories, we trained the model using the most pessimistic and optimistic temperature projections obtained from the NEX-GDDP-CMIP6 global downscaled climate scenarios[64]. For each set of training the pareto-approximate pathways were obtained for the five objectives mentioned above. We then reevaluated each set of pathways against the other temperature projections (Pathways generated using pessimistic scenarios were evaluated under optimistic scenarios and vice versa). Figure 7 shows the temperature projections used in each of the two training sets.

To analyze the relative performance of model under these two framings, we performed a DU reevaluation and robustness analysis. During this process, the optimized portfolios undergo a stress testing against the out of sample set of deeply uncertain SOWs. These SOWs utilize the temperature projections of the rival framing, as depicted in Fig. 7.

In the DU reevaluation phase, the performance of candidate policies is evaluated using the concept of satisficing[38,66], which measures the fraction of SOWs in which each solution meets a predetermined set of performance criteria. The satisficing score S and the satisficing test T are represented by the equation:

$$S = \frac{1}{N}\sum_{i=1}^{N} T_i \tag{3}$$

$$T(i) = \begin{cases} 1, \, if \, F(\theta) \leq \phi \\ 0, \, otherwise \end{cases} \tag{4}$$

where N is the number of SOWs, $F(\theta)$ is the calculated value for the metric under SOW i, θ is the selected solution, and ϕ is the value for performance criteria. In this study, robustness is analyzed against three separate metrics of equality (Gini index value), reliability (Maximum worse year mortality) and heat-related mortality increase. These metrics are then paired for calculating the satisficing score. Gini index in this study is calculated based on:

$$Gini\, index = \frac{\sum_{i=1}^{N_{regions}} \sum_{j=1}^{N_{regions}} |MR_i - MR_j|}{2 \times N_{regions} \times \sum_{i=1}^{N_{regions}} MR_i} \tag{5}$$

where $N_{regions}$ is the number of regions and MR is the heat related mortality rate for each region.

Given the limited application of Decision Making under Deep Uncertainty (DMDU) approaches in urban adaptation specifically for the city of Baltimore, we establish a baseline set of criteria for satisficing. These criteria are derived from extreme events observed in other urban areas: for reliability we compare the worst-case mortality with the Chicago 1995 Heat Event, and for distributional equality the Gini index value of 0.3 was chosen as the acceptable performance criterion as value below 0.3 generally points to a relatively low inequality[67,68].

Data availability

The datasets used and/or analyzed during the current study available from the corresponding author on request.

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Author contributions

A.E.: Conceptualization, Code, Visualization, writing-reviewing, and editing. B.Z.: Conceptualization. writing—reviewing and editing. B.H.: Conceptualization, Editing, reviewing. A.H.: Conceptualization, Editing, reviewing. R.H.: Conceptualization, Editing, reviewing.

Declaration

Competing interests
The authors declare no competing interests.

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Correspondence and requests for materials should be addressed to A.E.

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