Agricultural Urbanism Planning Agents

Enhancing agricultural productivity in Manchester through agent-based land fragmentation management

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Abstract. This research employs Agent-Based Modelling (ABM) to assess the impact of land pricing policies on urban agricultural land fragmentation, focusing on enhancing Urban Agricultural productivity. Targeted at policymakers, the study provides a predictive tool for evaluating and managing urban land use, emphasising how land fragmentation influences agricultural productivity within urban settings. By simulating different land pricing strategies in Manchester through 2042, it illustrates the potential for tailored policy interventions to effectively manage land fragmentation. The study specifically compares two policy scenarios: one advocating for price increases in low land price areas in the north, and another enforcing price reductions in high land price areas in the south. Findings suggest that price increase policies may be more effective than price reduction policies in reducing agricultural land fragmentation. This methodological approach offers actionable insights for developing robust AU policies and highlights the adaptability of the model for application in various urban contexts globally, underlining the need for precise land management strategies to foster successful urban agriculture amidst complex urbanisation challenges

Keywords. Agent-Based Modelling (ABM), Agricultural Land Fragmentation, Urban Land Development, Land Pricing Policies, Agricultural Urbanism, Capitalist Development, Land-Use Scenarios

1. Introduction

This study recognises agricultural productivity as a key indicator of Agricultural Urbanism (De la Salle & Holland, 2010) success. It investigates the strategic management of land fragmentation to optimise urban sustainability and enhance agricultural productivity. Introduced by Janine de la Salle and Mark Holland in 2010, AU promotes the integration of agricultural practices into urban planning to foster sustainable land use, addressing the multifaceted challenges exacerbated by expanding capitalism and its associated metabolic rift (Marx, K., 1894). This concept, which

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builds on Marx's analysis, underscores the deepening disconnection between human societies and natural processes, now manifesting as various aggravated social issues (Salle & Holland, 2010; McClintock, 2009).

McClintock (2009) argues that AU can significantly mitigate the adverse effects of the metabolic rift, presenting a viable approach to contemporary urban and ecological challenges by reintegrating agriculture into urban environments. However, the success of AU critically depends on effectively managing land fragmentation, which directly impacts agricultural productivity. Studies indicate a strong inverse relationship between land fragmentation (LF) and Agricultural productivity (AP) under the context of AU, suggesting that more fragmented landscapes substantially reduce agricultural productivity (Looga et al. 2018). Consequently, a precise understanding and management of land fragmentation are essential for maximising AP.

AU, as a complex urban system (Batty, 2005), involves numerous stakeholders—each with distinct interests—and their interactions significantly shape the urban agricultural landscape. This complexity, characteristic of systems where 'the behaviour of the whole can be quite different from the behaviour of its parts,' is aptly captured by Agent-Based Modelling (ABM) (Batty, 2005), which excels at simulating the interactions of diverse agents within an urban context (Holland, 2014). In AU, ABM facilitates detailed simulations of various entities, including local governments, commercial developers, and agricultural landscapes, all interacting within a shared urban environment.

ABM's utility in this study is demonstrated by its ability to model individual decisions and their collective impact on urban dynamics, crucial for addressing AU challenges. ABM simulates these interactions to offer detailed insights into how urban planning and land use policies affect agricultural productivity and sustainability. It also allows for scenario testing, providing a dynamic perspective on potential land management changes. Moreover, ABM facilitates "what-if" explorations in complex urban settings, essential for crafting effective urban agricultural strategies and evidenced by studies showcasing its policy analysis capabilities.

Thus, ABM is chosen not merely as a technical tool but as a strategic approach, informed by theoretical frameworks that recognise the interconnectedness and interdependence of urban systems. This method ensures that simulations reflect the real-world complexities of urban agriculture, providing policymakers with realistic, actionable insights that surpass the capabilities of traditional static models.

Through ABM, this research will simulate various scenarios of urban land-use changes in Manchester up to 2042, analysing how different urban development and land pricing policies might influence the city's agricultural landscape. By leveraging ABM's capabilities, this study aims to provide new insights that traditional methods often overlook, thereby contributing to more effective and sustainable AU policies. The flexibility of the model allows it to be use in other region.

2. Methodology

In this study, agent-based modelling (ABM) is used to simulate urban agricultural land use development in Manchester. Agents, representing land developers, navigate a digitally rendered landscape to select and develop plots. The process includes stages of plot selection, evaluation, and competitive development, reflecting real-world urban planning dynamics. Agents are divided into five groups, each with unique characteristics, moving through stages to assess and choose development sites. Competing agents at desirable plots engage in a mechanism to determine the winner. This approach demonstrates how ABM helps policymakers assess the impact of urban pricing strategies on LF and AP, as depicted in flowcharts Figure1and Figure 2.

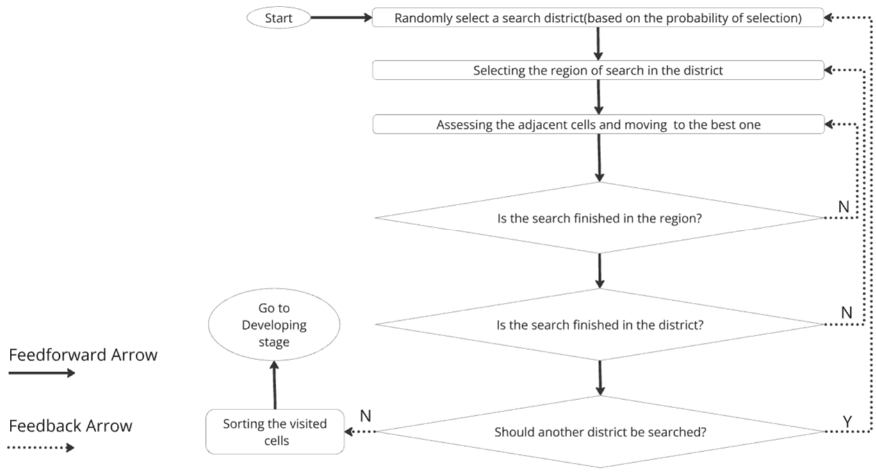

Figure 1. Flowchart of the model in the searching stage. (by author).

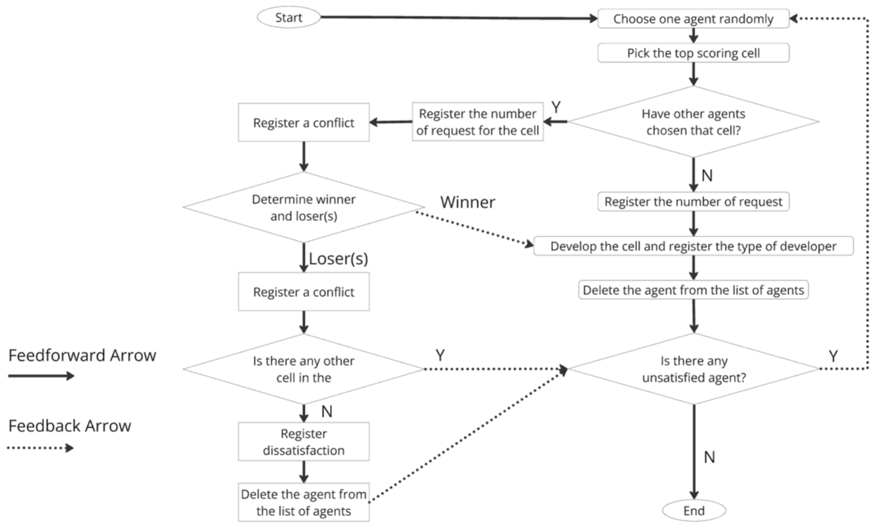

Figure 2. Flowchart of the model in the developing stage (by author).

2.1 CRITERIA FOR TARGET LOCATION SELECTION AND ADAPTIONS

Prior studies have highlighted various criteria used by agents to select development targets. Influential research in this domain (Matthews et al., 2007; Parker et al., 2003) has identified factors such as property price, demographic characteristics, and accessibility, which typically influence less than 30% of development decisions (Benenson & Torrens, 2004). These insights point to the limitations of traditional modelling approaches that fail to account for the interdependencies among decision-making factors.

To address these limitations, our model integrates three critical criteria: attractiveness, accessibility, and land value, customised to Manchester's urban landscape. This approach, based on relevant research: *Agent-based modelling of urban land-use development, case study: Simulating future scenarios of Qazvin city*, provides a solid framework for simulating urban land use and understanding complex urban dynamics (Hosseinali, Alesheikh, & Nourian, 2013). The decision-making framework for agents considers the unique spatial dynamics of the city, utilising GIS data to create a realistic simulation environment. This method allows for a nuanced understanding of how different urban zones attract various types of development based on their inherent characteristics, and each agent should assess whether to develop the undeveloped area based on these interdependency criteria.

2.2 AGENT CLASSIFICATION AND BEHAVIOUR

In refining our Agent-Based Model (ABM) for simulating urban land use development, accurately classifying agents is crucial to capture the diversity and complexity of developer interests within Manchester's urban landscape. Drawing on established methodologies, notably from Hosseinali, Alesheikh, & Nourian (2013) and Loibl and Toetzer, our model divides agents into five distinct groups. Each group represents specific economic statuses, developmental goals, and operational strategies.

- Young Moderate-Income Seekers: Seek affordably priced plots with good access to amenities and transportation.
- High-Income Developers: Aim for high-value land in desirable locations that balance cost with potential for future appreciation.
- Affluent Lifestyle Developers: Prefer locations with exceptional attractiveness for luxury residences or leisure developments.
- Low-Income Individuals: Focus on the least expensive options available, often in less sought-after locations.
- Balanced Income Developers: Evaluate land based on an equal consideration of price, accessibility, and attractiveness, aiming for plots that offer a comprehensive blend of these factors.

2.3 DISTRIBUTION OF AGENTS IN CELLS, MOVEMENT PATTERNS, SCANNING COVERAGE

After defining agent preferences for cell selection, the next step involves setting their distribution within cells, movement patterns, and scanning range.

Agents start on the map with randomised initial positions and then move based on their preferences. Upon entering the environment, they evaluate eight cells around their current location, considering price, traffic, and attractiveness. If scores are equal, agents make random selections. During cell scanning, agents record selected and neighbouring unselected cells, choosing the one with the highest value for development. If multiple agents compete for the same cell, they move to the competition phase.

2.4 COMPETITION

If multiple agents choose the same cell, they compete, and the agent to develop it is determined by their competitiveness score, here is the formula, where competitiveness score represented as *S*:

$$S = W_{Type} \times S_{Type} + W_F \times F \quad (1)$$

S_{Type} is an agent's assigned score, and F represents the frustration value quantified by units lost by agents failing to compete. W_{type} is the weight score for different land types, and W_F represents the weight for frustration.

Initially, all agents have zero frustration. As they move, 1 is added to frustration for each lost competition. Competitiveness depends on an agent's weight score and competition failures.

3. Study Area

The study area, situated in the heart of Greater Manchester, spans 35 kilometres in both length and width. Comprising 122,500 units of 100m x 100m, this urban planning challenge focuses on rationalising agricultural land allocation within the city's central area, as depicted in Figure 3.

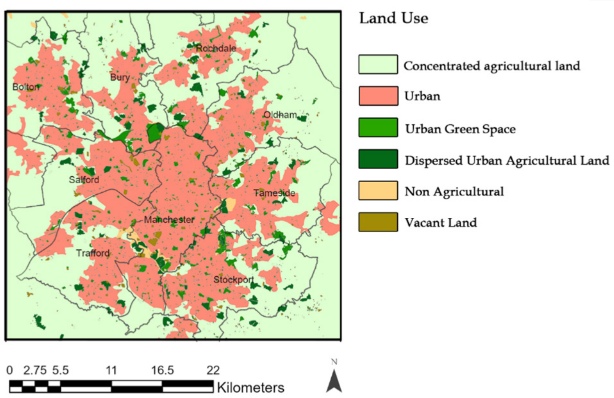

Figure 3. The study area

3.1. DATA PREPARATION AND CRITERIA MAPPING

The study utilised three essential criterion maps—land value, attractiveness, and accessibility—developed using GIS and sourced from OpenStreetMap to capture various characteristics across Manchester. Each map was normalised to have values between 0 and 1 to ensure uniformity as shown in Figure 4:

- Land Value Map: Assesses economic viability using land prices, development potential, topography, and soil quality.
- Accessibility Map: Measures connectivity by calculating the shortest travel times to urban centres.
- Attractiveness Map: Enhances location desirability with environmental features and scenic views.

The area was divided into several districts, each analysed for development potential based on historical growth from 2005 to 2022. This segmentation helps simulate future urban development scenarios. ArcGIS pro 3.0 (Esri 2022) and the NetLogo GIS extension (Wilensky, 2009) were pivotal in processing these maps facilitated spatial data processing, providing a realistic setting for our agent-based modelling.

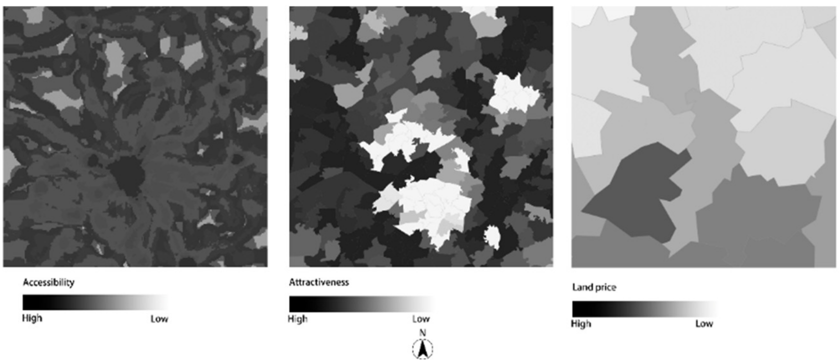

Figure 4. Maps of accessibility (left), attractiveness (middle), and land price(right)

3.2. SETTING PARAMETERS

To set the values of the parameters, settings were adopted from the reference article, 'Agent-based modelling of urban land-use development: a case study simulating future scenarios in Qazvin city,' with adjustments made based on the specific conditions of Manchester. The reliability of these adjustments is determined by comparing data from different years and calculating the kappa coefficient.

The referenced research identified key model parameters reflecting dynamics such as land price, accessibility, and attractiveness, which were initially set based on expert opinions and empirical data. While these parameters were initially applied to Qazvin, Iran, their methodology and settings have universal applicability and thus were adapted for use in Manchester. This adaptation involved adjustments and validations to ensure the parameters accurately reflect Manchester's urban development trends and policy impacts.

According to the reference, values of 9 and 10 were determined for W_{type} and $W_{Frustration}$.The number of agents for each type should also be determined. For the 289ha study area, the number of agents were determined as below:agent1 (90), agent2 (70), agent3 (10), agent4 (20), and agent5 (10). The agents can develop 1 hectare of land per year. The search area and development probability are initially set at 50%, 70%, and 90%. After comparing the kappa coefficient, the most stable results are obtained when each agent develops one-tenth of the scanned land cells with a 70% search area. To verify the reliability of the parameters, data for the year 2017 were entered into the model during calibration. Next, the results of the simulation conducted using the model were compared with data for the year 2020. We computed the Kappa statistic based on the calibrated model. The value of Kappa was 0.77, whichmeans that there is a good agreement between the results from themodel and the observed data.The calibration of the model utilised these parameters alongside those detailed in Table 1 (Table 1).

Table. 1. Parameters of the model

Type of agent	Type 1	Type 2	Type 3	Type 4	Type 5
Count	90	70	10	20	10
Weight of accessibility	3	1	1	2	1
Weight of attractiveness	1	2	2	1	1
Weight of land value	2	3	1	1	1
Number of searching district	9	9	9	9	8
Number of traverse cells	12	11	13	11	10
Number of Jumps in each district	2	2	2	2	1
$Score_{Type}$	2	5	2	1	3

Data up to 2022 of the study area has been obtained and utilised as the baseline for near-term analysis. Following the calibration of model parameters, the 2022 data was used to forecast Manchester's land use into 2042 and to determine the distribution of agent numbers and types, as illustrated in Figure 5

This result was first retained, followed by defining the impact of different policy measures for the model to explore how the future distribution of agricultural land in Manchester would be affected by the policy.

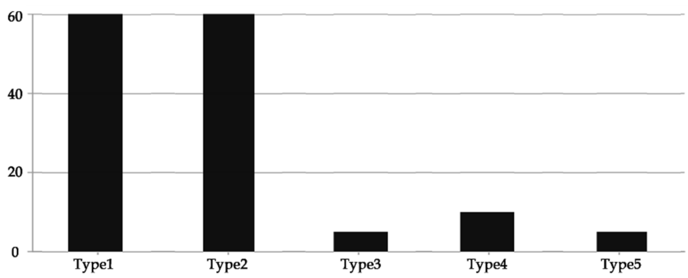

Figure 5. Distribution of the number and type of agents projected for 2042

4. Definition of policy scenarios

This model forecasts future changes and assesses the impacts of policy interventions on agricultural land distribution in Manchester using 2022 data (ArcGIS) as a baseline. Two scenarios are examined, extending up to the year 2042:

- Increase land prices Scenario: Increases land prices in Manchester's northern low-price areas to stimulate development and potentially concentrate agricultural activities.
- Reduces land prices Scenario: Reduces land prices in the southern high-price areas to discourage dense development and promote balanced urban growth.

Each scenario is simulated using the ArcGIS (3.0), providing a dynamic visualisation of land price adjustments and their implications for urban and agricultural planning, as depicted in Figure 6. These simulations help us understand how strategic adjustments in land pricing can direct and shape the future urban landscape, offering valuable insights for policy formulation and urban planning.

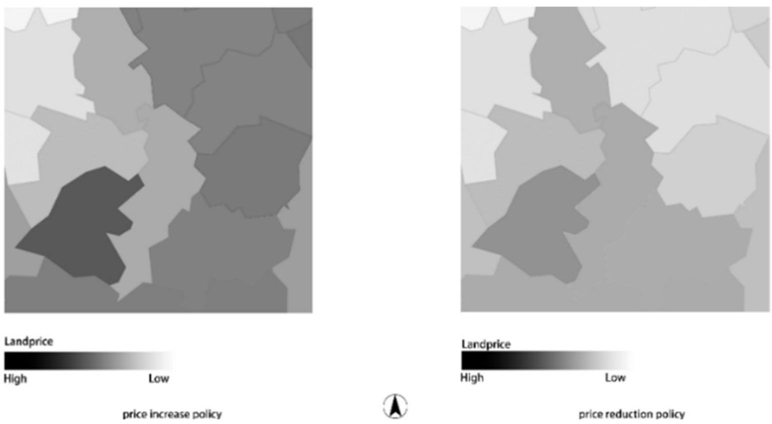

Figure 6. Map of land prices after the implementation of the price increase policy(left) and Map of land prices after the implementation of the price reduction policy(right)

5. Results and Discussion

The distribution of the number and type of agents under 2 different policy: price increase policy and price reduction policy is shown in the Table 3:

Table. 3. The distribution of the number and type of agents under the different policy for 2042

Type of agent	Type 1	Type 2	Type 3	Type 4	Type 5
Count under the price increase policy	50	70	5	10	20
Count under the price induction policy	95	60	5	5	5

5.1 ANALYSIS OF LAND FRAGMENTATION

To evaluate the LF of developed land in our simulations, we introduced the Schmook index（Schmook ,1976)：

$$K_s = \frac{\sum_{i=1}^{n} a_i}{A} \quad (2)$$

The Schmook index, represented as K_s, quantifies the fragmentation of land holdings. It is calculated using the area a_i of the i-th parcel and the area A of the convex hull that encloses all parcels of a single land holding. This index provides a measure of the fragmentation of parcels within the defined area.

A higher index value indicates a greater scattering of land fragments across the landscape, highlighting increased LF.

Following the methodology outlined by Looga et al. (2015), we calculated the Schmook index for each scenario run in our ABM to determine the effectiveness of different land pricing policies on reducing LF. When price increase policy be applied, the Schmook index is 30, while price reduction policy be applied the Schmock index is 70. Which indicate that comparing to the price reduction policy, when price increase policy be applied may reduce the LF in Manchester.

The model results clearly show that different land price policies have a significant impact. Under a price increase policy, there are more developers with low bids and fewer with high bids, resulting in reduced LF. Conversely, a price reduction policy leads to fewer low-bid developers, more high-bid developers, and increased LF. Adjusting land prices can be an effective way to manage LF and promote AU.

Through ABM simulations, it has been discovered that different land pricing policies do indeed impact the LF. Policies aimed at raising land prices in low-value northern areas and lowering land prices in high-value southern areas have shown significant effects. These policies influence the distribution of developers, encouraging lower bids in areas experiencing price increases and higher bids in areas with declining prices. The ABM provides a dynamic perspective on how to effectively implement these strategies.

This finding implies that policymakers possess a potent tool for regulating and controlling the LF Such control is crucial for the practical implementation of AU.

5.2. LIMITATION

While the ABM offers significant insights for urban planning, it faces challenges related to the precision and consistency of data. Enhancing its utility requires standardising data collection methods and integrating a broader spectrum of variables, such as socio-economic and environmental factors. This will more effectively capture the complexities of urban dynamics and refine the ABM's predictive capabilities, making it a more reliable tool for urban policymakers.

6. Conclusion

In summary, this study has employed the ABM to explore the influence of various land pricing policies on LF in Manchester. The simulations provide the following guidelines for enhancing policy effectiveness:

- Land pricing policies have a considerable influence on urban agricultural land dispersion.
- Price increase policies appear more effective than price reduction policy in reducing LF, potentially aiding in the implementation of more successful agricultural urbanism strategies.

While these findings are based on idealistic simulations, they illustrate the ABM's utility as an insightful tool for urban policymakers. The model offers specific insights into how diverse factors and policies might influence agricultural land distribution, aiding in the development of refined AU policies to reduce LF and therefore enhance AP, This approach confirms the ABM's potential applicability in various urban contexts, From the results of the experiment, it seems that the implementation of a price increase strategy in Manchester helps to reduce LF more than a price decrease strategy, providing a strategic tool for crafting policies that address the complexities of urban agriculture and land management.

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