
Adaptive Learning in Spatial Agent-Based Models for Climate Risk Assessment: A Geospatial Framework with Evolutionary Economic Agents

Yara Mohajerani
Quantile Labs*
Newmarket, Ontario, Canada
yara@quantile-labs.com

Abstract

Climate risk assessment requires modelling complex interactions between spatially heterogeneous hazards and adaptive economic systems. We present a novel geospatial agent-based model that integrates climate hazard data with evolutionary learning for economic agents. Our framework combines Mesa-based spatial modelling with CLIMADA climate impact assessment, introducing adaptive learning behaviours that allow firms to evolve strategies for budget allocation, pricing, wages, and risk adaptation through fitness-based selection and mutation. We demonstrate the framework using riverine flood projections under RCP8.5 until 2100, showing that evolutionary adaptation enables firms to converge with baseline (no hazard) production levels after decades of disruption due to climate stress. Our results reveal systemic risks where even agents that are not directly exposed to floods face impacts through supply chain disruptions, with the end-of-century average price of goods 5.6% higher under RCP8.5 compared to the baseline in our illustrative economic network. This open-source framework provides financial institutions and companies with tools to quantify both direct and cascading climate risks while evaluating cost-effective adaptation strategies.

1 Introduction

Physical climate risks pose systemic threats to economic systems through complex spatial and temporal dynamics that traditional econometric models struggle to capture [1]. Current climate-economy models often rely on static damage functions that fail to account for adaptive behaviours, spatial heterogeneity of hazards, and cascading effects through supply chain networks [2, 3]. Agent-based modelling (ABM) offers a promising alternative by enabling bottom-up simulation of heterogeneous agents with adaptive behaviours [4]. However, existing ABM frameworks typically focus on integrated assessment approaches for policymakers and optimal price of carbon [5, 6]. ABM approaches are less common for physical climate risk management through climate scenario analysis for financial institutions and corporations. This is in part due to challenges such as integration of geospatial climate data with economic ABM models, realistic agent behaviours that respond to local hazard conditions, and adaptive learning mechanisms that allow agents to evolve strategies under changing climate conditions.

We address these challenges by developing a spatial ABM framework ² that combines geospatial climate data integration with evolutionary learning mechanisms for economic agents. Our key contributions include: (1) a Mesa-based spatial framework that creates a spatial agent-based economic

*<https://www.quantile-labs.com>

²<https://github.com/yaramohajerani/spatial-climate-ABM>

network overlaid on climate projection maps with corresponding hazard and vulnerability functions, (2) implementation of evolutionary learning algorithms that allow firms to adapt budget allocation, pricing, wage-setting, and risk sensitivity strategies, and (3) demonstration of emergent adaptive behaviours under climate stress using real-world flood hazard data.

This work contributes to climate action by (1) enabling financial institutions and companies to better quantify climate risks for improved capital allocation and risk management, and (2) demonstrating that simple adaptive measures can significantly reduce climate impacts, providing evidence for cost-effective supply chain resilience strategies.

2 Model architecture

2.1 Spatial environment and climate impacts

We construct a network of economic agents on a spatial grid using the Mesa Python framework³ [7]. Climate hazards are overlaid and sampled independently for each grid cell based on return period frequencies. Damages to assets are calculated using CLIMADA⁴ [8] impact functions [9]. The damage ratio for each asset type and location is used to affect agents through 3 distinct pathways: (1) firm capital stock reduction, (2) temporary productivity losses via damage factors, and (3) inventory destruction.

2.2 Economic agents

Households supply labor and consume goods, with agent-specific employment choices based on wage-distance tradeoffs within their specialized sectors. They monitor local hazard conditions within randomly assigned radii (1-50 cells) and relocate when normalized hazard intensity exceeds 0.1. Consumption targets 2-3 different trophic level ranges [10, 11] to simulate demand for diverse goods.

Firms use Leontief production functions [12] requiring labor, capital, and material inputs from connected suppliers. A global supply chain network of firms in high-flood risk areas is generated, consisting of commodity producers and manufacturers.

2.3 Evolutionary learning system

We implement an evolutionary learning mechanism that allows firms to adapt six strategy parameters through fitness-based selection and mutation:

(1) *Labor budget weight*: Controls the fraction of available cash allocated to hiring workers. Higher values prioritize employment over other inputs, affecting production capacity and wage competitiveness.

(2) *Input budget weight*: Determines spending on intermediate goods from suppliers. Firms with higher values maintain larger input inventories, providing resilience against supply chain disruptions.

(3) *Capital budget weight*: Governs investment in productive capital. Higher values lead to greater capital accumulation, enabling higher production capacity and climate resilience through redundancy.

(4) *Risk sensitivity multiplier*: Modulates the firm's response to nearby climate events. Higher values cause larger increases in capital requirements when hazards occur within the firm's monitoring radius, representing proactive climate adaptation.

(5) *Price responsiveness factor*: Controls how aggressively firms adjust prices based on inventory levels and market conditions. Higher values lead to more volatile pricing but potentially higher profits during scarcity periods.

(6) *Wage adjustment sensitivity*: Determines the speed and magnitude of wage changes in response to labor market conditions. Higher values enable faster adaptation to changing employment conditions but may create wage volatility.

³<https://mesa.readthedocs.io/latest/>

⁴<https://climada-python.readthedocs.io/en/stable/>

Climate events create selection pressure favouring strategies that enhance survival and growth under stress. The evolutionary process thus drives the emergence of heterogeneous climate-adapted business strategies without explicit programming of adaptation behaviours.

Performance Memory: Each firm maintains a 10-step rolling window tracking money, production, capital stock, and limiting factors (labor/capital/input constraints), with fitness evaluation based on the most recent 5 steps.

Fitness Function: Combines four components with fixed weights: 1) Growth rate (40%): Money growth rate with diminishing returns via tanh transformation; 2) Production stability (30%): One minus the coefficient of variation in production (rewards consistent production with lower variability); 3) Survival bonus (20%): Longevity reward that increases linearly up to 20 steps; 4) Resource balance (10%): Diversity of limiting factors across labor, capital, and inputs.

Individual Adaptation: Each living firm independently evaluates and mutates its strategy parameters every 5 steps. Mutation strength adapts based on fitness changes: parameters have a 30% probability of mutation with Gaussian noise at standard deviation of 2.5% of current value (if fitness improved), 5% (baseline), or 10% (if fitness declined), implementing adaptive hill-climbing.

Evolutionary Replacement: Up to a quarter of failed firms are replaced every 10 steps – defined as firms that have less money than the minimum survival amount or their wealth reduced by more than 50% over 5 time-steps. Offspring are created from fitness-weighted selection of successful firms, inheriting parent strategy with a 50% probability of mutation per parameter with Gaussian noise at 10% standard deviation.

3 Results and Discussion

We demonstrate the framework using Aqueduct riverine flood data under RCP8.5 [13], compared with a baseline no-hazard scenario. Our test economy includes 15 firms across commodity and manufacturing sectors placed in flood-prone locations worldwide, with 75 households providing labor and consuming goods. Simulations run for 320 quarterly steps (80 years from 2020-2100). The results are shown in Figure 1.

The initial inventory and capital of the firms results in high production, with an average of 4.3 units per firm. However, the economy is initialized in a state of disequilibrium, and the firms fall into a stable regime of 0.4 units per firm by the end of the century in the baseline scenario (Figure 1a). Households transition from providing an average of 0.5 units of labour in 2020 to 0.1 by the end of the century. This drop is due to the affordability of labour by firms, as the baseline production bottleneck in Figure 1h shows the majority of firms (60% to 90% through the century) are labour-limited in their production.

The economy exhibits emergent inflation, as firm production drops by 91% throughout the century while household wealth drops by 3%. The strong demand for goods from households and the low supply by firms leads to the strong inflation shown in Figure 1d. While wages also increase (Figure 1e), they don't experience the same rise due to the downward pressure of affordability of labour and high unemployment (Figure 1f).

With the addition of hazards under RCP8.5, firms lose inventory, productivity, and capital due to extreme events. This results in diminished production. In 2050, the average per-firm production is 0.7 under RCP8.5, compared with 2.1 units in the baseline scenario. However, the evolutionary adaptation of firms results in comparable production between the scenarios by the end of the century. We find that without the evolutionary adaption, average firm production drops to just 0.1 by the end of the century. This demonstrates the importance of adaptation behaviour on reducing the effect of climate shocks through the supply chain as firms improve their budget allocation, dynamic pricing, and capital accumulation in response to regional climate risks. We see similar patterns in firm wealth and labour projections, each of which suffer under the RCP8.5 scenario, but converge or even surpass the baseline by the end of the century due to the evolutionary adaption.

Inflation is significantly higher under RCP8.5 due to the cumulative impact of lower supply from firms. The average price of goods by the end of the century is 5.6% higher under RCP8.5 compared to the baseline. The lower supply of firms is exacerbated by the higher wealth of households under RCP8.5 (Figure 1g). Households have higher wealth because of forced savings, where the limited

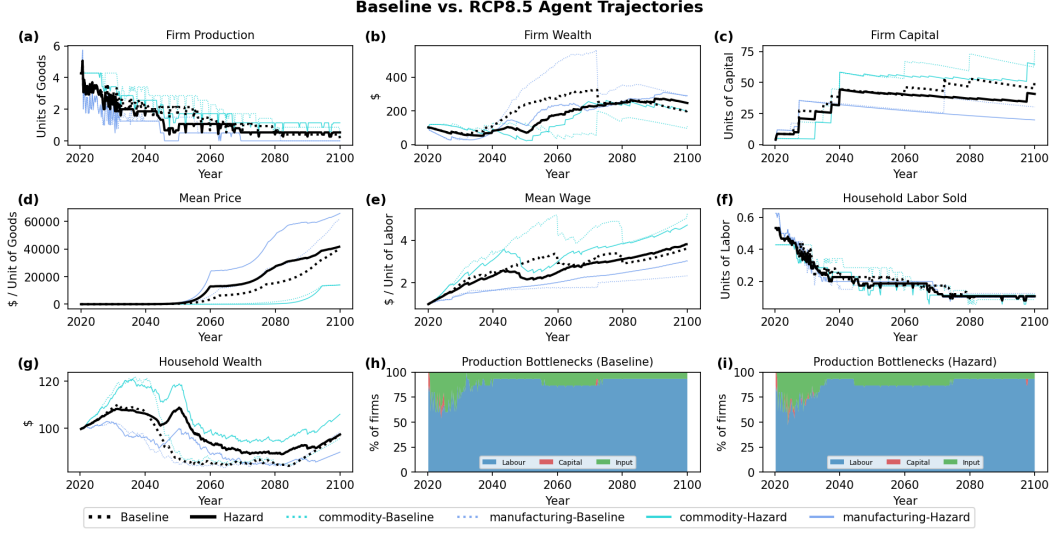


Figure 1: Agent trajectories under Baseline (no hazard) and Hazard (RCP8.5 riverine flooding) scenarios.

availability of goods constrains the spending of households despite increasing wages due to demand for labour. Figure 1*i* shows that under RCP8.5, most firms are still labour-limited in their production function. Compared with the baseline, there are more capital-limited firms in the first two decades, due to the effect of acute hazards on capital. However, through evolutionary adaptation, firms alleviate capital issues by pre-emptively increasing capital as regional risks increase, even before a firm is directly affected by an acute event.

These results highlight the importance of geospatial agent-based modelling in capturing systemic disruptions due to climate risk. Agents throughout the network are exposed to risks even if they are not directly affected by acute hazards. While hazards affect the capital, inventory, and productivity of firms, households face several system risks, including higher unemployment rates and higher inflation. Firms also experience indirect risks, as evident by the near doubling of the percentage of input-limited firms under RCP8.5 compared to baseline in 2050 (Figure 1*h* vs. 1*i*). However, firms are able to lower these risks by adapting to evolving climate stresses, as shown by the convergence of firm production and wealth under RCP8.5 with those of the baseline by the end of the century.

4 Conclusions

We presented a geospatial ABM framework that integrates climate hazard data with evolutionary learning to capture how economic agents adapt to climate risks. Our results show that incorporating spatial heterogeneity and adaptive behaviours is crucial for accurate climate risk assessment—firms with evolved strategies reach near-baseline production by the end of century despite severe climate stresses, while indirect impacts through supply chains affect even unexposed agents. This framework enables financial institutions to better assess portfolio climate risks and helps companies evaluate adaptation strategies for climate-induced supply chain risks, addressing the critical gap between climate projections and financial and operational decision-making. Our open-source implementation facilitates broader adoption for building climate-resilient economic systems.

Acknowledgments and Disclosure of Funding

This work was supported by Quantile Labs.

The complete source code and documentation are available at <https://github.com/yaramohajerani/spatial-climate-ABM>.

References

- [1] James A Rising, Charlotte Taylor, Matthew C Ives, and Robert ET Ward. Challenges and innovations in the economic evaluation of the risks of climate change. *Ecological Economics*, 197:107437, 2022.
- [2] Christian LE Franzke, Alessio Ciullo, Elisabeth A Gilmore, Denise Margaret Matias, Nidhi Nagabhatla, Anton Orlov, Shona K Paterson, Jürgen Scheffran, and Jana Sillmann. Perspectives on tipping points in integrated models of the natural and human earth system: cascading effects and telecoupling. *Environmental Research Letters*, 17(1):015004, 2022.
- [3] Francesco Lamperti, Antoine Mandel, Mauro Napoletano, Alessandro Sapio, Andrea Roventini, Tomas Balint, and Igor Khorenzhenko. Towards agent-based integrated assessment models: examples, challenges, and future developments. *Regional environmental change*, 19(3):747–762, 2019.
- [4] J Doyne Farmer and Duncan Foley. The economy needs agent-based modelling. *Nature*, 460(7256): 685–686, 2009.
- [5] Francesco Lamperti, Giovanni Dosi, Mauro Napoletano, Andrea Roventini, and Alessandro Sapio. Far-away, so close: coupled climate and economic dynamics in an agent-based integrated assessment model. *Ecological Economics*, 150:315–339, 2018.
- [6] Marcin Czupryna, Christian Franzke, Sascha Hokamp, and Jürgen Scheffran. An agent-based approach to integrated assessment modelling of climate change. *Journal of Artificial Societies and Social Simulation*, 23(3), 2020.
- [7] David Masad, Jacqueline L Kazil, et al. Mesa: An agent-based modeling framework. In *SciPy*, pages 51–58, 2015.
- [8] Gabriela Aznar-Siguan and David N Bresch. Climada v1: a global weather and climate risk assessment platform. *Geoscientific Model Development*, 12(7):3085–3097, 2019.
- [9] Jan Huizinga, Hans De Moel, and Wojciech Szewczyk. Global flood depth-damage functions: Methodology and the database with guidelines. Technical report, Joint Research Centre, 2017.
- [10] Pol Antràs, Davin Chor, Thibault Fally, and Russell Hillberry. Measuring the upstreamness of production and trade flows. *American Economic Review*, 102(3):412–416, 2012.
- [11] James McNerney, Charles Savoie, Francesco Caravelli, Vasco M Carvalho, and J Doyne Farmer. How production networks amplify economic growth. *Proceedings of the National Academy of Sciences*, 119(1): e2106031118, 2022.
- [12] W Leontief. *Input-output economics*. Oxford University Press, 1986.
- [13] Philip J Ward, Hessel C Winsemius, Samantha Kuzma, Marc FP Bierkens, Arno Bouwman, Hans De Moel, Andrés Díaz Loaiza, Dirk Eilander, Johanna Englhardt, Gilles Erkens, et al. Aqueduct floods methodology. 2020.