From Data to Policy: Weather Resilience Indices for Climate-Adaptive Shared Mobility Planning

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ABSTRACT

Designing climate-resilient public transportation requires data-driven tools that can identify vulnerabilities, measure infrastructure performance, and support targeted policy decisions, yet such tools remain scarce. This study addresses that gap by developing novel indices for climate-adaptive shared mobility planning: the Weather Resilience Transportation Index (WRTI), which quantifies station-level sensitivity to climate stress, and the Weather Resilience Infrastructure Factor (WRIF), which measures infrastructure-mediated resilience under varying weather conditions. Both indices are developed within the Hybrid Dynamical Systems Thinking Approach (HDSTA), integrating systems thinking, Object-Process Methodology (OPM), machine learning (ML), and causal inference. Applied to two contrasting case studies: bus ridership along Israel's Highway 2 and bike-sharing in New York City's Citi Bike system, the framework reveals nonlinear, location-specific climate responses and quantifies the ridership and resilience returns of infrastructure investment. The results demonstrate how combining data science with system-level thinking can translate complex climate-behavior interactions into actionable, evidence-based policy.

Keywords: climate resilience, explainable AI, machine learning, shared mobility, systems thinking, travel behavior

INTRODUCTION

Climate variability has become a central force shaping travel behavior across different transportation systems (Miao et al., 2019). Yet much of the existing literature still treats weather as a fixed covariate added late into transport models, rather than as a dynamic system driver with nonlinear and context-dependent effects (Pearl, 2009). As a result, models often fail to capture the heterogeneous, location-specific responses that characterize real-world shared mobility systems under climate stress.

Addressing this limitation requires not only better predictive models, but interpretable ones. Decision-makers need to understand why a model behaves as it does, particularly when its outputs are meant to inform infrastructure investment or service policy. Research highlights persistent gaps in tools that can explain systemic or causal behavior in an interpretable way (Hughes and Smith, 2020), underscoring the importance of Explainable AI (XAI) frameworks in transportation.

To address both challenges simultaneously, we apply the Hybrid Dynamical Systems Thinking Approach (HDSTA) (Grinberg-Rosenbaum et al., 2024), an integrated framework combining systems thinking, Object-Process Methodology (OPM) (Dori et al., 2005), and Machine Learning (ML), to two distinct shared mobility case studies. The first examines bus ridership along Israel's Highway 2, an interurban corridor sensitive to climatic stressors and infrastructural disparities. The second analyzes bike-sharing behavior in New York City's Citi Bike system, where newly added protected bike lanes allow for a clean measurement of infrastructure-mediated climate resilience. Together, these cases offer insight into how climate influences ridership patterns across shared mobility modes, and the extent to which transportation agencies can design adaptive, climate-responsive policies.

METHODOLOGY

We first developed OPM-based systemic maps to represent interactions among climate variables, infrastructure characteristics, user types, and temporal patterns. This structure ensures that subsequent predictive models reflect actual behavioral mechanisms rather than purely statistical correlations. Figure 1 illustrates the system-level OPM model capturing how the road 2 Transport Management Center (TMC) operating process integrates inputs, including historical boarding records, bus counts, traffic volumes, and climatic stress indicators, to generate predictions for ridership, traffic volume, and traffic speed. The diagram distinguishes controllable system components (solid lines) from environmental variables (dashed lines), and differentiates relationship types such as 'requires,' 'produces,' and 'governs' through directed arrows. This structural representation reveals the dynamic feedback loops of the system: Ridership Modeling outputs affect Bus Lane Speed, which in turn feeds back into subsequent ridership predictions, while Traffic Volume Modeling Influences General Lane Speed with spillover effects across road users.

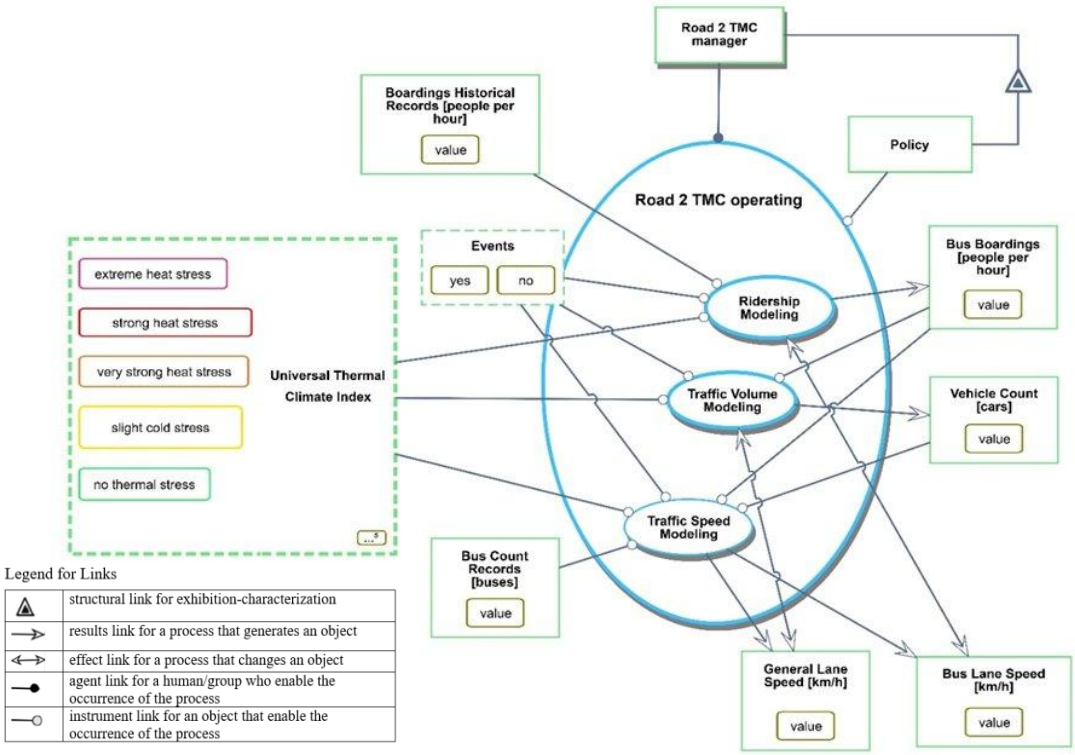


Figure 1: System-level OPM model of traffic management and ridership on Highway 2. *Green squares represent objects, blue ellipses represent processes, and arrows indicate relationships (requires, produces, governs). Dashed lines denote environmental variables; solid lines depict system-internal components.*

Data Sources

The Highway 2, Israel, dataset integrates bus boarding counts, traffic volumes, microclimate data, and event indicators from July 2023 to August 2024. For NYC, we utilized NYC Department of Transportation data and Citi Bike's public repository, covering 2022–2024, during which protected bike lanes expanded from 347 to 646 affected stations. In both cases, local meteorological data were used.

Weather Resilience Transportation Index (WRTI)

Based on these inputs, we developed the Weather Resilience Transportation Index (WRTI), which quantifies how individual stations respond to climate stress by calculating the likelihood of passengers avoiding travel during extreme weather compared to normal conditions. The index reveals localized

patterns of resilience and sensitivity, reflecting both physical infrastructure and behavioral adaptation. The WTRI formula includes two steps:

Step 1: Ridership Dropout Probability

For each weather condition w ∈ { Heat, Cold, Rain } and each station:

$$P_{dropout}(w) = \frac{\#\text{ incidents where } \Delta R < 0}{\text{Total weather incidents (w)}}$$

Where:

- **ΔR** $R_{weather} - R_{normal}$ (same station, hour, and weekday)
- **ΔR < 0** Ridership dropped under the weather condition → count as incident
- **W** One of: Heat | Cold | Rain

Step 2: WTRI Score
Aggregate the three dropout probabilities into a single station score:

$$WTRI = 1 - \frac{[\mathbf{P(Heat)} + \mathbf{P(Cold)} + \mathbf{P(Rain)}]}{3}$$

The interpretation of the score is as followed: High P_dropout →Weather-sensitive station → Low WTRI; while Low P_dropout →Resilient station → High WTRI.

Weather Resilience Infrastructure Factor (WRIF) for NYC

For the NYC case, Citi Bike trip data from 2022–2024 were combined with detailed GIS records of new protected bike lanes. To isolate the causal effect of the infrastructure, we built a sequence of paired predictive models following a controlled-comparison logic similar to that applied in prior causal machine-learning studies (Chen and Guestrin, 2016; Pedregosa et al., 2011).

One model predicted 2023 ridership based solely on 2022 patterns, unaware of any new infrastructure, while a parallel model incorporated the new bike lanes. Repeating this for 2023–2024 allowed us to compute the pure effect of the new lanes while holding constant time, location, and weather.

To assess the extent to which infrastructure improvements enhance resilience to adverse weather conditions, we analyzed variations in bicycle usage across two distinct implementation phases in New York City: Phase 1 (2022–2023) and Phase 2 (2023–2024). The analysis employed the Weather Resilience Infrastructure Factor (WRIF), a quantitative measure designed to capture the degree to which infrastructure mitigates reductions in bike usage under unfavorable weather conditions.
The WRIF is defined as:

$$WRIF = \frac{Affecred_Gap_{BadWather} - Unaffected_Gap_{BadWather}}{Unaffedted_Gap_{BadWeather}}$$

Where:

- **Affected_Gap** denotes the change in usage at stations located near improved infrastructure.
- **Unaffected_Gap** represents the change in usage at stations without infrastructure improvements.
- **BadWeather** encompasses a range of adverse conditions including rain, snow, cold, heat, mist/fog, and thermal stress (as measured by the Universal Thermal Climate Index, UTCI).

A higher WRIF value indicates greater resilience to weather-related disruptions, i.e., a reduced negative impact of weather on bike usage due to infrastructure interventions.

RESULTS AND DISCUSSION

On Highway 2, the WRTI revealed substantial heterogeneity along the corridor. Some stations exabit sharp ridership declines during rain, while others maintained stable demand. Cold weather produced an unexpected combination of high vehicle volumes and unusually high speeds, an emergent phenomenon that underscores the value of systemic modeling over single-variable analysis. Figure 2 illustrates this heterogeneity in climate sensitivity across Highway 2 bus stations probabilities for a decline in ridership.

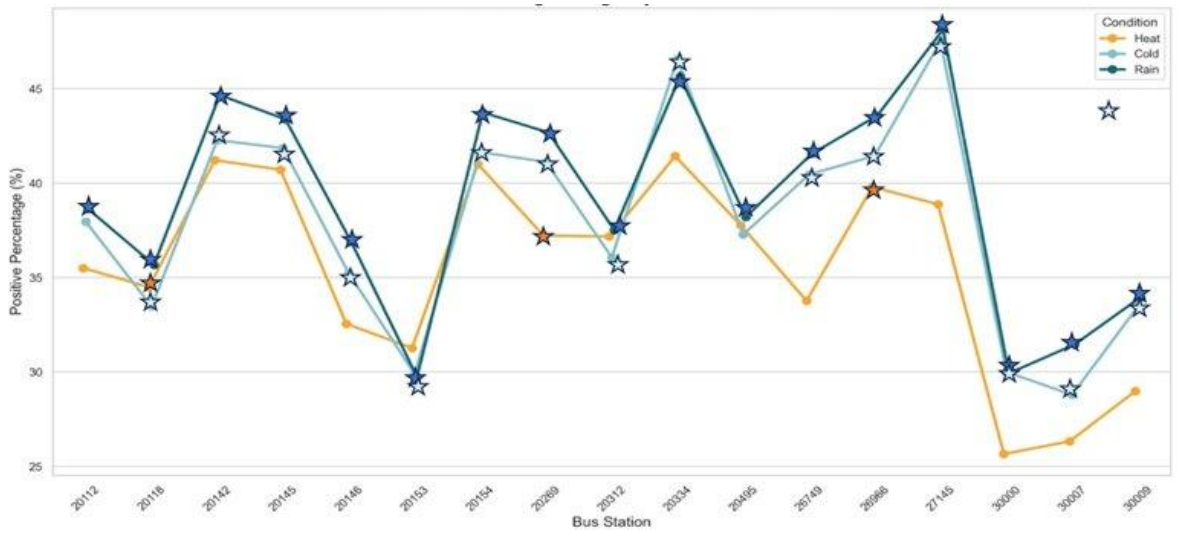


Figure 2: Ridership decline probabilities in bus stations (hot, cold, and rainy weather)

Results marked with filled stars are statistically significate. Notably, some stations performed better under cold conditions than heat, highlighting context-specific adaptation needs.

In New York City, results show that protected bike lanes generated an average of 830 additional rides per month per affected station, with policy effects increasing by 38% between 2023 and 2024. The WRIF improved from 1.85 to 1.97, indicating measurable gains in climate tolerance. Importantly, infrastructure effects extended beyond direct impact zones, with the combined system-level impact estimated at approximately 6.4 million additional trips per year across the network

Figure 3 presents WRIF values by weather category for 2023 and 2024, revealing that Mist/Fog and Snow conditions exhibit the highest resilience values, while the consistent improvement across all categories from 2023 to 2024 confirms that infrastructure expansion strengthened climate resilience system wide. Fog and heat showed the largest resilience gains, suggesting that protected lanes reduce exposure-related deterrence factors seen in earlier studies (Cantelmo et al., 2020).

Across both shared mobility systems, the findings underscore the importance of context-dependent climate responses. Interurban bus users adapt based on physical infrastructure and local connectivity, while urban cyclists rely more heavily on continuous, protected infrastructure to maintain stable behavior under climate stress. HDSTA proved effective in revealing these interactions, facilitating collaboration among transportation planners, climate specialists, and data scientists by making causal structures explicit and interpretable (Klein, 2001; Gössling et al., 2023).

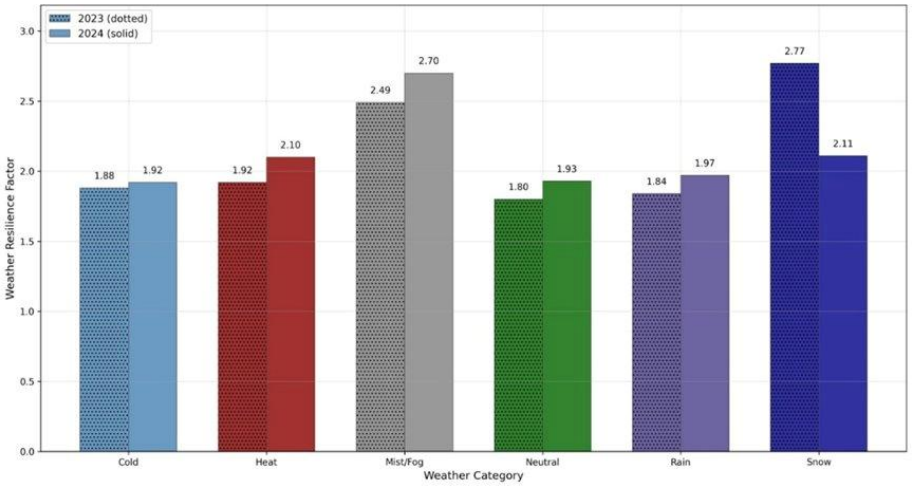


Figure 3: WRIF values by weather category for 2023 and 2024.

*Values above 1.0 indicate that infrastructure maintains or increases ridership under adverse weather conditions.

CONCLUSIONS

This study sets out to quantify climate resilience in two contrasting shared mobility contexts, addressing a gap in the literature where such resilience is frequently assumed but rarely measured. By integrating HDSTA across an interurban bus corridor and an urban bike-sharing system, the analysis demonstrates how data-driven indices, WRTI and WRIF, can transform complex climate-behavior interactions into actionable policy signals. WRTI helps identify which stations may benefit most from weather-related adaptations and prioritize improvements, such as adding shelter, heating, or cooling measures, according to each station's specific weather-related sensitivities, enhancing the commuting experience across all conditions. The WRIF contributes to a deeper understanding of how infrastructure improvements translate into increased cycling ridership under adverse weather conditions, enabling the quantification of this ridership gain and thereby providing an evidence-based justification for targeted infrastructure investments where they are most needed.

A key finding from Highway 2 is that substantial heterogeneity in climate sensitivity exists along what appears to be a structurally homogeneous corridor. Despite serving a continuous interurban route under similar regional weather conditions, individual stations exhibit markedly different responses to heat, cold, and rain. This heterogeneity, made visible through the WRTI, carries direct policy implications: aggregate or corridor-level planning risks misallocating resources by overlooking localized vulnerabilities. Stations with low WRTI scores under heat conditions signal a concrete need for targeted interventions as shading structures, cooling facilities, or scheduling adjustments, at precisely those locations. Rather than applying uniform infrastructure standards across an entire corridor, agencies can use the WRTI to prioritize investments where marginal improvements in comfort and protection are most likely to stabilize or recover ridership. The framework thus shifts the planning conversation from general climate awareness to spatially specific, evidence-based action.

For the NYC bike-sharing system, the results establish climate resilience as a measurable, policy-relevant outcome rather than a planning aspiration. Protected bike lanes generated measurable and growing ridership gains, approximately 830 additional rides per station per month, while the WRIF rose from 1.85 to 1.97 between 2023 and 2024, reflecting strengthening weather tolerance. Network-level spillover effects extended benefits beyond directly treated stations, reinforcing the value of coordinated corridor planning over isolated interventions. Taken together, these findings provide transport agencies with a replicable framework for prioritizing climate adaptation investments under budget constraints.

Across both systems, this study demonstrates that climate resilience in shared mobility emerges not from infrastructure alone, but from understanding the dynamic, spatially differentiated interactions between weather, users, and system design. The WRTI and WRIF offer practical tools for cities seeking to move from data to policy, identifying where intervention is most needed, and whether it works.

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REFERENCES

Cantelmo, G., Kucharski, R., & Antoniou, C. (2020). Low-dimensional model for bike-sharing demand forecasting that explicitly accounts for weather data. Transportation Research Record, Vol. 2674, No. 8, pp. 132–144.

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, USA, pp. 785–794.

Dori, D., Kheir, N., & Wengrowicz, N. (2005). Object-Process Methodology for systems engineering. Systems Engineering, Vol. 8, No. 5, pp. 1–20.

Gössling, S., Choi, A., & Verlinghieri, E. (2023). Climate vulnerability and transport systems. Journal of Transport Geography, Vol. 110, pp. 103627.

Grinberg-Rosenbaum, K.-O., Shiftan, Y., Pereira, F. C., & Nahmias-Biran, B. (2024). Best of both worlds: System thinking approach for transportation data-driven decision-making. Transportation Research Procedia, Vol. 82, pp. 3943–3959.

Heinen, E., Van Wee, B., & Maat, K. (2010). Commuting by bicycle: Influence of environmental and demographic factors. Transportation Research Part A: Policy and Practice, Vol. 44, No. 5, pp. 363–376.

Hughes, S., & Smith, P. (2020). Accountability and data-driven urban climate governance. Nature Climate Change, Vol. 10, No. 12, pp. 1085–1090.

Klein, G. (2001). Sources of Power: How People Make Decisions. MIT Press.

Miao, Q., Welch, E. W., & Sriraj, P. S. (2019). Extreme weather, public transport ridership and moderating effect of bus stop shelters. Journal of Transport Geography, Vol. 74, pp. 125–133.

Pearl, J. (2009). Causality (2nd ed.). Cambridge University Press.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., & Thirion, B. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, Vol. 12, pp. 2825–2830.