**Frontiers in Business, Economics and Management**
ISSN: 2766-824X | Vol. 25, No. 2, 2026

# Artificial Intelligence Applications, Urban Land Allocation Efficiency, and Urban Economic Development: An Analysis of the Mechanisms

**Hangzhi Zhang**

The Bartlett Development Planning Unit, University College London, London, WC1H 9EZ, United Kingdom

**Abstract:** This paper constructs a conceptual model of how applications of artificial intelligence can promote urban economic development by improving urban land allocation efficiency. Applications of artificial intelligence refer to machine learning, computer vision, predictive analytics and decision-support systems for land classification, change detection, demand forecasting, planning scenario comparison and implementation monitoring. Land allocation efficiency concerns how well urban land is distributed across locations, uses, intensities and time, whereas land-use efficiency concerns the outcomes achieved from those allocations under infrastructure, environmental, distributional and institutional constraints. The proposed mechanism may provide more information, reduce coordination costs, improve matching efficiency, and support flexible governance of land-use decisions that could benefit productivity, agglomeration, investment, accessibility and resilience. The link is not automatic ; bias in the data, opaque optimisation, weak property rights, fragmented institutions, and surveillance and automation bias can all lead to misallocation. Existing land-mapping research has studied the information channel; its wide-ranging impact on land allocation and economic development needs further investigation.

**Keywords:** Artificial Intelligence; Urban Land Allocation; Allocation Efficiency; Urban Economic Development; Spatial Governance; Mechanism Analysis.

## 1. Introduction

Urban land has fixed locations and varying levels of accessibility, and is organised by infrastructure, regulations, etc. Decisions on the location of housing, industry, commerce, public services, transport and ecological functions may affect commuting, investment, environmental exposure, municipal finance, and the opportunities for households and enterprises. Poorly coordinated decisions may lead to underutilisation of serviced land and development in areas with high social or environmental costs.

Artificial intelligence is now used to process satellite images, administrative records, sensor data, transactions, movement traces and planning documents, etc. More computation does not necessarily result in better land allocation. A system can accurately predict a trend; however, it may be optimised for the wrong goals, fail to consider informal activities, and thus lead decision-makers to believe that the uncertain output is objective truth. Therefore, the economic effect will vary depending on the range of application, available data and institutions.

This paper studies a conditional mechanism: AI applications can improve the information and coordination environment for urban land-use decisions; thus, changes in land allocation may affect urban economic development through productivity, agglomeration, accessibility, investment, public service delivery and resilience. Artificial intelligence applications are limited here to machine-learning, computer-vision, predictive-analytics, and decision-support systems used in land classification, change detection, demand forecasting, scenario comparison, and monitoring. Mechanisms and institutional conditions that can be studied in future city-level research are to be highlighted.

## 2. Concepts and Foundations

High-efficiency use of urban land should not be judged by the highest market price or the most favorable immediate fiscal benefits alone. Alonso's framework for land-use links location, rent, accessibility, commuting costs and competition for urban space [1]. The framework presents the economic reasons for decentralisation, and public policies also consider the living environment, environmental protection, infrastructure capacity, public spaces, cultural heritage and distributional fairness. Here, land allocation efficiency concerns the distribution of land across locations, uses, intensities and time, while land-use efficiency concerns the resulting socially valued outcomes under explicit constraints.

One development channel works by agglomeration. Duranton and Puga list sharing, matching and learning as the micro-foundations of urban agglomeration economies [2]. Land-use arrangements can support the above mechanisms by allowing firms to share facilities and suppliers, improving the matching of workers with jobs, and promoting knowledge interaction. But density without transport, services, environmental protection and affordable access may lead to congestion and exclusion. Thus, the benefits and costs of concentration vary according to the region and who has access.

Secondly, there is the misallocation theory. Restuccia and Rogerson have found that, in a calibrated theoretical model, producer-specific distortions reduce aggregate output and measured productivity [3]. Hsieh and Klenow then used the established microdata to study resource misallocation and manufacturing productivity in China and India [4]. These studies focus on the capital and labour of producers, not directly on urban land. Relevance to urban land is an analogy: when land or development rights are disassociated from socially productive uses due to distorted prices,

administrative fragmentation or unequal access, the urban economy may be harmed.

Urban economic development is also about long-term gross output. Glaeser believes a city is a place of interaction, innovation, skills and economic opportunities [5]. Therefore, the development in this analysis includes productivity, employment, entrepreneurship, housing and service accessibility, fiscal sustainability, innovation and resilience. These results may differ. The allocation of central land for a high-value project may increase assessed values and displace low-income residents or extend essential-worker commutes. A single aggregate index cannot inform us of the actual beneficiaries, the associated costs, places, and durations.

Institutional arrangements determine what can be optimised. The joint World Bank and Development Research Centre report on urban China links land-use reform, market-based allocation, denser development, connectivity and more sustainable urbanisation [6]. It is a report for policy planning, and we cannot assume that all the cities have implemented the reforms successfully. Property rights, conversion regulations, pricing, planning, local finance and official incentives all affect the results of land-use change. AI planning tools cannot replace explicit rights, laws and regulations, nor stable fiscal and planning responsibilities.

# 3. AI as Urban Infrastructure

The first is to provide information. Batty reports that urban big data often includes location and time stamps to promote the development of real-time observation and management in city planning [7]. Computer vision can be applied in land administration for land-cover classification, physical-change detection and multi-temporal image analysis. Natural-language processing can organise permits and plans, and forecasting tools can predict service demand. These functions can reduce the cost of producing decision-relevant evidence, but automatically detected physical changes are not the same as a legal violation, ownership determination or verified socio-economic interpretation.

Kitchin's analysis of the real-time city foresees the prospect of data-driven urban management but also points out the politics, deficiencies and governance issues of urban data [8]. Data are generated unevenly. Formal property transactions are relatively frequent compared to informal tenancy agreements, the distribution of mobile phone data differs among different groups, and administrative divisions do not correspond to functional urban areas. An AI system trained on this data may amplify the existing disparity in visibility. Therefore, the expansion of allocation needs data provenance, coverage assessment, uncertainty reporting, and a channel for affected communities to appeal the classification. A study in Hangzhou has used Sentinel-2 imagery and other urban data to classify land-use types. The random-forest model had a validation accuracy of 79.88% for Level I land-use classes, and transportation land remained a problem [9]. The above results help to strengthen the evidence basis for planning but do not alter the allocation outcome.

The second is scenario analysis. Artificial intelligence can process a large number of spatial arrangements more readily than human planners to find correlations among land-use types, transportation, hazards, services, market activities, etc. Scenario tools can compare the zoning options and find plots where the planned capacity conflicts with infrastructure. It is not to be expected that an ideal map will be presented. The goals of affordability, accessibility, economic benefits, reduced emissions and ecological protection need to be selected and weighted through proper public consultations. A mathematically optimal solution may still be socially unacceptable.

The third is the administrator function. The shared data model and decision-support tool can link the planning, transportation, utility, tax-and-housing, environment departments, etc. Find the inconsistent data, help build a sequence, and confirm that the approvals match the results of the construction. Interoperability is still relatively poor. Access control, correction procedure, retention limit and separation of planning and enforcement functions should be applied to data collected for one purpose and used again for another.

# 4. Mechanisms Linking AI to Allocation

The four links above are connected. First, an AI application modifies the cost, speed, scope or quality of information. Second, officials, enterprises and residents use the information for decision-making. Third, rules and incentives change the decision into a modification of land-use type, intensity, time, tenure or infrastructure. Fourth, the resulting spatial arrangement affects access to jobs, schools and other facilities. The development benefits will not be realised unless these links function properly; otherwise, there will be a failure.

The other is improved matching. Demand forecasts and accessibility analyses can be used to compare sites for housing, logistics, schools, clinics, offices, etc. If the system cannot find a suitable area for housing development, others will have to be considered. Predicted demand is not the same as socially necessary demand. A model normalised to purchasing power may underestimate the demand of low-income households. Thus, the model's predictions need to meet the goals of policy, basic-needs services and distribution fairness.

A second mechanism is the early detection of underutilization and conflicts. Image analysis and administrative records can be used to find vacant serviced plots, unauthorised changes, suspended projects, etc. Mao and others applied deep learning to high-resolution satellite images of 36 major Chinese cities. Their method for vacant-land identification was about 15 times faster than manual identification and achieved over 90% of the accuracy of professional auditors [10]. These are enhancements to detection, not increases in land allocation or economic growth. Verification is still needed to exclude temporary vacancies, protected open land and old administrative records. The authorities should investigate the high-priority cases first and only then issue fines or reallocations; they must also record the reasons for these decisions.

The third way is adaptive planning. Traditional plans may no longer meet the current needs of the population, economy and environment. Periodically updated indicators can be used to conduct a regular review of whether the city's infrastructure and land-use assumptions are still reasonable. Adaptation should not be continuous algorithmic re-zonation; otherwise, there will be instability and a risk of intentional manipulation. Stable rules and regular review cycles are needed for investment and public trust.

The fourth way is transaction and coordination costs. Digital workflows can reduce the amount of record search and

standardise the regular inspection of flagged applications. Savings are not guaranteed, and a lack of data integration, model errors, procurement dependencies, and parallel paper-and-digital systems will all increase costs. Administrative efficiency should consider all the costs of implementation and verification, cybersecurity, training, appeal and maintenance, not only the speed of model output.

# 5. Urban Development Channels

Optimising land use may enhance access to production factors. Better coordination of workplaces, housing, transport and services can reduce space friction and expand opportunities for workers and enterprises. This may be due to agglomeration effects; however, there is also reverse causality, as large enterprises attract infrastructure investment and increase the demand for land. To study the causal effect of this channel, the parallel planning reform and digital investment should be excluded.

AI can also automate office work. Acemoglu and Restrepo distinguish the displacement effect of automation from the countervailing effects of productivity gains and the creation of new tasks [11]. Automation of urban land-use classification may reduce some routine operations but may increase demand for data governance, field verification, public communication, model auditing and interdisciplinary collaboration. The net effect on employment and skills is unknown. The implementing agency will be responsible for addressing the problem and retraining staff.

Productivity gains may be delayed due to the demand for support investments. Brynjolfsson, Rock and Syverson believe that the gap between the expectation of AI and actual productivity is due to late implementation, lack of organisation-wide adjustments, skill deficiencies and intangible assets [12]. A good prediction model cannot overcome the absence of land registry data, inconsistent policies and weak enforcement. The reasons for the benefits are: standardised data, high-quality staff, procurement reform, supporting facilities and optimised operations. Economic changes are not solely due to the purchase of an AI platform.

Another channel is municipal finance. Consistent parcel information and scenario analysis can support the revision of valuations, infrastructure charges, and long-term capital planning. A revenue-oriented system will favour profitable projects and be less likely to invest in housing, public spaces and ecological protection. Fiscal indicators should align with the overall development goals. Assumptions should be explicit. Where local governments both regulate development and receive land-related revenues, their decisions should be subject to independent oversight.

Resilience is also a way. Spatial models can integrate hazard information with population, building, network and land-use data to study exposure and service disruption. Such analysis may inform the siting of new industrial parks. Uncertain extreme weather, missing information on unplanned construction and interacting risks are still problems. Due to the considerable distribution costs of relocation or development restrictions, authorities should engage in risk assessment and support measure discussions with the affected community and not issue model outputs unilaterally.

# 6. Risks and Countervailing Effects

The same technology may also lead to misallocation. Historical approval and transaction data may include exclusionary zoning, unequal credit access, selective enforcement, or speculative cycles. A model that learns the above patterns can reproduce them under the same circumstances. Proxy variables can still be used without the inclusion of protected attributes. Fairness assessment should examine who benefits from investment, whose land-use changes are deemed inefficient, whose records require correction, and who bears the costs of false positives and false negatives.

Optimisation may be in conflict with the public interest if the aim is too limited. Land is at the same time an economic factor, habitat, home, source of identity, fiscal foundation and political rights. A single score cannot show all the different weights of the various goals. Multiple scenarios, sensitivity analysis and accessible explanations are preferred over a single ranking. Some decisions should not be included in the automatic optimisation if the risks to rights and irreversible environmental damage and displacement exceed the marginal efficiency gains.

Market response may offset desired gains. The published forecasts and infrastructure plans may lead to speculation before the start of construction and residents' relocation. Proprietary tools can give large enterprises information advantages. Too much secrecy evades public scrutiny. Separate the required disclosure information for accountability from sensitive personal or security-related prior-decision data in the disclosure provisions. At the same time, there will be rules on timing, conflict of interest and anti-speculation.

Automation bias and gaps in responsibility are organisational risks. Officials may defer to a model and not question the results; vendors will not be responsible for the policy outcome. A person's signature is insufficient if they cannot assess the data and assumptions, uncertainties and alternatives in the study. Decision records should contain the purpose of the model, supporting data, exceptions and the responsible person. Appeals should be able to alter the result; otherwise, they are only a late justification.

# 7. Governance and Empirical Tests

Governance measures should be proportionate to risk. The values proposed in the OECD Recommendation on Artificial Intelligence are inclusive growth, human-centred values and fairness; transparency and explainability; robustness and safety; and accountability [13]. The rules for land-use decisions need to record the reasons, use the data lawfully, provide understandable explanations and ensure the security of the system over time. Economic efficiency should not violate rights and distribution considerations.

Urban digital transformation should be people-centred. UN-Habitat's assessment of smart-city governance has both prospects and governance challenges, and shows capabilities, regulatory systems, cooperation, inclusion and human rights protection [14]. Participation should take place before the setting of goals and not after the construction of a map. Residents, enterprises and technical staff can identify missing land-use data and local problems in the administrative data. Public participation may involve conflicting interests and does not necessarily lead to consensus.

NIST AI Risk Management Framework provides the functions of govern, map, measure and manage for voluntary AI risk activities [15]. A city can govern by issuing authority and policies; map by specifying the use case, affected groups

and damage, measure through tests of validity, robustness, privacy and differential performance; and manage by controlling deployment, monitoring incidents and establishing withdrawal criteria. The general framework is not adequate for the urban land-use planning decisions. It should be in accordance with land law, planning standards, environmental assessment, procurement regulations and specific circumstances.

The three objects of future empirical research are AI adoption, land allocation efficiency and urban economic development. Adoption should be based on actual functions and use, not procurement announcements. Different goals are aimed for by the various efficiencies: accessibility, land-use intensity, vacancies, service coverage, environmental costs, and spatial disparities. At an appropriate time and place, the results need to be observed. Selection bias is also present; well-resourced or rapidly developing cities have introduced AI earlier.

If other reasons are excluded, a plausible evaluation can be constructed by means of staged implementation or institutional modification. Mixed methods can be used to combine administrative records, spatial analysis, document collection, interviews and field research in the study. Public databases can provide some reference materials, but the content may be incorrect. Definitions, missing data, boundary changes, model versions, code and restrictions need to be reported. The results of a single tool in a particular city should not be applied to all other places.

# 8. Summary

Artificial intelligence may change land-use patterns in the development of the urban economy, but the actual effects of these mechanisms remain to be tested empirically. The first possible advantages are improved observation and forecasting, scenario analysis, coordination and monitoring. Only when institutions alter the better evidence into lawful and socially acceptable changes of location, use, intensity, time, tenure or infrastructure will they be implemented. These changes in spatial arrangements may affect access, concentration, efficiency, investment, services, fiscal health and resilience.

These possible benefits may not occur. Biased or incomplete data, unsuitable targets, opaque models, fragmented authority, speculation, automation bias, privacy violations, and a lack of appeal mechanisms can all lead to misallocation of funds or cost shifting for less visible groups. Efficiency should be evaluated in terms of actual economic, social, environmental and distribution goals. Effective human supervision needs relevant skills, supportive data and time, and authority.

A conditional analysis of the impact of AI-assisted information and coordination on land-use decisions is performed, and institutional safeguards are introduced to prevent misallocation. The above-mentioned paths do not provide evidence of a causal economic effect; in the future, opening up indicators, field data and reasonable research designs will be employed for testing. Cities can begin with limited, reversible applications in practice; assess the distribution of benefits; disclose uncertainty; and keep records of decision-making accountability.

# References


[1] Alonso, W. (1964). Location and land use: Toward a general theory of land rent. Harvard University Press.

[2] Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J.-F. Thisse (Eds.), Handbook of regional and urban economics (Vol. 4, pp. 2063–2117). Elsevier. https://doi.org/10.1016/S0169-7218(04)07048-0

[3] Restuccia, D., & Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. Review of Economic Dynamics, 11(4), 707–720. https://doi.org/10.1016/j.red.2008.05.002

[4] Hsieh, C.-T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. The Quarterly Journal of Economics, 124(4), 1403–1448. https://doi.org/10.1162/qjec.2009.124.4.1403

[5] Glaeser, E. L. (2011). Triumph of the city. Penguin Press.

[6] World Bank, & Development Research Center of the State Council, the People's Republic of China. (2014). Urban China: Toward efficient, inclusive, and sustainable urbanization. World Bank. https://doi.org/10.1596/978-1-4648-0206-5

[7] Batty, M. (2013). Big data, smart cities and city planning. Dialogues in Human Geography, 3(3), 274–279. https://doi.org/10.1177/2043820613513390

[8] Kitchin, R. (2014). The real-time city? Big data and smart urbanism. GeoJournal, 79, 1–14. https://doi.org/10.1007/s10708-013-9516-8

[9] Mao, W., Lu, D., Hou, L., Liu, X., & Yue, W. (2020). Comparison of machine-learning methods for urban land-use mapping in Hangzhou City, China. Remote Sensing, 12(17), 2817. https://doi.org/10.3390/rs12172817

[10] Mao, L., Zheng, Z., Meng, X., Zhou, Y., Zhao, P., Yang, Z., & Long, Y. (2022). Large-scale automatic identification of urban vacant land using semantic segmentation of high-resolution remote sensing images. Landscape and Urban Planning, 222, 104384. https://doi.org/10.1016/j.landurbplan.2022.104384

[11] Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation and work (NBER Working Paper No. 24196). National Bureau of Economic Research. https://doi.org/10.3386/w24196

[12] Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 23–57). University of Chicago Press.

[13] OECD. (2019). Recommendation of the Council on Artificial Intelligence (OECD/LEGAL/0449). OECD.

[14] UN-Habitat. (2022). Global review of smart city governance practices. United Nations Human Settlements Programme.

[15] Tabassi, E. (2023). Artificial Intelligence Risk Management Framework (AI RMF 1.0). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.100-1