

Coupled Human–Infrastructure Systems: Socio-Behavioral and Spatial Dynamics in Green Stormwater Infrastructure Adoption

KOOROSH AZIZI

`koorosh.azizi@austin.utexas.edu`

University of Texas at Austin <https://orcid.org/0000-0002-0786-7323>

Margaret Garcia

Arizona State University <https://orcid.org/0000-0002-2864-2377>

Dev Niyogi

The University of Texas at Austin

Patrick Bixler

University of Texas, Austin

Article

Keywords:

Posted Date: May 7th, 2025

DOI: <https://doi.org/10.21203/rs.3.rs-6397766/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: There is **NO** Competing Interest.

Coupled Human–Infrastructure Systems: Socio-Behavioral and Spatial Dynamics in Green Stormwater Infrastructure Adoption

Koorosh Azizi^{1*}, Margaret Garcia², Dev Niyogi^{1,3}, and R. Patrick Bixler⁴

¹Department of Earth and Planetary Sciences, Jackson School of Geosciences, The University of Texas at Austin, Austin, TX, 78712, USA

²School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ 85287, USA

³Maseeh Department of Civil, Architectural, and Environmental Engineering, Cockrell School of Engineering, The University of Texas at Austin, Austin, TX, 78712, USA

⁴LBJ School of Public Affairs, The University of Texas at Austin, Austin, TX, 78712, USA

*Corresponding author: Koorosh Azizi (koorosh.azizi@austin.utexas.edu)

Urban stormwater management faces unprecedented challenges as weather extremes and rapid urbanization intensify flood risks and overwhelm aging gray infrastructure. Green stormwater infrastructure (GSI) offers a sustainable, decentralized alternative; however, its household-level adoption is hindered by socio-behavioral barriers and is studied here. We address the socio-behavioral knowledge gap where we integrate empirical survey data, structural equation modeling (SEM), and agent-based modeling (ABM) to investigate these dynamics, taking the example of rapidly growing urban region of Austin, Texas. The analysis quantified how environmental attitudes, social capital, financial capacity, and spatial factors influence GSI adoption decisions. The resulting parameters informed an ABM that simulated neighborhood-scale diffusion, revealing that strong pro-environmental mindsets and cohesive community networks significantly boost adoption, whereas high costs and spatial limitations deter participation, generating clusters of adoption. Study findings highlight the need for targeted financial incentives to overcome behavioral and economic obstacles, thereby accelerating GSI diffusion and enhancing urban resilience against weather extremes and associated stormwater impacts.

Main

Rapid urbanization, intensified by the escalating impacts of weather extremes, is reshaping global landscapes, ecosystems, and socio-economic structures of cities¹. As urban populations grow, the need for resilient and sustainable infrastructure becomes increasingly urgent, challenging both planners and managers to balance economic, environmental, and social objectives². In this context, effective stormwater management is increasingly essential due to the expansion of impervious surfaces (e.g., roads, parking lots, and buildings) which inhibit water infiltration and drive-up overland runoff³. This intensification worsens flooding, water pollution, and the heat island effect⁴. Although traditional gray infrastructure (featuring large-scale drainage and sewer networks) has historically served as the backbone of urban stormwater management, its capacity to address evolving and spatially dispersed challenges remains limited⁵. Retrofitting or enlarging these conventional systems to accommodate growing runoff can be prohibitively expensive⁶. Consequently, practitioners are increasingly turning to nature-based solutions and integrated water management approaches that not only mitigate runoff but also foster urban livability, ecological resilience, and broader community benefits⁷.

Within this context, Green Stormwater Infrastructure (GSI) has gained attention as a promising alternative, offering both environmental and socio-economic advantages^{8,9}. GSI integrates natural processes to manage runoff, while simultaneously enhancing urban biodiversity, improving air quality, expanding urban green spaces, and promoting overall community well-being¹⁰. Despite these benefits, GSI adoption at the household level has been inconsistent, with sporadic implementation across different urban areas¹¹. This inconsistency persists even though research indicates that GSI is highly effective when implemented collectively on larger spatial scales¹². Over the past two decades, research has primarily focused on optimizing the technical aspects of GSI, such as maximizing stormwater retention and refining spatial deployment for efficiency^{13,14}. However, there remains a significant gap in translating these technical advancements into widespread household adoption^{15,16}. This underscores the critical need to explore socio-environmental factors that influence individual decision-making around GSI¹⁷.

A major barrier to GSI adoption relates to perception. Many residents perceive GSI as a large-scale, government-driven public initiative rather than a household-level solution^{18,19}. In flood-prone areas, skepticism persists that GSI—often framed around aesthetics or long-term sustainability—can meaningfully mitigate immediate flood risks²⁰. While municipalities can invest in GSI on public lands, efforts to encourage private property retrofits encounter regulatory, bureaucratic, and volunteer-related hurdles²¹. Moreover, barriers such as limited awareness, budget constraints, and a lack of coordinated outreach across government and other sectors (e.g., industrial and nonprofit) further hinder GSI's potential²⁰. Furthermore, because GSI effectiveness hinges on cumulative implementation over broader spatial scales, homeowners may view their individual contributions as negligible—thus creating a disconnect between GSI's theoretical merits and its perceived household-level relevance²².

Despite various efforts to increase GSI adoption—including community engagement practices and incentives such as technical assistance, subsidies, stormwater fee reductions, tax incentives, and rebates—participation remains low, particularly among households in disadvantaged neighborhoods²³. This low uptake is compounded by socio-cultural and institutional barriers, such as cognitive limitations (e.g., underestimating personal flood risk or misunderstanding GSI's operational benefits) and socio-institutional arrangements (e.g., fragmented agency oversight or bureaucratic processes), which underscore the need for enhanced public education and governance reforms^{8,24}. Many of these hurdles persist because trust, community capacity, and social norms significantly shape household decisions²⁵, yet current GSI scholarship often remains narrowly focused on technical cost-benefit analyses—frequently driven by extreme weather events—while neglecting the underlying social dimensions of decision-making^{26,27}. For

example, while subsidies may lower financial barriers, factors such as awareness, trust in government initiatives, and prevailing social norms play a decisive role in whether households opt to implement GSI solutions²⁸. In fact, social norms and perceived control over resources have been identified as critical determinants of residential GSI adoption, sometimes outweighing even financial incentives^{29,30}.

Recent studies emphasize that successful GSI strategies must integrate physical design with insights into social and cultural factors^{7,31}. Socio-demographic profiles, local cultural values, economic constraints, and behavioral intentions all intersect to shape the trajectory of GSI adoption³². For instance, households with higher environmental awareness or those residing in communities with strong green values are more likely to implement GSI practices³³. Theoretical frameworks like the Theory of Planned Behavior (TPB) and Social Cognitive Theory (SCT) offer valuable insights into these socio-behavioral influences^{34,35}. TPB elucidates how attitudes (individuals' positive or negative evaluations of adopting GSI), subjective norms (perceived social pressures from peers, family, and community), and perceived behavioral control (the extent to which individuals feel capable of adopting GSI, influenced by resources and knowledge) affect intentions and actions regarding GSI adoption¹⁷. SCT, on the other hand, highlights the roles of observational learning, self-efficacy (belief in one's ability to execute necessary behaviors), and social influences (the impact of social interactions and relationships) in shaping behavior³⁶. These frameworks underscore the necessity of a holistic approach to GSI promotion, integrating behavioral and social factors with technical and environmental considerations³⁷. Ignoring these factors can lead to suboptimal outcomes, where technically sound strategies fail to garner the community support necessary for successful implementation³⁸.

Another critical reason for addressing these socio-behavioral factors is the need to reduce disparities in GSI adoption across different urban contexts. Multiple spatial analyses reveal that GSI adoption is often unequally distributed, mirroring broader patterns of socio-economic and demographic disparity⁹. In response, conservation efforts and environmental planning increasingly seek to align with principles of social justice, demanding fair policy solutions that address the needs of local communities³⁹. Although federal policies like the Infrastructure Investment and Jobs Act and the Clean Water State Revolving Fund highlight equity as a core goal⁴⁰, political risk-aversion and institutional inertia continue to stymie broad GSI adoption⁴¹.

This study bridges these gaps by integrating environmental and socio-behavioral dimensions into a cohesive analytical framework^{14,42}. We employ Agent-Based Modeling (ABM) to simulate how household-level attributes, social interactions, and environmental contexts collectively influence GSI adoption⁴³. Our approach integrates quantitative modeling with qualitative insights, illuminating the interplay between technical considerations and the behavioral realities that shape urban decision-making. Specifically, our study explores several key questions: (1) How does GSI adoption evolve across distinct socio-demographic contexts over time? (2) How do spatial and neighborhood characteristics drive variability in adoption rates? (3) What are the dynamics of behavioral variables that shape the diffusion of GSI adoption? (4) What policy interventions could effectively impact household-level GSI implementation?

To address these questions, we conducted a case study in Austin, Texas, a rapidly growing city with diverse neighborhoods and significant stormwater challenges that make it an effective context for examining GSI adoption. Our methodology integrates extensive survey data and Structural Equation Modeling (SEM) to represent latent constructs (e.g., personal norms, attitudes, awareness, and social capital) that shape household decisions. In our Agent-Based Modeling (ABM) framework, both the TPB and SCT theories define behavioral rules, while SEM quantifies the relationships between observed and latent variables^{44,45}. We also incorporate economic elements, such as income-based price sensitivity¹⁹, and modelling peer effects on GSI diffusion⁴³.

Spatial Distribution and Patterns of GSI Adoption

The adoption of structural and rain-catching measures across Austin's districts demonstrates varying trajectories influenced by socio-demographic, physical, and social factors (Fig. 1a and 1c). We note adoption rates vary in different regions ranging from 1% to 6% for structural practices and 5% to 15% for rain-catching practices. Structural GSI practices, requiring higher investments and significant yard modifications, display a smaller growth trajectory but overall rise to around 3% by the simulation's end, with variability across districts gradually increasing. District ranks show initial volatility before stabilizing, with District 6 consistently performing best and District 4 notably improving after mid-simulation. On the other hand, rain-catching practices exhibit higher overall adoption, stabilizing around a 10% mean adoption rate with higher variability. Rankings fluctuate significantly at early stages but stabilize later, with District 6 maintaining a consistently high rank followed by Districts 10 and 8.

In terms of spatial heterogeneity (Fig. 2), western Austin exhibits notably higher adoption rates for both structural and rain-catching practices. Districts 5, 6, 8, and 7 show above-average increases in each measure, likely due to mixed land uses and moderate to high housing densities that facilitate social interactions. Moreover, favorable socio-demographic factors—such as higher income levels, greater educational attainment, and stronger social capital (See Table S3 in Supplementary Materials for further details)—tend to boost latent variables like awareness, attitudes, and personal norms, further reinforcing GSI propensity. In contrast, the eastern side exhibits lower adoption rates, mostly below average for both practices (Districts 1 and 2, Fig. 2c). These areas typically have larger lot sizes and lower housing densities, limiting social interactions due to greater distances between homes. This reduction weakens social influence on GSI adoption. Additionally, larger properties often already include ample green spaces or have less impervious surface coverage, diminishing the perceived need for additional GSI practices. Socio-demographic factors further hinder adoption in these areas. Lower income and education levels, combined with lower social capital and a higher percentage of communities of color, are compounded with financial barriers and limited access to supportive networks. Consequently, these challenges limit the impactful improvement in behavioral dynamics, reducing the likelihood of adopting cost-intensive structural GSI practices. The interplay between a less suitable built environment and socio-demographic obstacles contributes to the lower adoption rates observed.

Some districts also display distinctive adoption patterns linked to their built environment. For instance, Districts 10 and 8 see large increases in rain-catching measures but only moderate growth in structural practices. This may be due to yard-space limitations or other physical barriers that make structural changes harder. While income levels in these areas are high enough to support the adoption of lower-cost rain-catching systems, they may not be sufficient—or residents may be less willing—to cover the higher costs of structural GSI. Meanwhile, District 9, located downtown, is characterized by multi-family buildings and minimal yard space, limiting opportunities for GSI installations unless done by the city programs or by the homeowner associations.

Behavioral Dynamics and Latent Variables

Interpreting the dynamics of latent variables (attitudes, awareness, personal norms, and social capital) is challenging due to the large, and varying, number of agents within each district or census tract. Statistical measures across such samples tend to converge toward mean values, confounding subtle differences and making it difficult to discern. Consequently, the analysis next focuses specifically on households that have adopted GSI. Overall, as GSI adoption increases across all districts, a positive feedback loop emerges. However, the intensity of this feedback varies according to the initial latent variable conditions,

socioeconomic characteristics, and environmental context. We observe broadly similar behavioral patterns for structural and rain-catching practices across most variables, with the notable exception of awareness (Fig. 3).

Attitudes among adopters gradually increase and reach a steady state approximately halfway through the simulation (which consists of 40 cycles, each representing six months), coinciding with the period when adoption growth slows down (Figs. 3a and 3b). This suggests that positive attitudes stabilize at a point where additional growth in attitude provides diminishing returns for adoption rates. The rise in attitudes correlates with early increases in both awareness and personal norms. Personal norms exhibit a sharp initial increase due to the rapid adoption uptake, followed by a slight decrease before settling into a steady state (Figs. 3e and 3f). This stabilization likely occurs as pro-environmental behaviors become socially normative following initial adoption by innovators. Awareness dynamics differ somewhat between practices. For structural practices, adopters' awareness increases in early steps before plateauing around step 15 (Fig. 3c). On the other hand, awareness levels for rain-catching practices show less variation over time, reflecting possibly higher baseline awareness at the simulation's start (Fig. 3d). Social capital among adopters gradually increases throughout the simulation, aligning with expectations of higher adoption rates facilitating improved knowledge sharing and social connectivity (Figs. 3g and 3h). However, the magnitude of this growth depends heavily on initial conditions and how adoption diffusion unfolds. For instance, in districts such as District 2, lower adoption growth correlates with initially lower social capital and weaker networks. Despite these areas having higher baseline personal norms, relatively positive attitudes, and sufficient awareness, the diffusion rate is hindered by combined socioeconomic and built environment constraints, including economic challenges, higher density, and larger lot sizes.

Demographic Outcomes

Building on the temporal dynamics shaped by socio-demographic factors, the simulation results (Fig. 4) demonstrate how income, education, and demographic subgroups (i.e., race/ethnicity) intersect to influence GSI adoption trajectories across different socio-geographic areas, raising questions related to the socio-spatial patterns of adoption. Census tracts with median household incomes below \$50 k typically exhibit very low structural GSI adoption; as median income surpasses \$50 k (vertical dashed line), adoption increases to around 5–6%. Although rain-catching practices—being less capital-intensive—can reach higher adoption rates (often above 12% in well-resourced districts), lower-income tracts still remain closer to 5–8%.

Meanwhile, predominantly nonwhite districts consistently report lower adoption rates than comparable white-majority areas, both for structural GSI (e.g., 1–3% vs. 5–6%) and rain-catching (6–10% vs. 12–16%). Educational attainment further amplifies these disparities: where a greater proportion of residents hold bachelor's degrees or higher, both structural and rain-catching GSI achieve the upper ends of their respective ranges. Conversely, lower education levels correlate with reduced adoption. Taken together, the intersections of income with demographic subgroups, education with income, and demographic subgroups with education highlight the persistent influence of socio-demographic variables on GSI uptake. Without targeted policy interventions to address cost barriers, outreach deficits, and financing inequities, lower-income, predominantly nonwhite communities with lower education levels risk being excluded from the benefits of green infrastructure.

Discussion

Our simulation underscores the pivotal role of latent behavioral variables—attitudes, awareness, personal norms, and social capital—in driving the adoption of GSI practices. These variables are not static; they evolve over time through social interactions and internal feedback mechanisms. The results demonstrate that households with initially high positive attitudes and strong environmental awareness are more inclined to adopt GSI practices. This inclination is reinforced by positive feedback loops whereby early adoption enhances social influence, further improving community attitudes and norms. However, the evolution of these latent variables is sensitive to social dynamics. In areas with strong social networks, the diffusion of information and normative pressures amplifies these feedback loops, leading to higher adoption rates. In contrast, weaker social cohesion and limited reinforcing interactions can constrain the diffusion and growth of positive attitudes—even when environmental awareness is initially high. Consequently, non-adopting households exhibit stagnant or fluctuating patterns in their latent variables, failing to benefit from the social reinforcement that drives adoption.

Despite these positive behavioral drivers, financial constraints emerge as a significant barrier that can override the benefits of strong environmental awareness and favorable attitudes. The simulation indicates that even in areas where households demonstrate robust pro-environmental behaviors, the costs associated with implementing GSI practices can deter adoption. For example, households with high initial positive attitudes toward GSI but located in low-income regions did not achieve the same adoption rates as their higher-income counterparts. This dynamic shows that financial limitations not only impede the translation of positive attitudes into action but can also initiate negative feedback loops. Socio-demographic factors such as race/ethnicity, income, and education intensify these dynamics, creating inequities in GSI adoption and uneven distribution of environmental benefits^{46–48}.

With the urgency around sustainable development, transitioning to sustainable solutions like GSI requires us not only to understand these practices but also to prioritize and implement them effectively. Although the technical expertise for sustainable transitions is available, the real challenge lies in mobilizing public actors and individuals. The question remains: how do we advance systems toward a more sustainable state while aligning with broader objectives within interconnected, multi-layered systems? Striking a balance between, what can be often times conflicting goals (such as between efficiency and fairness) demands careful negotiation of trade-offs, resilience to resource constraints, and an adaptable approach that supports both immediate needs and long-term sustainability⁴⁹.

Our study's findings have significant implications for urban water management strategies and policy development. The simulation results highlight that financial constraints can negate the positive effects of pro-environmental attitudes and awareness, underscoring the need to integrate economic support mechanisms into GSI promotion efforts⁵⁰. Policies that provide financial assistance—such as subsidies, rebates, or low-interest loans—can strategically target areas where residents already exhibit high initial attitudes and personal norms but are hindered by economic barriers. This approach has the potential to maximize intervention outcomes by preventing the onset of negative feedback loops driven by financial limitations. Moreover, our simulation provides estimates of population segments requiring varying levels of financial assistance, ranging from full (100%) to partial (50% or 25%) subsidies, or even no support for installation costs. This analysis can inform the allocation of fixed budgets to maximize overall adoption rates, taking into account the interplay between social influence and financial barriers. Policymakers can use these insights to design tiered financial support programs that distribute resources for optimal impact—for instance, offering more substantial subsidies in areas with greater economic need while providing smaller incentives elsewhere.

For example, historically under-resourced communities, particularly those with lower incomes and higher percentages of minority populations, face greater barriers to GSI adoption. By aligning cost-effective strategies with the distribution of financial assistance to priority communities – a trade-off approach that weighs efficiency against fairness – ensures that the benefits of GSI are accessible to all.

Finally, the importance of fostering and maintaining strong social networks is evident in our findings, as higher social capital correlates with increased GSI adoption. In areas where social capital is lower, targeted programs can strengthen community ties through neighborhood GSI workshops, community-led projects, and platforms for sharing success stories. Such initiatives not only enhance social influence but also sustain the positive feedback mechanisms essential for widespread adoption by increasing awareness, improving attitudes, and reinforcing personal norms. While education and awareness campaigns remain critical, they must be coupled with practical support to translate positive attitudes into action. Tailored messaging that addresses cost concerns and provides information on available financial assistance can be particularly effective in areas with lower initial awareness. Involving community leaders and leveraging existing social structures can further enhance the reach and impact of these campaigns, ultimately driving higher GSI adoption rates. Moreover, the benefits of strengthened social networks and increased civic engagement can extend beyond GSI, supporting broader community resilience and collective capacity to address other environmental and social challenges.

Our methodology simplifies the representation of the built environment by abstracting complex hydrological dimensions and stormwater risk associations into generalized spatial factors. In this approach, potential single-family households are identified through basic filtering of parcel and building sizes, though refining this initialization could enhance accuracy. The spatial grid, while computationally efficient, does not fully capture real-world complexities; accurately positioning agents would increase computational demands and require sensitive data.

Data limitations also constrained our ability to differentiate between specific rain-catching and structural GSI measures, leading to a collective representation that may obscure distinct socio-behavioral drivers. Socio-demographic and latent variables were assigned based on census tract distributions rather than through more robust Bayesian methods, and our assumption of no initial GSI adoption—addressed via adjusted thresholds—may not accurately reflect baseline conditions. Calibration based on plan-to-action survey data lacked precise temporal alignment with real-world adoption cycles.

Despite these limitations, the study contributes to the literature by integrating socio-behavioral insights with technical considerations to inform sustainable urban stormwater management and by clarifying how targeted interventions can overcome both financial and socio-cultural barriers, emphasizing the role of neighborhood-level interactions and economic mechanisms (e.g., tiered subsidies) in facilitating equitable GSI adoption.

In conclusion, this study provides an in-depth analysis of the complex interplay between socio-behavioral factors, economic constraints, and spatial characteristics influencing the adoption of Green Stormwater Infrastructure (GSI) at the household level. By integrating empirical data into an ABM framework, we have illuminated how internal behavioral characteristics and socio-demographic factors converge to shape GSI adoption patterns. The findings reveal that while positive attitudes and environmental awareness are crucial drivers, financial barriers can negate these advantages, leading to negative feedback loops that hinder widespread adoption.

References

1. Fowler, H. J., Wasko, C. & Prein, A. F. Intensification of short-duration rainfall extremes and implications for flood risk: current state of the art and future directions. *Philos Trans A Math Phys Eng Sci* 379, 20190541 (2021).
2. Dhakal, K. P. & Chevalier, L. R. Urban Stormwater Governance: The Need for a Paradigm Shift. *Environ Manage* 57, 1112–1124 (2016).
3. Fletcher, T. D. *et al.* SUDS, LID, BMPs, WSUD and more – The evolution and application of terminology surrounding urban drainage. *Urban Water J* 12, 525–542 (2015).
4. Shandas, V., Matsler, A. M., Caughman, L. & Harris, A. Towards the implementation of green stormwater infrastructure: perspectives from municipal managers in the Pacific Northwest. *Journal of Environmental Planning and Management* 63, 959–980 (2020).
5. Cousins, J. J. & Hill, D. T. Green infrastructure, stormwater, and the financialization of municipal environmental governance. *Journal of Environmental Policy & Planning* 23, 581–598 (2021).
6. Shrestha, A. & Garcia, M. Influence of Precipitation Uncertainty and Land Use Change on the Optimal Catchment Scale Configuration of Green Stormwater Infrastructure. *J Sustain Water Built Environ* 9, 04023001 (2023).
7. Novaes, C. A. & Marques, R. C. Institutional paradigm shift: transitions in stormwater management principles. *Environ Sci Pollut Res Int* 30, 17179–17192 (2023).
8. Jezzini, Y. *et al.* Assessing the Costs and Benefits of Green Infrastructure Plans Using Agent-Based Modeling and Scenario Analysis: Evaluating Social and Economic Values. *J Urban Plan Dev* 150, 04024050 (2024).
9. Mandarano, L. & Meenar, M. Equitable distribution of green stormwater infrastructure: a capacity-based framework for implementation in disadvantaged communities. *Local Environ* 22, 1338–1357 (2017).
10. Wang, M., Sun, C. & Zhang, D. Opportunities and challenges in green stormwater infrastructure (GSI): A comprehensive and bibliometric review of ecosystem services from 2000 to 2021. *Environ Res* 236, (2023).
11. Ureta, J., Motallebi, M., Scaroni, A. E., Lovelace, S. & Ureta, J. C. Understanding the public's behavior in adopting green stormwater infrastructure. *Sustain Cities Soc* 69, 102815 (2021).
12. Golden, H. E. & Hoghooghi, N. Green infrastructure and its catchment-scale effects: an emerging science. *Wiley Interdisciplinary Reviews: Water* 5, e1254 (2018).
13. Jia, Z., Tang, S., Luo, W., Li, S. & Zhou, M. Small scale green infrastructure design to meet different urban hydrological criteria. *J Environ Manage* 171, 92–100 (2016).
14. Kuller, M., Farrelly, M., Deletic, A. & Bach, P. M. Building effective Planning Support Systems for green urban water infrastructure—Practitioners' perceptions. *Environ Sci Policy* 89, 153–162 (2018).
15. Carlet, F. Understanding attitudes toward adoption of green infrastructure: A case study of US municipal officials. *Environ Sci Policy* 51, 65–76 (2015).

16. Ureta, J., Motallebi, M., Vassalos, M., Alhassan, M. & Ureta, J. C. Valuing stakeholder preferences for environmental benefits of stormwater ponds: Evidence from choice experiment. *J Environ Manage* 293, (2021).
17. Eanes, F. R. & Zhou, X. The Role of Attitudes, Social Norms, and Perceived Behavioral Control as Factors Influencing Urban and Suburban Residential Adoption of Stormwater Best Management Practices. *Environ Manage* 65, 737–747 (2020).
18. Kertesz, R., Green, O. O. & Shuster, W. D. Modeling the hydrologic and economic efficacy of stormwater utility credit programs for US single family residences. *Water Sci Technol* 70, 1746–1754 (2014).
19. Tasca, F. A., Finotti, A. R. & Goerl, R. F. A stormwater user fee model for operations and maintenance in small cities. *Water Sci Technol* 79, 278–290 (2019).
20. Meenar, M., Heckert, M. & Adlakha, D. ‘Green Enough Ain’t Good Enough:’ Public Perceptions and Emotions Related to Green Infrastructure in Environmental Justice Communities. *Int J Environ Res Public Health* 19, (2022).
21. Carlson, C., Barreteau, O., Kirshen, P. & Foltz, K. Storm Water Management as a Public Good Provision Problem: Survey to Understand Perspectives of Low-Impact Development for Urban Storm Water Management Practices under Climate Change. *J Water Resour Plan Manag* 141, 04014080 (2015).
22. Qi, J. & Barclay, N. Addressing the social barriers to green stormwater infrastructure in residential areas from a socio-ecological perspective. *J Environ Manage* 313, (2022).
23. Rogers, E. M., Singhal, A. & Quinlan, M. M. Diffusion of Innovations. *An Integrated Approach to Communication Theory and Research* 432–448 (2014) doi:10.4324/9780203887011-36.
24. Qiao, X. J., Kristoffersson, A. & Randrup, T. B. Challenges to implementing urban sustainable stormwater management from a governance perspective: A literature review. *J Clean Prod* 196, 943–952 (2018).
25. Chaffin, B. C. *et al.* A tale of two rain gardens: Barriers and bridges to adaptive management of urban stormwater in Cleveland, Ohio. *J Environ Manage* 183, 431–441 (2016).
26. Kamanmalek, S. & Alamdari, N. Advancing equitable stormwater management: A decision support tool integrating best practices for nutrient removal and environmental justice. *Ecol Inform* 80, 102496 (2024).
27. Liu, W., Chen, W., Feng, Q., Peng, C. & Kang, P. Cost-Benefit Analysis of Green Infrastructures on Community Stormwater Reduction and Utilization: A Case of Beijing, China. *Environ Manage* 58, 1015–1026 (2016).
28. Chaffin, B. C., Gosnell, H. & Cosens, B. A. A decade of adaptive governance scholarship: synthesis and future directions. 19, (2014).
29. Le, T., Kyle, G. T. & Tran, T. Determining social-psychological drivers of Texas Gulf Coast homeowners’ intention to implement private green infrastructure practices. *J Environ Psychol* 90, 102090 (2023).
30. Shi, C. *et al.* Exploring public attitudes toward implementing green infrastructure for sponge city stormwater management. *Scientific Reports* 2024 14:1 14, 1–16 (2024).

31. Wilfong, M. & Pavao-Zuckerman, M. Rethinking Stormwater: Analysis Using the Hydrosocial Cycle. *Water* 2020, Vol. 12, Page 1273 12, 1273 (2020).
32. Gao, Y., Church, S. P., Peel, S. & Prokopy, L. S. Public perception towards river and water conservation practices: Opportunities for implementing urban stormwater management practices. *J Environ Manage* 223, 478–488 (2018).
33. Berland, A. *et al.* The role of trees in urban stormwater management. *Landsc Urban Plan* 162, 167–177 (2017).
34. Ajzen, I. The theory of planned behavior. *Organ Behav Hum Decis Process* 50, 179–211 (1991).
35. Bandura, A. Social Foundations of Thought and Action. *The Health Psychology Reader* 94–106 (1986) doi:10.4135/9781446221129.N6.
36. Anzola, D. The Theory-Practice Gap in the Evaluation of Agent-Based Social Simulations. *Sci Context* 34, 393–410 (2021).
37. Dogmusoz, B. B., Tekbudak, M. Y. & Rice, A. The factors affecting residents' willingness to implement green infrastructure strategies on their property. *Journal of Green Building* 18, 17–35 (2023).
38. Pons, V. *et al.* Practice makes the model: A critical review of stormwater green infrastructure modelling practice. *Water Res* 236, (2023).
39. Langenheim, N. & White, M. Green Infrastructure and Urban-Renewal Simulation for Street Tree Design Decision-Making: Moderating Demands of Stormwater Management, Sunlight and Visual Aesthetics. *Int J Environ Res Public Health* 19, (2022).
40. Moravej, M. *et al.* Transitions to Sustainable Urban Water Systems. 57–77 (2025) doi:10.1007/978-981-97-7671-9_3.
41. Dhakal, K. P. & Chevalier, L. R. Managing urban stormwater for urban sustainability: Barriers and policy solutions for green infrastructure application. *J Environ Manage* 203, 171–181 (2017).
42. Zellner, M. L. Embracing Complexity and Uncertainty: The Potential of Agent-Based Modeling for Environmental Planning and Policy. *Planning Theory & Practice* 9, 437–457 (2008).
43. Brown, S., Ferreira, C., Houck, M. & Liner, B. Conceptual ex ante simulation for Green Stormwater Infrastructure Adoption on private property using agent-based modeling. *Water Environment Research* 93, 2648–2669 (2021).
44. Ullman, J. B. & Bentler, P. M. Structural Equation Modeling. *Handbook of Psychology, Second Edition* (2012) doi:10.1002/9781118133880.HOP202023.
45. Schubring, S., Lorscheid, I., Meyer, M. & Ringle, C. M. The PLS agent: Predictive modeling with PLS-SEM and agent-based simulation. *J Bus Res* 69, 4604–4612 (2016).
46. Anguelovski, I., Connolly, J. & Brand, A. L. From landscapes of utopia to the margins of the green urban life. *City* 22, 417–436 (2018).
47. Prudencio, L. & Null, S. E. Stormwater management and ecosystem services: a review. *Environmental Research Letters* 13, 033002 (2018).
48. Djalante, R., Holley, C., Thomalla, F. & Carnegie, M. Pathways for adaptive and integrated disaster resilience. *Natural Hazards* 69, 2105–2135 (2013).

49. Ahern, J. From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world. *Landsc Urban Plan* 100, 341–343 (2011).
50. Mandarano, L. & Meenar, M. Equitable distribution of green stormwater infrastructure: a capacity-based framework for implementation in disadvantaged communities. *Local Environ* 22, 1338–1357 (2017).

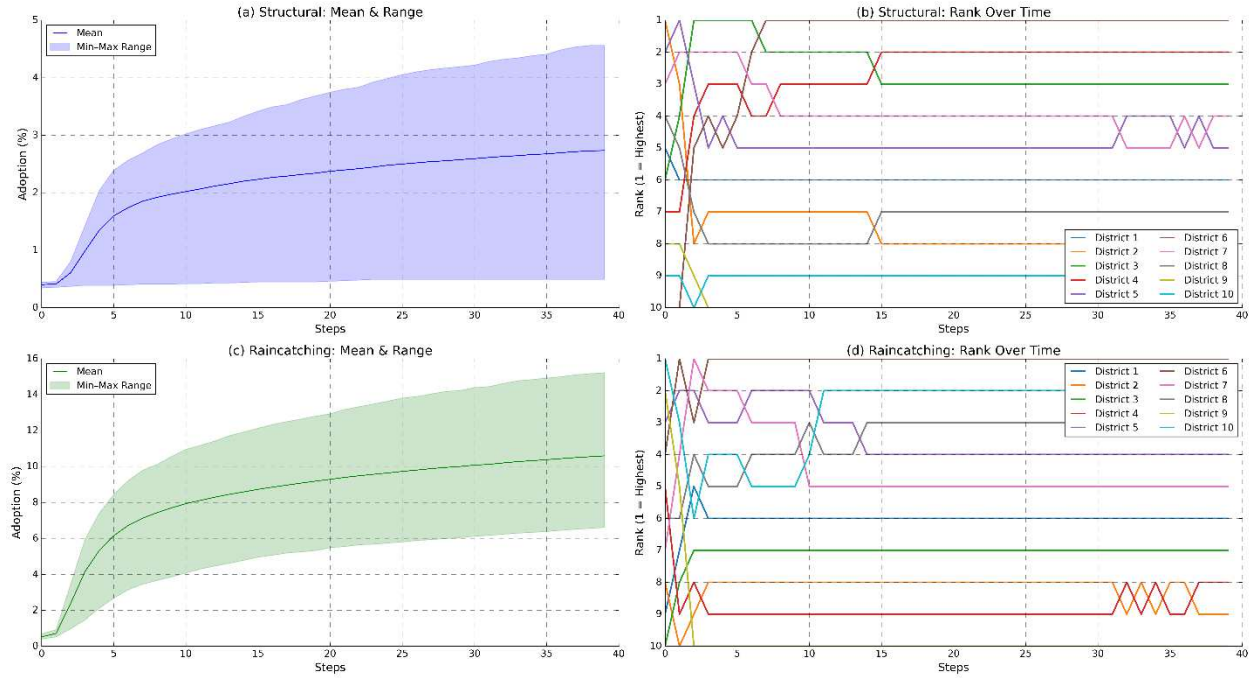


Fig. 1 | Time-series plots of GSI adoption for structural and rain-catching measures. Panels (a) and (c) illustrate the mean adoption rates (solid lines) and their corresponding min–max district adoption percentage ranges (shaded areas) for structural and rain-catching practices, respectively, aggregated across all districts over the simulation steps. Panels (b) and (d) depict the district rankings for structural and rain-catching practices, respectively, displayed as a bump plot, with the x-axis representing time steps and the y-axis indicating district rank.

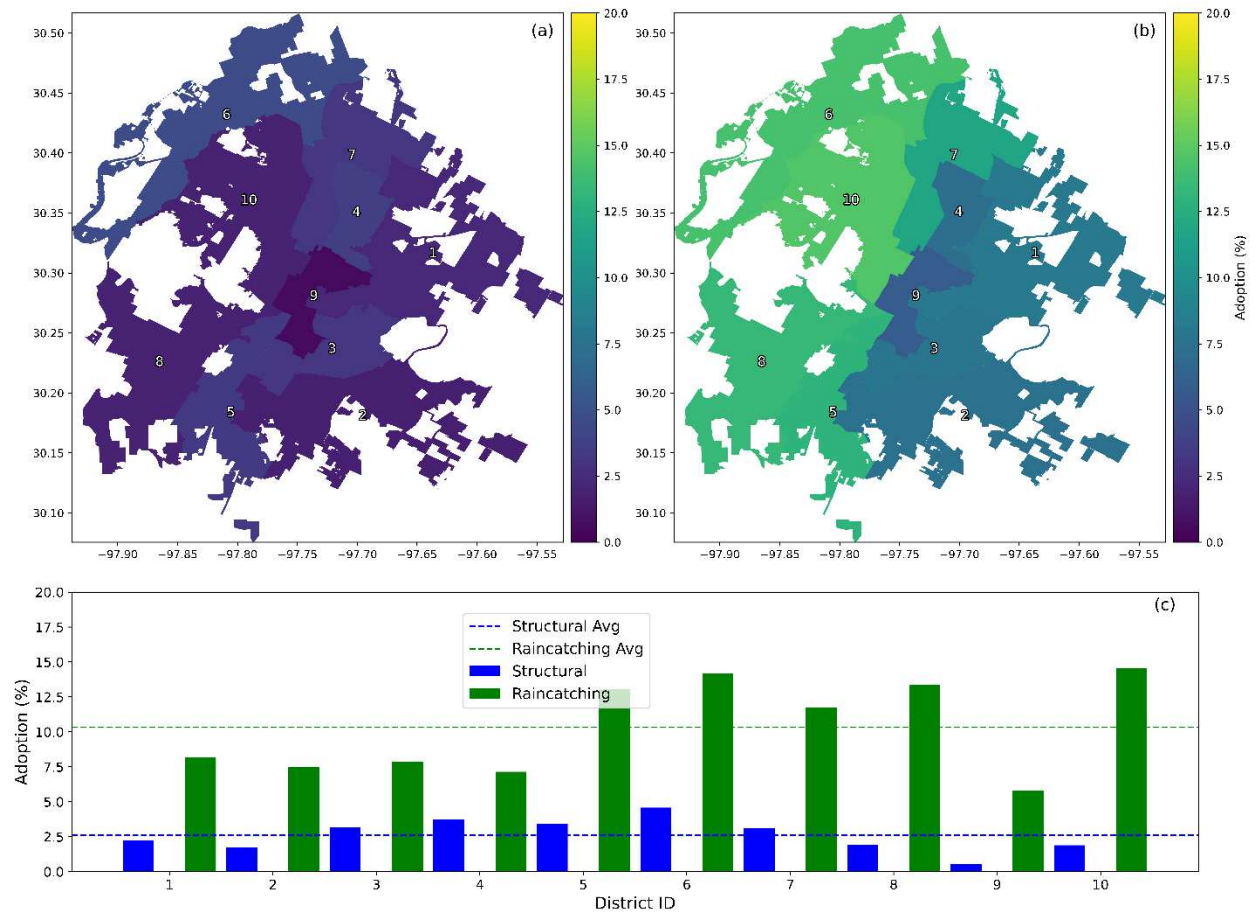


Fig 2 | Spatial distribution of GSI adoption at the district level. Panels (a) and (b) illustrate the percentage of single-family households that adopted structural and rain-catching practices, respectively, in the final step of the simulation. These maps provide a detailed view of the spatial patterns of adoption across the city. Panel (c) quantifies the adoption rates for each district and compares them with the citywide averages (indicated by the dotted lines).

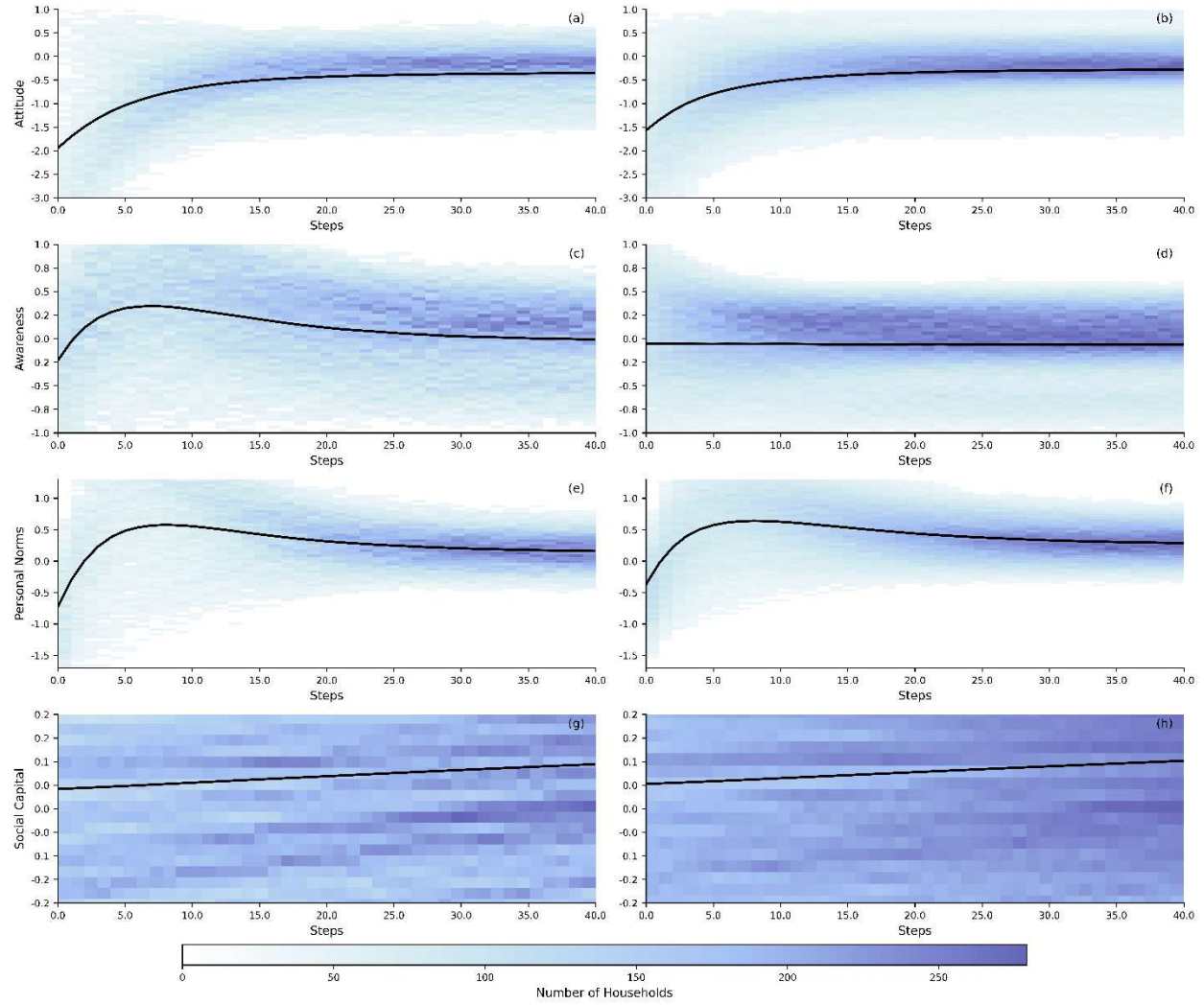


Fig. 3 | Dynamics of latent variables among final adopters for structural (left column) and rain-catching (right column) GSI practices. Panels (a) and (b) illustrate the evolution of attitudes, (c) and (d) show awareness, (e) and (f) depict personal norms, and (g) and (h) present social capital. In each subplot, the heatmap indicates the density of each latent variable's values over the simulation steps, with darker shades representing higher density. The black line shows the mean trajectory over time. This visualization highlights how attitudes, personal norms, awareness, and social capital evolve and eventually stabilize as GSI adoption proceeds, revealing variations in the feedback dynamics between structural and rain-catching practices.

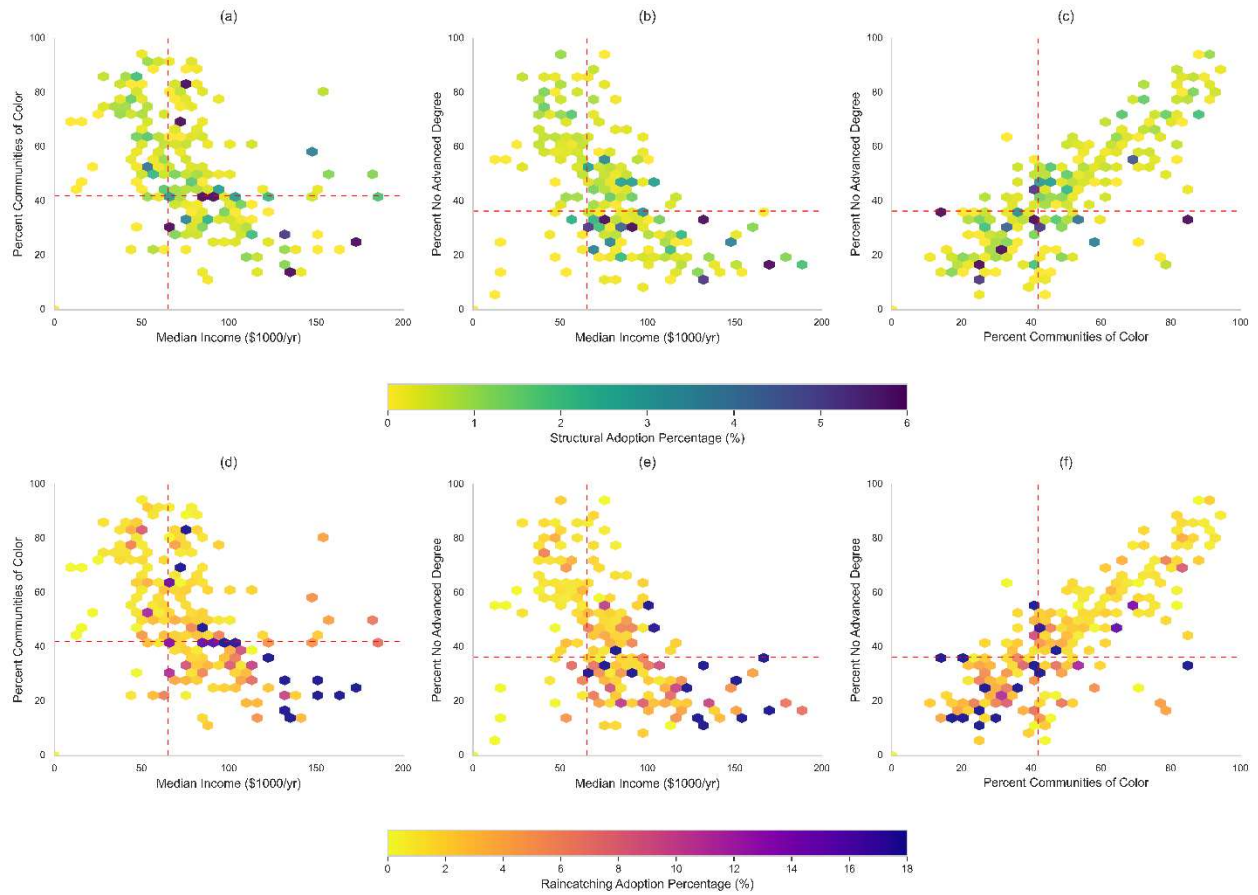


Fig. 4 | Socio-demographic influences on GSI adoption. The top row (Panels (a), (b), and (c)) illustrates structural GSI adoption percentages, and the bottom row (Panels (d), (e), and (f)) depicts rain-catching GSI adoption percentages. Each panel shows a pair of socio-demographic variables—median household income, percentage of communities of color, and percentage of residents without advanced degrees—on the x- and y-axes. The hexagonal bins represent census tracts plotted by these socio-demographic characteristics, with the color scale indicating the mean adoption rate in each bin. Red dashed lines mark average values for the corresponding axes, highlighting how adoption levels vary relative to citywide means. By intersecting income, race, and educational attainment against structural and rain-catching adoption, this figure reveals clear disparities in GSI uptake.

Methods

Empirical Data Collection and Processing

Our modeling framework for understanding Green Stormwater Infrastructure (GSI) adoption draws on multiple empirical sources and comprehensive statistical analyses, enabling both citywide coverage and nuanced representation of household decision-making. We began with a household survey in Austin, Texas, which was designed through mixed methods to capture diverse demographic, economic, and behavioral profiles. Random postcard invitations and targeted outreach in underrepresented communities yielded 592 valid responses. To preserve data integrity and avoid bias from missing entries, we applied Bayesian multiple imputation (see Supplementary Material), ensuring that partially completed surveys were still usable. Our survey instrument included questions on socio-demographic characteristics (e.g., income, education, race/ethnicity), as well as sets of Likert-scale items measuring latent behavioral constructs: Attitudes toward stormwater management, Awareness of water issues, Personal Norms regarding environmental responsibility, and Social Capital reflecting neighborhood networks. We verified that these items reliably captured each construct via factor analysis and confirmatory modeling, providing each respondent with scores on these latent variables.

To complement survey results, we obtained census data from the American Community Survey (ACS) to align our synthetic population with the real-world distribution of household attributes. Using census tract-level ACS 5-year estimates for income, demographic subgroup, and education levels, we constructed probability distributions from which synthetic households were sampled. Because incomes are typically right-skewed, log-normal curves were fitted to ACS income brackets, ensuring that randomly generated household incomes resembled local economic patterns. Similarly, demographic and education attributes were assigned to agents based on tract-specific proportions, so that aggregate synthetic demographics match observed values. When integrating the smaller survey sample, which did not represent every tract proportionally, we aggregated respondents at the City Council District level and drew from those district-level distributions to assign latent behavioral scores (see Supplementary Material).

We also integrated parcel-level spatial data from the City of Austin's GIS layers, focusing on single-family properties where individual households directly influence GSI adoption. By intersecting parcel shapefiles with building footprints, we calculated each lot's total area and building footprint, helping to determine physical feasibility for GSI measures. We filtered out multi-family or outlier parcels based on lot and building sizes, leaving a sample more consistent with typical single-family residential contexts. Using this spatial information, we computed site-specific indices to estimate each household's potential for different GSI practices—such as how much roof area is available for a rain barrel or cistern, or how much yard space might accommodate a rain garden or slope modifications.

Our survey captured both present and future adoption behavior by asking respondents about any GSI practices they already use and whether they plan to adopt them moving forward. These details of self-reported data helped us identify households at different stages of the adoption process. We explicitly tracked six GSI practices, divided into two categories:

- Rain-catching practices: Rain Barrel, Cistern, and Rain Garden
- Structural practices: Yard Slope Modification, Yard Vegetation Change, and Irrigation Reduction

Cost estimates were combined with perceived importance values from scenario-based survey questions, which varied potential rebate levels (e.g., 100%, 50%, 25%, or no subsidy) to assess how financial incentives might influence adoption decisions. From these analyses, we derived a Financial Constraint Index that measures the extent to which a household depends on subsidies to finance GSI installations—a

higher index indicates greater reliance on external support, while a lower index suggests the ability to self-finance installations.

To integrate and interpret these variables, we employed several analytical methods (see Supplementary materials for further details). First, we used structural equation modeling (SEM) to confirm that each set of latent factors—Attitude, Awareness, Personal Norms, Social Capital—exhibited strong internal consistency and significantly correlated with GSI adoption intentions. The SEM also helped quantify how these factors interrelate (e.g., whether high social capital reinforces awareness). Next, we constructed multiple linear regression models to estimate household-level adoption propensity for structural GSI and for rain-catching GSI, based on both socio-demographic predictors and the latent behavior factors' value. The resulting regression coefficients yielded formulae that compute a baseline GSI adoption likelihood for any combination of household attributes, ensuring that, for example, higher-income or more environmentally oriented households receive correspondingly higher propensity to adopt.

During model initialization, each household in Austin is assigned its demographic attributes through Monte Carlo draws from the census-based distributions and is given a corresponding set of latent behavior variables value. We then combine these attributes and the regression-based propensity scores to determine whether a given practice (e.g., rein-catching or structural) is feasible and attractive. If the physical capacity index and the household's baseline interest are sufficiently high—adjusted by any financial constraints—then that agent is more likely to adopt the practice in the model's early stages. Over time, household decisions can also shift as they gain awareness or observe peers. At the city scale, aggregating these individual adoption trajectories allows us to capture potential spatial and socio-demographic patterns.

Finally, to validate this integrated dataset, we compared synthetic households' aggregated profiles against observed census benchmarks for income, demographic, and education distributions. We also checked alignment between district-level average latent factor scores among our modeled agents and the survey's actual district-level means; minor discrepancies were within acceptable sampling variability (see Supplementary Material). The result is a coherent, citywide dataset in which each household agent has realistic demographic, spatial, behavioral, and financial characteristics, all consistent with empirical evidence. This thorough integration of data sources—survey responses, ACS statistics, GIS parcels, and adoption trajectories—provides the robust empirical foundation needed to simulate how financial incentives, social factors, and property characteristics collectively shape GSI adoption in Austin.

Agent-Based Modeling Framework

GSI adoption can be viewed as a dynamic socio-behavioral, economic, and environmental process unfolding over time and space. An ABM is used to simulate this process by representing individual households as autonomous decision-making agents and modeling their interactions. By capturing heterogeneity among households and the influence they exert on one another, the ABM produces emergent patterns of GSI adoption at the neighborhood scale. This bottom-up approach enables exploration of how local decisions aggregate into citywide diffusion trends, often yielding the characteristic S-shaped adoption curve of innovations (slow start, rapid growth, plateau). The model is empirically grounded with real-world data (survey responses, census statistics, GIS layers) and behavioral theory, allowing it to account for both quantitative factors (e.g. income, parcel size) and qualitative drivers (e.g. social norms, perceived benefits).

Our ABM consists of four major components that together simulate the GSI adoption process (Extended Data Fig. 1). These components are:

- **Household Agents:** Individual households characterized by socio-demographic profiles, property attributes, and behavioral traits.
- **Social Interactions:** Network mechanisms through which agents influence each other via local neighbors and broader community ties.
- **Behavioral Evolution:** Dynamic updates of each agent’s attitudes, awareness, norms, and social capital over time through self-reflection and social influence.
- **Adoption Decision Rules:** Criteria and thresholds that determine if and when a household implements a GSI practice, given its constraints.

Each component is described in detail below, along with how they interconnect to model the adoption process.

Household Agent Design

Household agents are assigned static socio-demographic variables, property characteristics, and dynamic latent behavioral attributes. Static attributes include income bracket, ethnicity, educational attainment, and a property “potential” index(P_i) for installing structural or rain-catching GSI. The potential index captures parcel-level feasibility, such as roof size for rainwater storage or yard area. Latent behavioral attributes are drawn from survey-derived distributions of Attitude (At), Awareness (Aw), Personal Norms (Pn), and Social Capital (Sc).

From these attributes, each agent’s baseline propensity to adopt GSI is quantified by behavior scores for two categories of practices: (1) structural measures and (2) rain-catching measures. We compute these scores using equations below, calibrated on the survey data (further details in Supplementary Materials).

$$B_{s,i}^0 = (1.51 - 0.45 \times I(\text{Demographic subgroup}_i = \text{NonWhite}) + \beta_{\text{IncomeB}}(\text{IncomeB}) \\ - 0.16 \times I(\text{Education}_i = \text{NoAdvDegree}) + 0.37 \times Pn_i^0 + 0.23 \times Sc_i^0 \\ - 0.02 \times At_i^0 + 0.02 \times Aw_i^0) \times P_{s,i}$$

$$B_{r,i}^0 = (0.39 - 0.18 \times I(\text{Demographic subgroup}_i = \text{NonWhite}) + \beta_{\text{IncomeB}}(\text{IncomeB}) \\ - 0.05 \times I(\text{Education}_i = \text{NoAdvDegree}) + 0.22 \times Pn_i^0 + 0.07 \times Sc_i^0 \\ + 0.005 \times At_i^0 - 0.02 \times Aw_i^0) \times P_{r,i}$$

where Income (B refers to income bracket), Demographic Subgroup, and Education are categorical variables integrated into the regression models to influence behavior scores, with specific coefficients assigned to each category to reflect their impact on the likelihood of adopting GSI practices (Supplementary Material). The P_i is potential index for agent i , the subscript s , and r refer to structural and rain-catching, respectively. Additionally, we also assign each agent a price sensitivity factor between 0 and 1 based on their income percentile and survey responses about willingness to pay. A value of 1 indicates the household would require a full rebate to afford the GSI (high financial barrier), whereas a value of 0 indicates little to no subsidy is needed. This factor does not initially alter the behavior score but will modulate the adoption decision as is described later.

Finally, during initialization, each agent is assigned an adoption threshold that determines the level of motivation required to implement a GSI practice. This threshold reflects the agent's willingness to act. We draw thresholds from a sigmoid (S-shaped) distribution ranked by each agent’s baseline behavior scores (B_i^0) (higher baseline = lower threshold). This approach creates heterogeneity in adoption readiness: *early adopters* have low thresholds and will act with minimal prompting, whereas *late adopters* require much stronger drivers (social pressure, subsidies, etc.) to participate. This approach, grounded in Rogers’ (2003)²³ diffusion of innovations theory, ensures an initial variety in adoption resistance across the population,

helping the model produce a realistic sigmoidal adoption curve over time (few early adopters, then acceleration, then saturation). The whole process is defined using following equation.

$$\theta_i = B_{\text{base}} + \left(1 / (1 + e^{(-k(R_i - 0.5))})\right) \times B_i^0 \times (1 + 0.5(1 - R_i))$$

where θ_i is agent-specific threshold, B_{base} is the median of all B_i^0 scores, R_i is the percentile rank of agent i 's score, and k controls the steepness of the sigmoid function (further details in Supplementary Material).

Social Network and Interaction Rules

Household agents do not make decisions in isolation – they are embedded in social networks through which they influence each other's attitudes and actions. In our implementation, each agent is placed on a spatial grid that represents Austin's census tracts and distribute agents within these regions proportional to the number of households in each tract, with multiple agents potentially occupying a single grid cell in denser neighborhoods. The grid wraps toroidally (edges connect), which prevents artificial boundary effects in neighbor interactions.

Within this space, agents interact through two distinct mechanisms—Neighborhood Influence and Social Network Influence—each governed by different spatial radius to capture varying degrees of interaction. Neighborhood Influence remains localized, where each agent considers others within a fixed radius of one grid cells as its immediate neighbors. However, broader social interactions extend beyond these immediate neighbors. To account for slightly wider influence through social ties, Social Network Influence extends to a radius of three grid cells, allowing agents to interact with a larger pool of connections beyond their immediate neighborhood. Each agent's social network size is bounded by its social capital level, linking the breadth of social interactions to the agent's networking capability. Agents with high social capital maintain larger networks and therefore have greater exposure to adopting peers and more capacity to influence others.

Peer influence in the model is a function of multiple factors that determine how strongly one household affects another. We define a weighted interaction index (I_{ij}) between any two agents i and j , composed of four factors: Similarity, Spatial Proximity, Communication, and Visual cue. The Similarity component gives higher weight to interactions between agents who share socio-demographic traits (e.g., similar income or education), representing homophily. Spatial Proximity gives higher weight to neighbors that are physically closer on the grid, acknowledging that very nearby neighbors exert stronger influence than those farther away. The Communication Influence component represents social interactions such as conversations or online exchanges; it is modeled as a function of the social capital of both the influencer and the receiver, emphasizing that an agent with higher social capital (strong social networks) can more strongly sway others. Finally, Visual Influence captures observational learning – if a neighbor has visibly adopted a GSI practice (e.g., one can see a rain barrel or rain garden), that neighbor's influence on the agent is increased. These factors are combined into the interaction index, which is used each time step to update agent i 's behavioral state based on the adoption status of agent j . Importantly, in our implementation, Attitude, Awareness, and Personal Norms are updated based on interactions with broader “social network” neighbors, who contribute these four influence factors (further details in supplementary).

Social capital is conceptualized as a distinct latent variable. By treating social capital as an independent factor, the model captures the network-level dynamics that influence individual behaviors without conflating them with individual-level behavioral constructs. We incorporate two positive mechanisms for social capital growth from the interactions. First, positive reinforcement from network adopters, where the presence of adopters within an agent's social network directly increases social capital by enriching the

agent's access to resources and connections. Second, neighborhood-based feedback loops, these activate only when both the agent and its neighbors adopt GSI practices, leveraging shared traits to strengthen mutual trust and coordination. These two intersecting feedback loops ensure that agents experience both direct and indirect social capital benefits, enhancing their network connections and reinforcing positive feedback loops (Extended Data Fig. 2).

The model mitigates the influence of non-adoption by reducing the weight of non-adopters in interaction calculations, thereby minimizing negative peer pressure. Specifically, agents who have not adopted GSI contribute much less to social influence, as all influence components (e.g., similarity, communication) are assigned lower weights when interacting with a non-adopter. This ensures that agents are not strongly discouraged by others' inaction. Since GSI adoption is not a highly salient community issue, non-adoption lacks strong normative weight. This perspective aligns with a number of studies in innovation diffusion and social contagion that argue visible adoption acts as an active signal—both conveying the innovation's benefits and generating a normative pull toward adoption—whereas non-adoption (i.e., the absence of behavior) remains largely silent^{23,51,52}. Consistent with TPB and SCT, social influence is primarily shaped by the presence of a behavior rather than its absence⁵³. By downplaying the impact of non-adopters, the model prevents scenarios where hesitant neighbors indefinitely suppress adoption in their area. Instead, diffusion is driven by the presence of adopters (positive examples), while non-adoption remains a weak counterforce⁵⁴.

Behavioral Update

At each time step t , agents update their Personal Norms, Awareness, and Attitude for each behavior—structural and rain-catching—through the influence of (1) social interactions and (2) internal feedback effects among the latent variables derived from SEM relations. The update process is governed by the following equation:

$$L_{i,z,b}^t = \alpha \times L_{i,b}^{t-1} + \beta \times \left(\frac{\sum_{j \in N_i} I_{ij} \times L_{j,z,b}^{t-1}}{\sum_{j \in N_i} I_{ij}} \right) + \gamma_b \times \Delta L_{i,z,b}^t$$

where $L_{i,z,b}^t$ is the latent variable for behavior b with z explicitly representing the specific latent factor (Attitude, Awareness, or Personal Norms), α is the self-influence weigh, β is the network-influence weight, γ is the SEM influence weight scaling the internal feedback term, $\Delta L_{i,z,b}^t$ represents the net change to the latent variable due to interdependencies uncovered by SEM – essentially, how much $L_{z,b}$ should shift because other latent factors have changed, and N is the set of network connections for agent i .

In our model, SEM analysis of survey data provided path coefficients indicating, for example, how a change in social capital (Sc_i^t) could lead to a change in personal norm ($Pn_{s,i}^t$), or how increased awareness (Aw_i^t) could affect attitude (At_i^t), etc. We encode these relationships as additive adjustments each time step. In practice, for each latent variable and behavior type, there is an equation (further details in supplementary material).

We calibrate the weights α , β , and γ to ensure a balance between stability and social influence⁵⁵. In the baseline configuration, we set $\alpha = 0.85$ and $\beta = 0.15$, meaning an agent's own prior state has a large influence (85%) on its next state while network collectively has a moderate influence (15%)⁵⁶⁻⁵⁸. These values reflect the idea that attitudes and norms are generally stable but can be shifted to some extent by social interactions. However, as the overall adoption in the community increases, we gradually decay the neighbor influence weight β , representing the diminishing marginal effect of social pressure in a saturated environment. Intuitively, if most people have adopted, the incremental influence of each additional adopting

neighbor on a holdout household is smaller (because adoption is already normative). We implement this by tying β to the global adoption rate of each GSI behavior – β is high when few have adopted (neighbors are crucial to kickstart the trend) and decreases as adoption becomes widespread (late-stage adopters are less sensitive to peers). The self-influence weight α is adjusted in tandem to keep the sum $\alpha + \beta$ roughly constant, ensuring the update equation remains properly normalized.

Meanwhile, the agent’s social capital (Sc) is updated (as described earlier) in parallel each step using following equation.

$$\begin{aligned}
Sc_{i,t} = Sc_{i,t-1} + & \\
& \frac{\Delta Sc_{\text{network}}}{1 + e^{-\sum_{j \in N_i} I_{ij} \times A_j}} \times \text{network influence rate} \times \sum_{j \in N_i} I_{ij} \times A_j + \\
& \frac{\Delta Sc_{\text{neighborhood}}}{1 + e^{-\sum_{j \in \text{Neighborhood}_i} I_{ij} \times A_j}} \times \text{neighborhood influence rate} \times \sum_{j \in \text{Neighborhood}_i} I_{ij} \times A_j \\
& \times I(\text{agent has adopted any behavior})
\end{aligned}$$

Where $Sc_{i,t}$ is social capital of agent i at time t . $\Delta Sc_{\text{network}}$ captures direct contributions from network adopters. $\Delta Sc_{\text{neighborhood}}$ captures additional synergy if both the agent and neighbors adopt GSI practices. The exponential terms ($e^{-\sum_{j \in N_i} I_{ij} \times A_j}$) saturate social-capital gains when many neighbors have already adopted. I_{ij} is interaction weight between agents as calculated in previous section. A_j is the adoption state of neighbor j (1 if j has adopted; 0 otherwise). I is indicator function (1 if the agent has adopted any GSI practice; 0 otherwise).

Adoption Decision Process

Once an agent’s behavior scores (for structural and rain-catching practices) have been updated in a given time step, the model determines whether the agent will adopt any new GSI practices (Figure S3, supplementary materials). This decision-making rule accounts for financial constraints via price sensitivity, practice-specific requirements, and individual thresholds, ensuring that both personal motivation and feasibility align before an adoption occurs (further details in supplementary material).

Financial Constraints and Price Sensitivity: If an agent’s price sensitivity for a given practice is high, its effective adoption score for that practice is substantially reduced, indicating that the agent cannot proceed without subsidies (if it’s equal to 1, drop the adoption score to zero). A sensitivity of zero leaves the full behavior score intact. This mechanism ensures that households needing significant financial help do not adopt costly GSI practices prematurely, even if they are otherwise motivated.

Practice-Specific Likelihood: To compute final adoption propensity, each agent’s category-level score (structural or rain-catching) is decomposed into sub-scores for the six GSI practices, weighted by cost and complexity. More expensive practices (e.g., major yard regrading) command higher “importance” shares of the total score. Price sensitivity then partially or fully nullifies sub-scores for practices the household cannot afford. Re-summing the adjusted sub-scores produces an effective overall score, preventing lower-cost practices from inflating an agent’s adoption propensity while still leaving higher-cost measures viable if finances allow.

Suitability and Final Criteria: Lastly, two conditions must be met for adoption: (a) the adjusted score surpasses the agent's threshold, and (b) the parcel meets fundamental suitability requirements (e.g., adequate yard space). If both are satisfied, the agent adopts that practice and retains it thereafter (no "un-adoption"). Adoption is tracked cumulatively: once a household adopts at least one practice, it is no longer a complete non-adopter.

We ran the model over a 20-year horizon (40 cycles, with each cycle representing 6 months). All calibration procedures, including parameter tuning against observed adoption intentions, and one-at-a-time sensitivity testing to assess model robustness, are documented in the Supplementary Material.

Data Availability

All spatial data for the Austin area are publicly available at the City of Austin GIS Data Portal (<https://www.austintexas.gov/department/gis-data>). Map boundary shapefiles were obtained from the U.S. Census Bureau (<https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.html>). Census tract-level demographic data are available at: <https://www.census.gov>. The survey data used for reproduction, along with the extended data is available for this paper can be found in the supplementary materials.

Code availability

All codes used to analyze data and create figures will be made available on a GitHub repository once the review comments are incorporated.

References

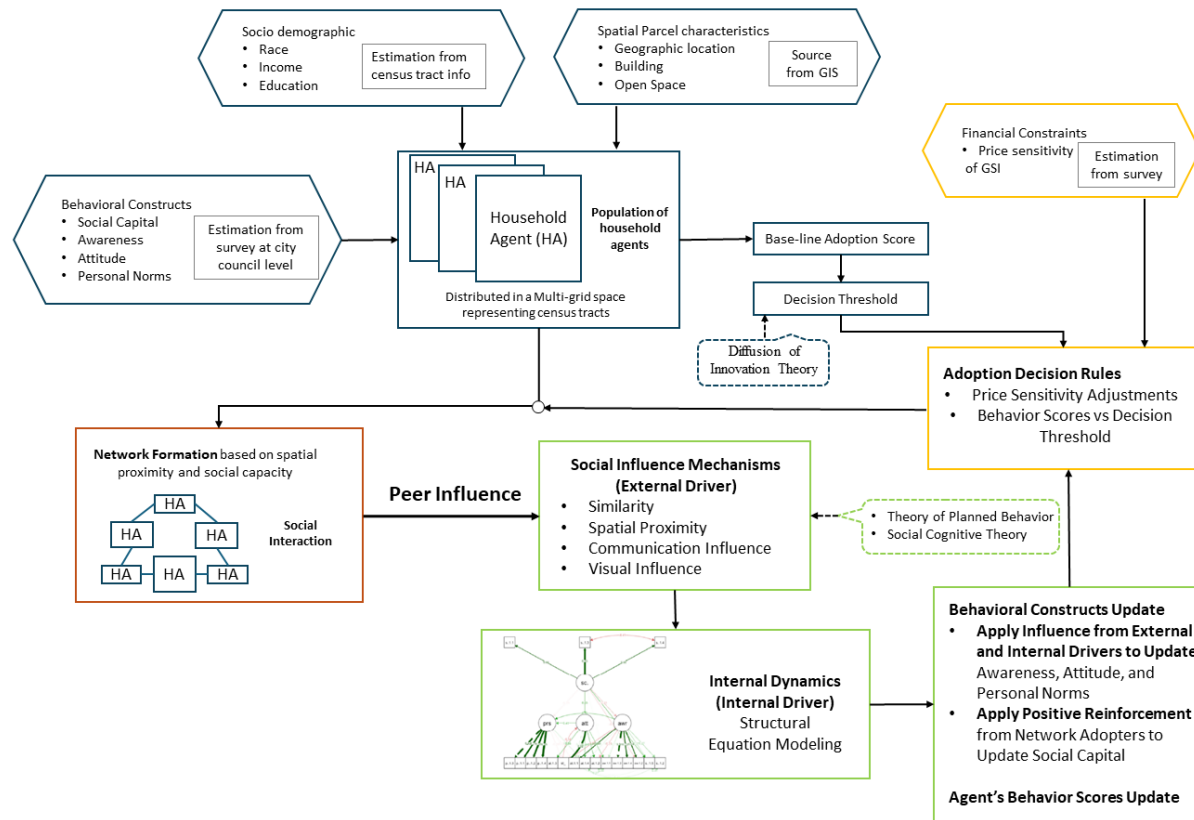
51. Stavrakas, V., Papadelis, S. & Flamos, A. An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers. *Appl Energy* 255, 113795 (2019).
52. Centola, D. & Macy, M. Complex contagions and the weakness of long ties. *American Journal of Sociology* 113, 702–734 (2007).
53. Valente, T. W. Social network thresholds in the diffusion of innovations. *Soc Networks* 18, 69–89 (1996).
54. Akhatova, A. & Kranzl, L. Agent-based modelling of building retrofit adoption in neighbourhoods. *Energy Build* 328, 115172 (2025).
55. Friedkin, N. E. & Johnsen, E. C. Social influence and opinions. *Journal of Mathematical Sociology* 15, 193–206 (1990).
56. Lorenz, J., Rauhut, H., Schweitzer, F. & Helbing, D. How social influence can undermine the wisdom of crowd effect. *Proc Natl Acad Sci U S A* 108, 9020–9025 (2011).
57. Moussaïd, M., Kämmer, J. E., Analytis, P. P. & Neth, H. Social influence and the collective dynamics of opinion formation. *PLoS One* 8, (2013).
58. Raikes, J., Henstra, D. & Thistlethwaite, J. Public Attitudes Toward Policy Instruments for Flood Risk Management. *Environ Manage* 72, 1050–1060 (2023).

Acknowledgments

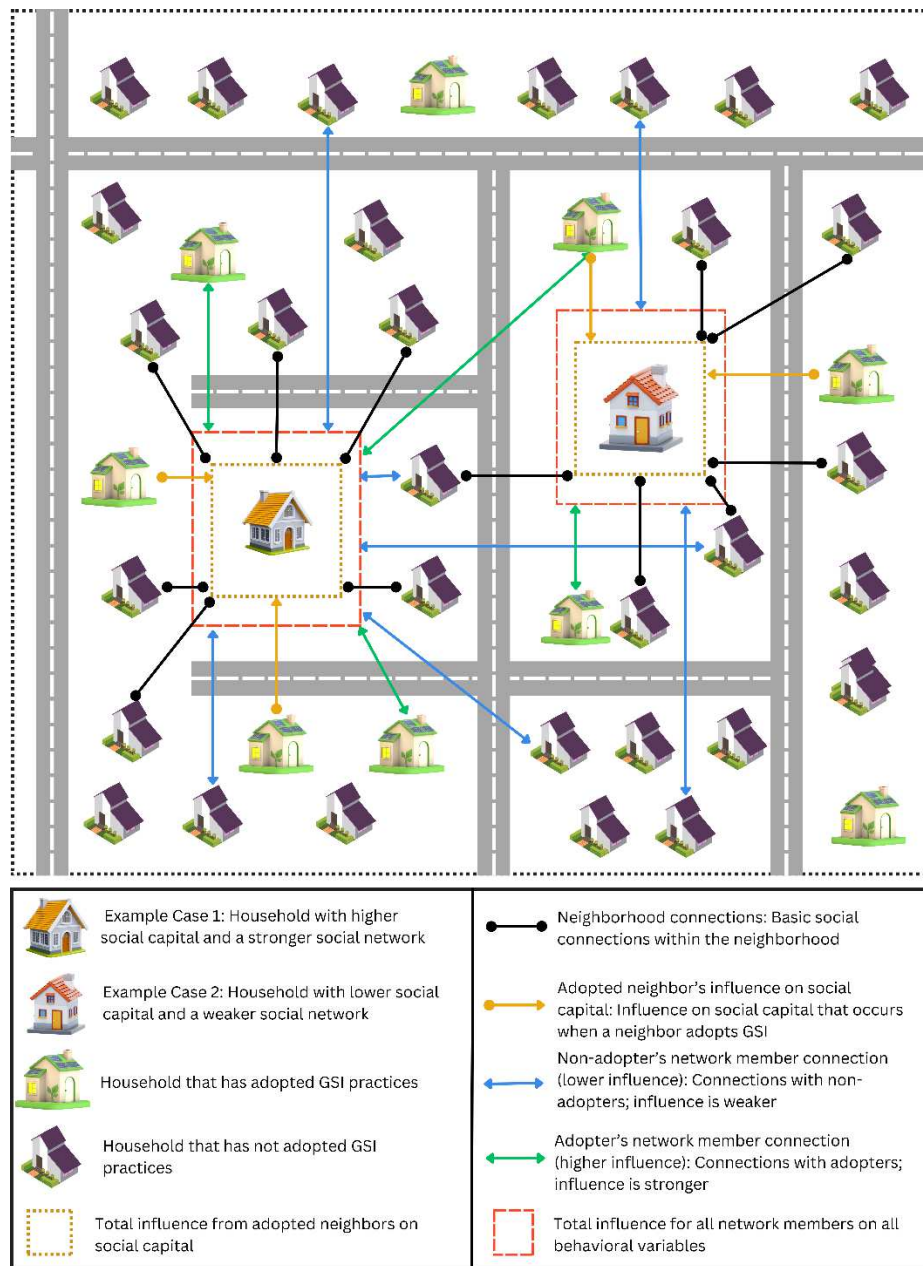
This work was supported by funding from the National Oceanic and Atmospheric Administration (NOAA) – AdSci program (Award # NA21OAR4310285), the National Science Foundation (NSF RISE 2228205) as part of Project CRESSLE, and PlanetTexas2050, a research grand challenge at the University of Texas at Austin. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NOAA or the National Science Foundation.

Competing interests

The authors declare no competing interests



Extended Data Fig. 1 | Agent-based modeling framework for GSI adoption. Hexagons represent data sources or model inputs (e.g., socio-demographics, GIS layers), while rectangular boxes indicate key processes or decision modules within the simulation. The color-coded boundaries correspond to the four major components of the model: blue for Household Agents (demographics, property attributes, and behavioral traits), red for Social Interactions (network formation and peer influence), green for Behavioral Evolution (dynamic updates of attitudes, awareness, norms, and social capital), and orange for Adoption Decision Rules (criteria and thresholds for GSI implementation). Together, these interconnected components capture how individual household decisions, shaped by both internal states and social networks, evolve over time to produce emergent citywide adoption patterns.



Extended Data Fig. 2 | Schematic illustration of household-level social interactions and network formation, highlighting two contrasting scenarios. In Case Example 1, the focal household has higher social capital and maintains a stronger social network, evident from multiple connections extending to the broader network (red dashed rectangle) and direct links to immediate neighbors (brown dotted rectangle). In Case Example 2, the focal household (outlined in orange) exhibits lower social capital, resulting in fewer overall connections to the broader network, though some ties to immediate neighbors remain. Network influence (connections to the red dashed rectangle) is two-way for all linked households—regardless of whether they have adopted GSI—though adopters (green houses) exert stronger influence. By contrast, immediate neighbor influence (brown dotted rectangle) is one-way and activates only when those neighbors have adopted a GSI practice. This distinction illustrates how variations in social capital and network reach can shape both the spread of adoption and the strength of peer influence at the neighborhood level.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplemenatryMaterials.docx](#)