ETH zürich

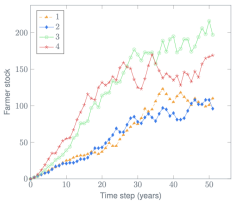
Computational Social Science

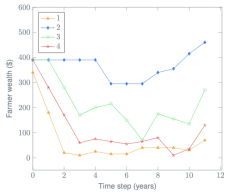
CropWar

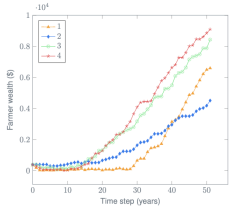
851-0101-86 S Complex Social Systems: Modeling Agents, Learning, and Games

CropWar: Agent-based simulation of agricultural interactions

C.Golling, G.Mourouga, A.Moser, O.Schmidt, A.H.Keshavarzzadeh







Content

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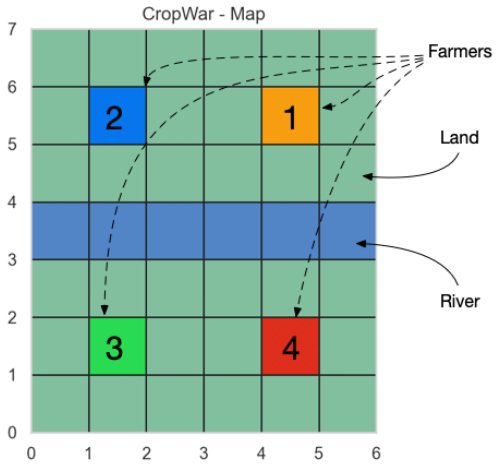
Deterministic versions

Basic version: selling and stocking

v1.1: Basic version

Deterministic versions

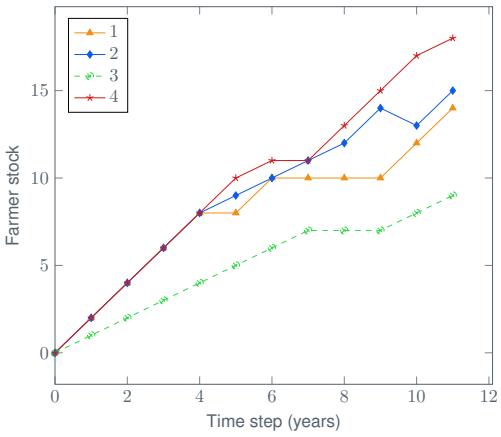
Basic version: selling and stocking



In v1.1 farmers only have access to one cell on which they can choose to grow one of two crops (A or B)

Deterministic versions

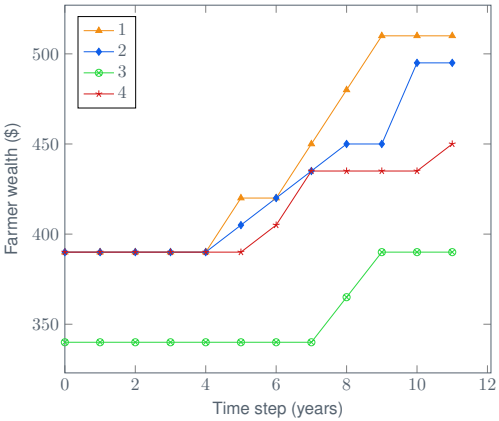
Basic version: selling and stocking



This plot shows the evolution of stock as a function of time:
Farmers 1,2 and 4 grow crop A
Farmer 3 grows crop B
At each time step, they chose to stock or sell their yield

Deterministic versions

Basic version: selling and stocking

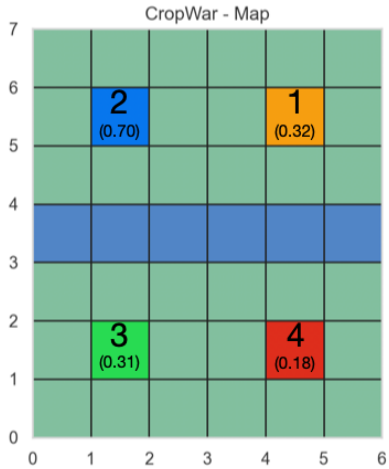


This plot shows the corresponding evolution of the farmer's wealth as a function of time. Selling corresponds to an increase in wealth, stocking to a constant value.

v1.2: Spatial expansion

Deterministic versions

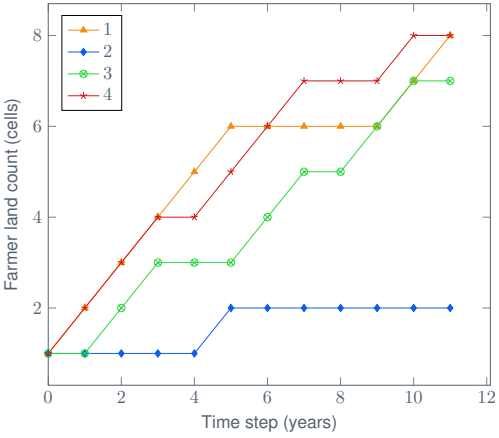
The Map class: expansion

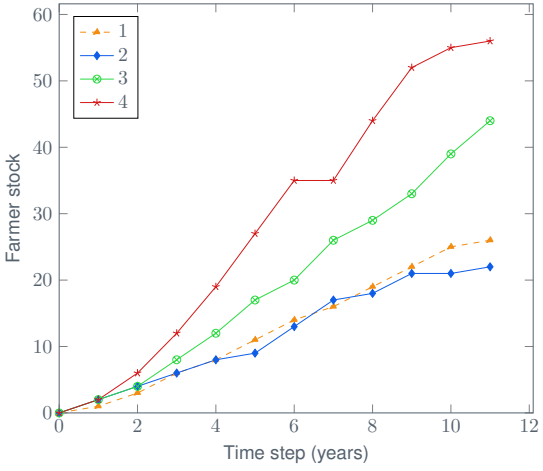


The `buy_threshold` (in brackets) indicates the tendancy of farmers to expand their farms by buying neighbouring land in order to grow more crops

Deterministic versions

The Map class: expansion





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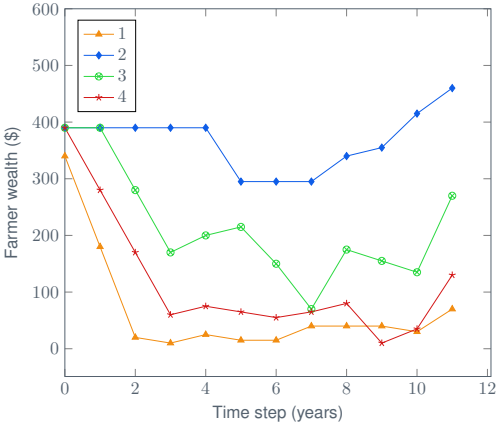

Farmer 2 seems to remain wealthier than other farmers over 10 time steps, due to not spending money to expand

Deterministic versions

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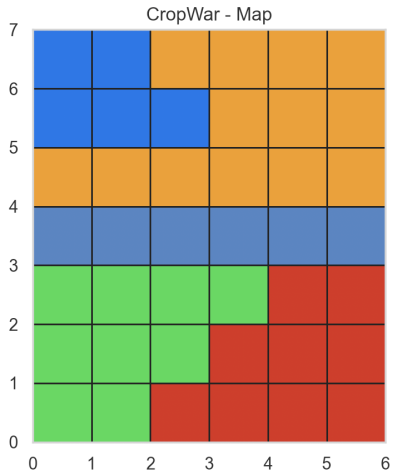

If we extend the simulation to 50 time steps, all available land is bought by farmers

Deterministic versions

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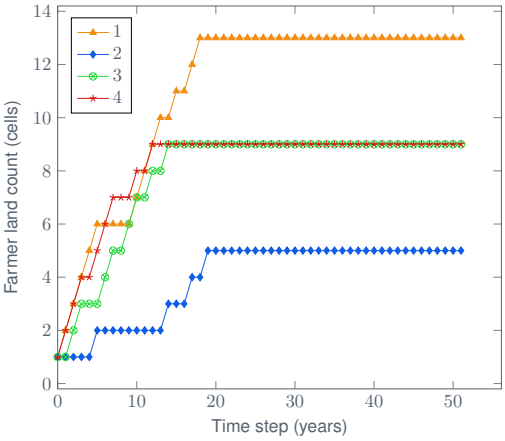

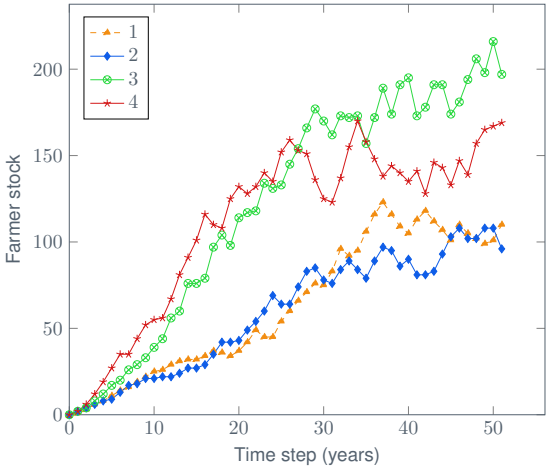

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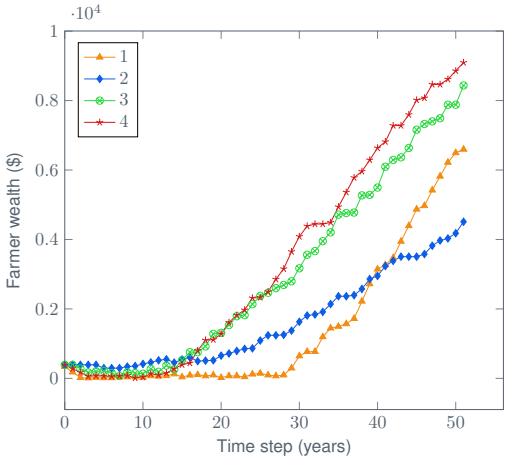

On the long run, farmers with more land become wealthier, although the type of crop also seems to have an importance

v1.3: Dynamic pricing of crops

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2. Interaction period: market interaction takes place.
3. Strategy period: the Agent's personality influences its decision for the next time step.

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Deterministic versions

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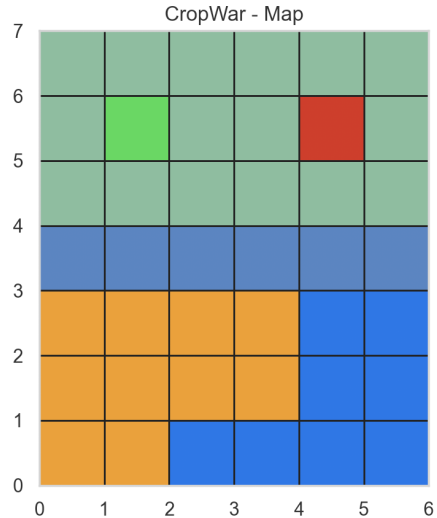
- Stationary agents remain on their initial cell
- Expanding agents may buy neighbouring land



Simulation with 2 stationary `Introverts` and 2 expanding `Traders`

Deterministic versions

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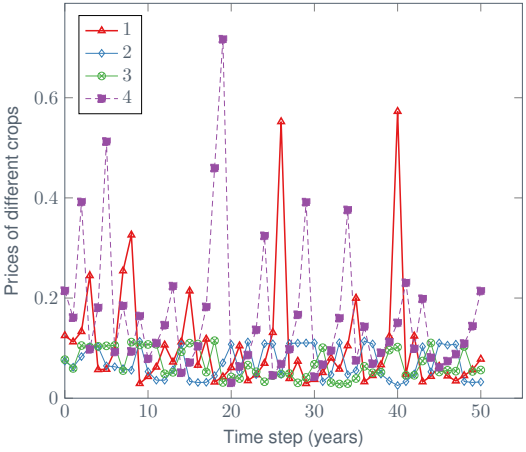

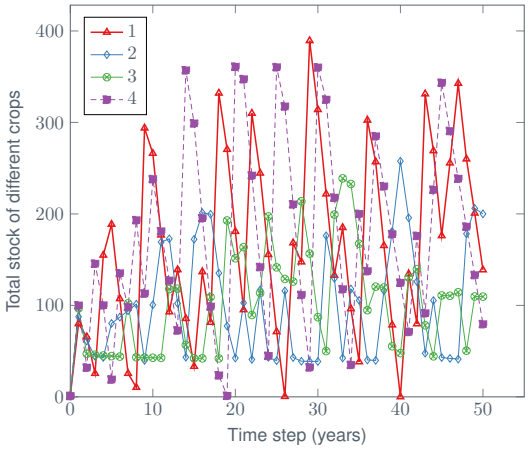

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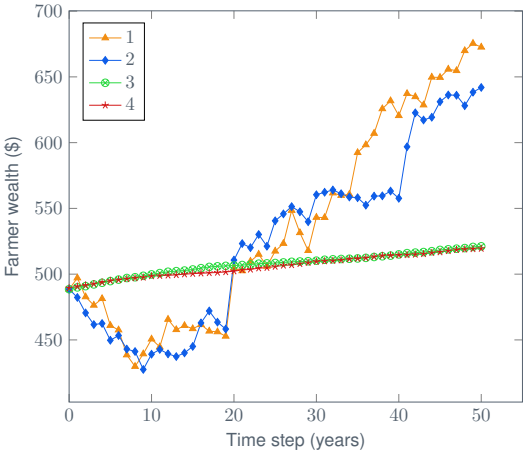

Farmer wealth as a function of time: expanding `Taders` agents take more risks, which seem to pay off on the long term

Reinforcement Learning

Reinforcement Learning versions

Introduction

The preceding versions v1.1 - v1.3 defined the deterministic agents and the model of the environment in which actions take place.
In order to see unpredictable, emerging behaviour, the agents would need to adjust to evolutions of the market and learn.

Reinforcement Learning versions

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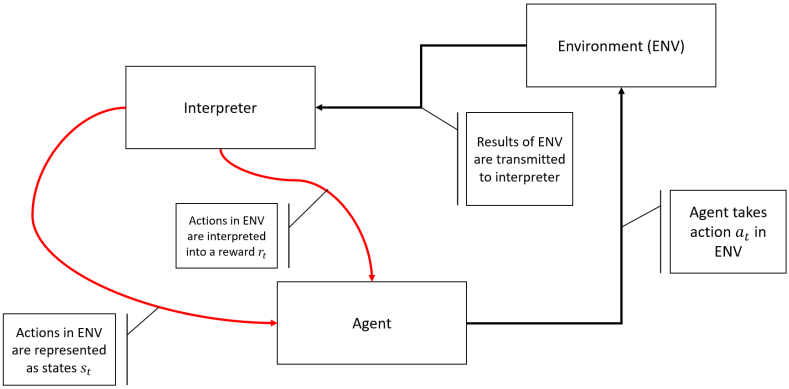

Feedback loop in RL. An agent decides to do a certain action a_t based on his observation of the environment. This affects the environment, which yields a new state. The effect of the agents' action is then interpreted to update the strategy of the agent.

Reinforcement Learning versions

Proximal Policy Optimization

$$\underbrace{L(\theta)}_{\substack{\text{Policy}\\ \text{loss}\\ \text{function}}} = \underbrace{\hat{\mathbf{E}}_t}_{\substack{\text{expectation}\\ \text{at iteration}\\ t}} \left[\log(\underbrace{\pi_\theta(a_t|s_t)}_{\substack{\text{stochastic}\\ \text{policy}}}) \underbrace{\hat{A}_t}_{\substack{\text{estimator of}\\ \text{advantage of}\\ \text{current action}}} \right] \tag{1}$$

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- $\pi_\theta(a_t|s_t)$ is given as transition probabilities in the MC of taking action a_t in state s_t. It is a neural network, that suggests an action for a given state based on previous training experience.

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where:

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- $\hat{A}_t$ is computed as a discounted reward. This neural net is updated with the experience (i.e. reward) that the agent collects in an environment.

Reinforcement Learning versions

ML agent trained against introverts

v2.1: RL agent trained againt Introvert farmers

The reward function that was used for training is given by

$$\frac{1}{3}\Big(\underbrace{b^2}_{\substack{\text{Fraction of}\\ \text{Global Budget}}} + \underbrace{r^2}_{\substack{\text{Current}\\ \text{Ranking}}} + \underbrace{s^2}_{\substack{\text{Fraction of}\\ \text{Global supply}}}\Big) \tag{2}$$

where r is 1 for first, 0.66 for second, 0.33 for third, and 0.0 for last agent.

Reinforcement Learning versions

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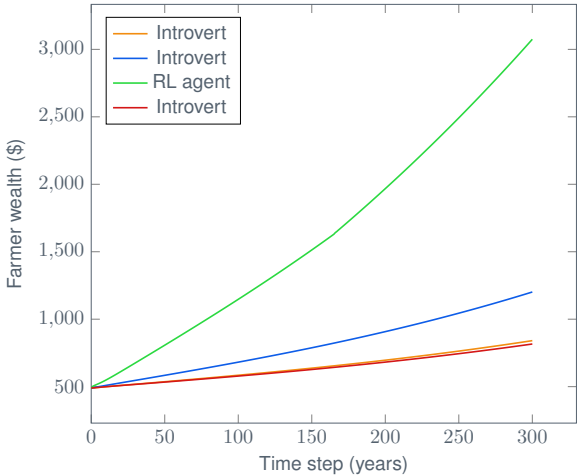

Figure: Budget evolution over 300 iterations

Reinforcement Learning versions

ML agent trained against traders

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Reinforcement Learning versions

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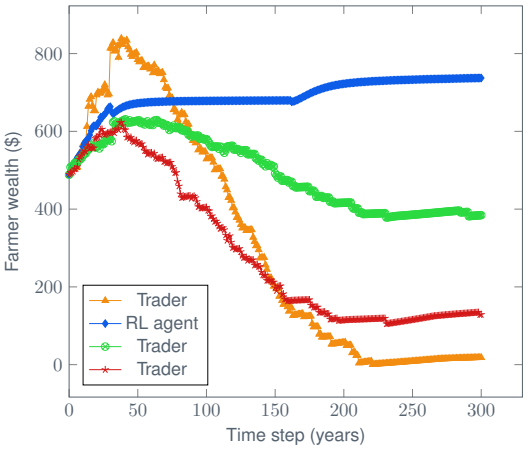

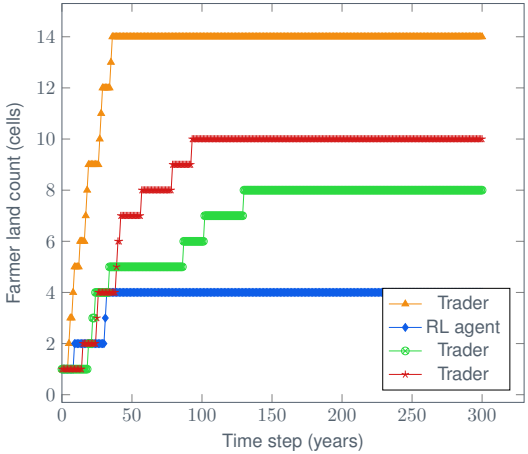

Reinforcement Learning versions

ML agent trained against traders

Figure: Stock evolution for the three `Trader` agents and the RL agent.

Crop War in perspective

Outlook and Perspective