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

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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.

Motivation and Goal

- 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.
- Agent-based modelling (ABM) offers a promising alternative by enabling bottom-up simulation of heterogeneous agents with adaptive behaviours.
- This approach has been limited 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 that combines geospatial climate data integration with evolutionary learning mechanisms for economic agents.

Framework

- We construct a network of economic agents on a spatial grid using the Mesa Python framework (mesa.readthedocs.io).
- Climate hazards are overlaid and sampled independently for each grid cell. Damages to assets are calculated using CLIMADA impact functions (climada-python.readthedocs.io).
- Climate damage affects agents through 1. firm capital stock reduction, 2. temporary productivity losses, 3. inventory destruction
- A network of economic agents is created, composed of **households** that supply labor and consume goods, and **firms** that production goods using labour, capital, and material inputs from other firms.

Adaptive Learning

- 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.
  2. Input budget weight: Determines spending on intermediate goods from suppliers.
  3. Capital budget weight: Governs investment in productive capital.
  4. Risk sensitivity multiplier: Modulates the firm's response to nearby climate events.
  5. Price responsiveness factor: Controls how aggressively firms adjust prices based on inventory levels and market conditions.
  6. Wage adjustment sensitivity: Determines the speed and magnitude of wage changes in response to labor market conditions.
  - **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; 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.

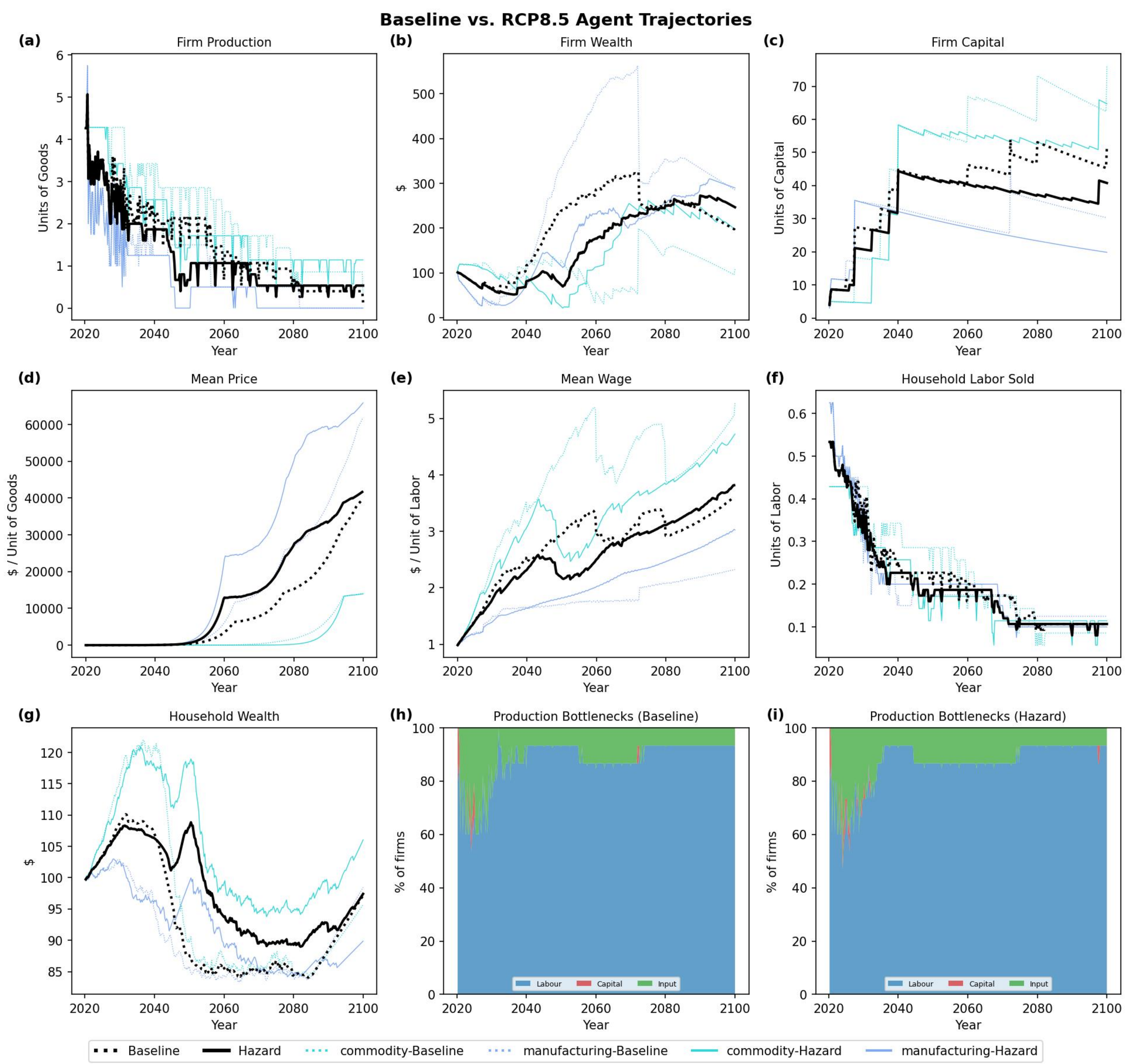

Figure 1. Agent trajectories under baseline (no hazard) and RCP8.5 riverine flooding scenarios.

Results

- A sample network of 15 firms and 75 households is implemented with WRI Aqueduct riverine flood data (https://www.wri.org/data/aqueduct-floods-hazard-maps) under RCP8.5 compared with a baseline no-hazard scenario
- **Baseline scenario**: The firms start with an average production of 4.3 units / firm, which falls into a stable regime of 0.4 units / firm (Figure 1a). Households transition from providing an average of 0.5 units of labour in 2020 to 0.1 by the 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% over time) 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 in the same rise due to the downward pressure of affordability of labour and high unemployment (Figure 1f).
- **RCP8.5 scenario:** Under climate stress, firms lose inventory, productivity, and capital, resulting in diminished production. In 2050, the average per-firm production is 0.7, 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. 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 compared to the baseline. The lower supply of firms is exacerbated by the higher wealth of households (Figure 1g). Households have higher wealth because of forced savings, where the limited availability of goods constrains the spending of households despite increasing wages due to demand for labour. Figure 1i 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.

Conclusions

The 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 1h vs.1i). However, firms are able to lower these risks by adapting to evolving climate stresses through improved budget allocation, dynamic pricing, and capital accumulation, as evident by the convergence of firm production and wealth under RCP8.5 with those of the baseline by the end of the century under the adaptive learning regime.

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.

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