

PiperABM: A Python Library for Resilience-Based Agent Modeling

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Summary

PiperABM is an open-source Python library for building agent-based simulations that couple human behavior with degrading infrastructure on real-world geospatial layouts. It provides lightweight primitives to enable agents with a customizable decision loop, infrastructure with spatial graphs whose effective travel costs evolve, and built-in analysis for accessibility to resources and travel distance, plus optional animation. Because it is implemented with familiar scientific tools like NumPy and NetworkX, researchers can inspect and extend models directly, integrate empirical data, and reuse standard workflows. *PiperABM* targets research questions centered on resilience, where people's choices and infrastructure conditions co-evolve, seeking to reduce the setup overhead typical of one-off models while remaining flexible enough for diverse hazards, places, and policies.

Statement of Need

Agent-based models (ABMs) represent systems “from the bottom up” using heterogeneous, interacting agents whose local rules and behaviors generate macro-level patterns (Joshua M. Epstein, 1999; Joshua M. Epstein & Axtell, 1996; Schelling, 2006). ABM has also been highlighted as a framework that engages diverse stakeholders, enables the forecasting of equitable futures, and empowers policy (Hicks et al., 2021; Noorghasemi et al., 2025). Over the several decades, ABM has matured from theoretical demonstrations to a practical research method supported by accessible tooling and the scientific Python ecosystem (Hoeven et al., 2025). This paradigm is well-suited to infrastructure and community resilience, particularly within the Food–Energy–Water (FEW) nexus, where access to essential resources depends on both physical networks and human decisions, and where nonlinear feedbacks, thresholds, and cascades are common (Cansino-Loeza et al., 2022; Xue et al., 2024; Zhang et al., 2019).

Resilience studies pose several practical modeling needs that are not well served by ad hoc scripts or purely equation-based approaches:

- Partial service levels and progressive degradation:** Models should represent graded performance (e.g., rougher roads increasing cost/time) rather than only binary failure, reflecting well-studied pavement deterioration processes and performance impacts, e.g., IRI-based assessments (Altarabsheh et al., 2021; Llopis-Castelló et al., 2024).
- Two-way coupling of behavior and infrastructure:** People adapt routes, priorities, and exchanges as networks evolve; these adaptations, in turn, load and degrade networks. Coupled human–infrastructure ABMs have demonstrated such feedbacks in flood-risk systems and related reviews emphasize capturing co-evolution (Anshuka et al., 2022; Michaelis et al., 2020).

- **Real geospatial layouts for place-based analysis:** Integrating GIS data (maps/satellite-derived inputs) enables site-specific scenarios and stakeholder communication; recent work in the Python ABM ecosystem formalizes GIS ingestion and spatial operations for ABMs (Wang et al., 2022).
- **Ensemble experiments and reproducibility:** Parameter sweeps, stochastic replications, and uncertainty and sensitivity analysis require clear, standardized reporting and careful data handling; community guidelines for documenting agent-based models and recent work on calibration and sensitivity analysis support replicable workflows (Grimm et al., 2020; McCulloch et al., 2022; Razavi et al., 2021).
- **Custom metrics and analysis pipelines:** Familiar data structures expose model state for domain-specific metrics, such as spatiotemporal accessibility under disruption (Enderami et al., 2024; Tariverdi et al., 2023).

PiperABM is built to meet these needs. It offers simple building blocks in pure Python: a society network comprised of agents and their relationships; an infrastructure network that can wear down over time; tools to load real maps; built-in measures such as accessibility and travel distance; and optional animation for evaluating face validity. With these pieces, researchers can quickly pose hypotheses, run “what-if” scenarios, and study how people’s choices and the infrastructure around them influence one another and analyze socio-technical feedbacks.

Intended users are researchers and practitioners in infrastructure and community resilience, including urban planners, policymakers, and decision-makers who need transparent, reproducible, place-based simulations.

Model Overview

At each time step, agents follow OODA-style decision logic—observing current conditions, orienting, deciding, and acting (Brehmer, 2005; Johnson, 2023). Agents choose actions such as where to travel, whom to meet, and whether to trade. Routing between locations uses an A* search on the evolving network to approximate human-like paths (Foead et al., 2021). Trades between agents are resolved using a Nash bargaining formulation (Nash, 1950). Infrastructure elements degrade due to both exogenous aging and endogenous usage by agents, increasing effective travel cost and feeding back into subsequent decisions. Simulation results are stored using human-readable delta differencing (KeepDelta), which is compact and easy to debug (Noorghasemi & McComb, 2025).

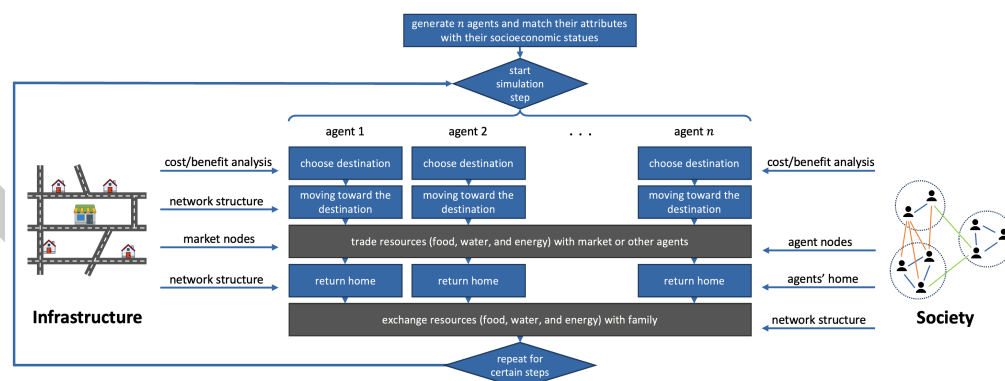


Figure 1. The computational model of PiperABM emulates the relation between the elements of infrastructure and social networks.

Comparison to Existing Tools

We group related work into two domains: (1) General frameworks intended to be reusable across problems, and (2) Purpose-built models created for a single, specific study.

Domain 1: General frameworks (Python)

Mesa is a widely used general-purpose ABM framework that makes it easy to define agents, schedule steps, collect data, and visualize models in the browser, ideal for rapid prototyping and analysis (Hoeven et al., 2025). Trade-off: domain logic is do-it-yourself; researchers typically hand-roll infrastructure degradation, accessibility metrics, and behavior–infrastructure coupling. InfraRisk is an infrastructure-centric Python platform for interdependent networks (power, water, transport) with hazard, cascade, recovery, and resilience modules that is strong on network physics and restoration (Balakrishnan & Cassottana, 2022). Human decision-making and accessibility-driven behavior are typically added on top, so tight socio-technical feedbacks can be awkward. Repast4Py is a Python interface to an HPC engine for distributed/parallel ABMs; models can run across many cores or machines for large studies (Collier & Ozik, 2022). It does not provide resilience-specific logic (e.g., continuous degradation, accessibility metrics), which the modeler must supply.

Like Mesa and Repast4Py, PiperABM stays flexible and Pythonic, but it elevates resilience features to first-class concepts: continuous infrastructure degradation (e.g., rougher roads increasing travel cost), built-in accessibility/travel metrics, a lightweight OODA-style policy interface, geospatial ingestion, and optional animation. Unlike InfraRisk’s “network-first with agents layered on,” PiperABM starts from coupled behavior–infrastructure dynamics, making socio-technical feedbacks straightforward to model and analyze.

Domain 2: Purpose-built, one-off models

Examples include multilayer post-disaster recovery (e.g., Hurricane Harvey) (Xue et al., 2024), RecovUS for household recovery after Sandy (Moradi & Nejat, 2020), storm-induced power-outage restoration with crew dispatch (Walsh et al., 2018), community resilience under tornado hazards (Aghababaei & Koliou, 2023), and flood risk–insurance dynamics (Dubbeldboer et al., 2017). These models capture exactly what they need but are hard to reuse and often re-implement similar scaffolding.

PiperABM offers the custom feel of bespoke models while reducing rework: degradation and accessibility are built in; OODA-style decision logic is plug-and-play; infrastructure and agents live on an inspectable NetworkX backend; and results can be analyzed with standard Python tools. This makes it easier to adapt a single codebase to new hazards, geographies, and policies, and to compare scenarios consistently.

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References

- Aghababaei, M., & Koliou, M. (2023). Community resilience assessment via agent-based modeling approach. *Computer-Aided Civil and Infrastructure Engineering*, 38(7), 920–939. <https://doi.org/https://doi.org/10.1111/mice.12916>

- Altarabsheh, A., Altarabsheh, R., Altarabsheh, S., & Asi, I. (2021). Prediction of pavement performance using multistate survival models. *Journal of Transportation Engineering, Part B: Pavements*, 147(1), 04020082. <https://doi.org/10.1061/JPEODX.0000241>
- Anshuka, A., Ogtrop, F. F. van, Sanderson, D., & Leao, S. Z. (2022). A systematic review of agent-based model for flood risk management and assessment using the ODD protocol. *Natural Hazards*, 112(3), 2739–2771. <https://doi.org/10.1007/s11069-022-05286-y>
- Balakrishnan, S., & Cassottana, B. (2022). InfraRisk: An open-source simulation platform for resilience analysis in interconnected power–water–transport networks. *Sustainable Cities and Society*, 83, 103963. <https://doi.org/10.1016/j.scs.2022.103963>
- Brehmer, B. (2005). The dynamic OODA loop: Amalgamating boyd's OODA loop and the cybernetic approach to command and control. *Proceedings of the 10th International Command and Control Research Technology Symposium*, 365–368.
- Cansino-Loeza, B., Munguía-López, A. del C., & Ponce-Ortega, J. M. (2022). A water-energy-food security nexus framework based on optimal resource allocation. *Environmental Science & Policy*, 133, 1–16. <https://doi.org/10.1016/j.envsci.2022.03.006>
- Collier, N., & Ozik, J. (2022). Distributed agent-based simulation with Repast4Py. *2022 Winter Simulation Conference (WSC)*, 192–206. <https://doi.org/10.1109/WSC57314.2022.10015389>
- Dubbelboer, J., Nikolic, I., Jenkins, K., & Hall, J. (2017). An agent-based model of flood risk and insurance. *Journal of Artificial Societies and Social Simulation*, 20(1), 6. <https://doi.org/10.18564/jasss.3135>
- Enderami, S. A., Sutley, E., Helgeson, J., Dueñas-Osorio, L., Watson, M., & Lindt, J. W. van de. (2024). Measuring post-disaster accessibility to essential goods and services: Proximity, availability, adequacy, and acceptability dimensions. *Journal of Infrastructure Preservation and Resilience*, 5(1). <https://doi.org/10.1186/s43065-024-00104-0>
- Epstein, Joshua M. (1999). Agent-based computational models and generative social science. *Complexity*, 4(5), 41–60.
- Epstein, Joshua M., & Axtell, R. (1996). *Growing artificial societies: Social science from the bottom up*. Brookings Institution Press; MIT Press. ISBN: 9780262550253
- Foad, D., Ghifari, A., Kusuma, M. B., Hanafiah, N., & Gunawan, E. (2021). A Systematic Literature Review of A* Pathfinding. *Procedia Computer Science*, 179, 507–514. <https://doi.org/10.1016/j.procs.2021.01.034>
- Grimm, V., Railsback, S. F., Vincenot, C. E., Berger, U., Gallagher, C., DeAngelis, D. L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., Johnston, A. S. A., Milles, A., Nabe-Nielsen, J., Polhill, J. G., Radchuk, V., Rohwäder, M.-S., Stillman, R. A., Thiele, J. C., & Ayllón, D. (2020). The ODD protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism. *Journal of Artificial Societies and Social Simulation*, 23(2), 7. <https://doi.org/10.18564/jasss.4259>
- Hicks, S., McComb, C., & Alessa, L. (2021). *Agents and the Arctic: The Case for Increased Use of Agent-Based Modeling to Study Permafrost* — [thearcticinstitute.org](https://www.thearcticinstitute.org). <https://www.thearcticinstitute.org/agents-arctic-case-increased-use-agent-based-modeling-study-permafrost/>.
- Hoeven, E. ter, Kwakkel, J., Hess, V., Pike, T., Wang, B., rht, & Kazil, J. (2025). Mesa 3: Agent-based modeling with Python in 2025. *Journal of Open Source Software*, 10(107), 7668. <https://doi.org/10.21105/joss.07668>
- Johnson, J. (2023). Automating the OODA loop in the age of intelligent machines: Reaffirming the role of humans in command-and-control decision-making in the digital age. *Defence Studies*, 23(1), 43–67. <https://doi.org/10.1080/14702436.2022.2102486>

- 164 Llopis-Castelló, D., Camacho-Torregrosa, F. J., Romeral-Pérez, F., & Tomás-Martínez, P.
165 (2024). Estimation of pavement condition based on data from connected and autonomous
166 vehicles. *Infrastructures*, 9(10). <https://doi.org/10.3390/infrastructures9100188>
- 167 McCulloch, J., Ge, J., Ward, J., Heppenstall, A., Polhill, J. G., & Malleson, N. (2022).
168 Calibrating agent-based models using uncertainty quantification methods. *Journal of*
169 *Artificial Societies and Social Simulation*, 25(2), 1. <https://doi.org/10.18564/jasss.4791>
- 170 Michaelis, T., Brandimarte, L., & Mazzoleni, M. (2020). Capturing flood-risk dynamics with a
171 coupled agent-based and hydraulic modelling framework. *Hydrological Sciences Journal*,
172 65(9), 1458–1473. <https://doi.org/10.1080/02626667.2020.1750617>
- 173 Moradi, S., & Nejat, A. (2020). RecovUS: An agent-based model of post-disaster household
174 recovery. *Journal of Artificial Societies and Social Simulation*, 23(4), 13. <https://doi.org/10.18564/jasss.4445>
- 175 Nash, J. F. (1950). The Bargaining Problem. *Econometrica*, 18(2), 155–162. <https://doi.org/10.2307/1907266>
- 176 Noorghasemi, A., & McComb, C. (2025). KeepDelta: A Python Library for Human-Readable
177 Data Differencing. *Journal of Open Source Software*, 10(110), 8075. <https://doi.org/10.21105/joss.08075>
- 178 Noorghasemi, A., Xiao, M., & McComb, C. (2025). *Evaluating community well-being and*
179 *resilience via agent-based models*. <https://doi.org/10.22541/essoar.173687385.52831340/v1>
- 180 Razavi, S., Jakeman, A., Saltelli, A., Prieur, C., Iooss, B., Borgonovo, E., Plischke, E., Lo
181 Piano, S., Iwanaga, T., Becker, W., Tarantola, S., Guillaume, J. H. A., Jakeman, J.,
182 Gupta, H., Melillo, N., Rabitti, G., Chabridon, V., Duan, Q., Sun, X., ... Maier, H. R.
183 (2021). The future of sensitivity analysis: An essential discipline for systems modeling and
184 policy support. *Environmental Modelling & Software*, 137, 104954. <https://doi.org/10.1016/j.envsoft.2020.104954>
- 185 Schelling, T. C. (2006). *Micromotives and macrobehavior* (Revised). W. W. Norton &
186 Company. <https://doi.org/10.2307/134812>
- 187 Tariverdi, M., Nunez-del-Prado, M., Leonova, N., & Rentschler, J. (2023). Measuring
188 accessibility to public services and infrastructure criticality for disasters risk management.
189 *Scientific Reports*, 13(1). <https://doi.org/10.1038/s41598-023-28460-z>
- 190 Walsh, T., Layton, T., Wanik, D., & Mellor, J. (2018). Agent based model to estimate time
191 to restoration of storm-induced power outages. *Infrastructures*, 3(3). <https://doi.org/10.3390/infrastructures3030033>
- 192 Wang, B., Hess, V., & Crooks, A. (2022). Mesa-Geo: A GIS Extension for the Mesa
193 Agent-Based Modeling Framework in Python. *Proceedings of the 5th ACM SIGSPATIAL*
194 *International Workshop on GeoSpatial Simulation*, 1–10. <https://doi.org/10.1145/3557989.3566157>
- 195 Xue, J., Park, S., Mondal, W. U., Reia, S. M., Yao, T., & Ukkusuri, S. V. (2024). An agent-
196 based model of post-disaster recovery in multilayer socio-physical networks. *Sustainable*
197 *Cities and Society*, 115, 105863. <https://doi.org/10.1016/j.scs.2024.105863>
- 198 Zhang, P., Zhang, L., Chang, Y., Xu, M., Hao, Y., Liang, S., Liu, G., Yang, Z., & Wang,
199 C. (2019). Food-energy-water (FEW) nexus for urban sustainability: A comprehensive
200 review. *Resources, Conservation and Recycling*, 142, 215–224. <https://doi.org/10.1016/j.resconrec.2018.11.018>
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