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EVALUATING LAND USE TRANSITIONS THROUGH DATA-DRIVEN AGENT-BASED MODELING WITH RANDOM FOREST CLASSIFICATION

Abstract. *Urban growth is making it harder to plan for land use that is beneficial for the environment. This study looks at how land use changes from 2020 to 2040 by using a combined modeling approach that uses both agent-based simulation and machine learning. We model changes in three main types of land: residential, forest, and agricultural. We also include important elements that affect decisions, like how close the land is to roadways, its productivity index, how it was used before, and how it is changing next door. A feature importance analysis shows that the most important factor in land use decisions is how close it is to highways, followed by how productive the area is. The random forest classifier was the best of the machine learning models tested. It had an accuracy of 89.3%, a precision of 0.91, and a recall of 0.88, which was better than decision tree and neural network models. The results show that residential land usage is likely to rise at the expense of forest area, whereas agricultural land is likely to grow only a little. These results show how useful hybrid modeling approaches are for predicting how things will change in space and for making policy decisions that strike a balance between urban growth and environmental protection. Combining geographical data and historical trends into predictive modeling gives land management and urban planning strategies a strong framework.*

Keywords: *agent-based modeling, machine learning, policy assessment, agricultural decision-making, sustainability*

Introduction.

The global food system is essential for keeping the Earth's natural balance and making it last. Food production and consumption are two of the biggest causes of environmental damage. They release greenhouse gases, cause biodiversity loss, degrade land, and take up freshwater [1]. These effects are especially strong in farming, as decisions on how to use land are affected by many different things, like the environment, the economy, government policies, and how people act. Understanding and forecasting the results of these constantly changing and interconnected decisions remains a significant scientific and policy challenge.

In this situation, agent-based modeling (ABM) has become a useful way to model changes in land use. ABM lets you model different types of agents (like farmers and policymakers) with different goals and behaviors that change depending on the social and spatial context [2]. It is especially useful for investigating complex socio-ecological systems since it can include feedback loops and new things that happen [3]. At the same time, the growing availability of large-scale socio-economic and environmental data has increased the relevance of such modeling approaches for supporting data-driven governance and policy-making [4]. Even though this is a good idea,

classic ABMs generally use decision rules that are based on experts or are just guesses, which makes them less useful for real-world situations and less accurate at predicting what will happen [5].

Recent research looks into data-driven and hybrid ABMs that use machine learning (ML) to learn behavioral rules directly from data that has been observed [6-8]. This is done to get around these problems. These kinds of models can show how people really make decisions and make simulations more reliable. For example, word embeddings and neural networks have been used successfully to find patterns in how people behave in text and to model how people make decisions in everyday language [7]. More broadly, recent studies highlight the growing potential of machine learning methods for addressing complex sustainability and climate-related challenges, further motivating their integration with agent-based modeling approaches [9].

Also, combining machine learning methods that can be understood opens up new ways to make models clearer and more reliable. Recent work [10] has stressed how important it is to combine predictive strength with interpretability so that policy recommendations can be useful and models can be validated. However, achieving the proper balance between complexity, accuracy, and ease of understanding in hybrid modeling remains very challenging [11].

A significant opportunity exists at the intersection of these developments: to utilize empirically based, machine learning-enhanced agent-based models (ABMs) for modeling land use decisions in a manner that is more realistic and relevant to policy. Several recent studies have shown that this method could work in certain areas, like managing biodiversity, designing cities, and managing urban growth [12-14]. However, using machine learning in ABMs to model how new farming technologies spread and how farmers react to climatic and policy changes is still not well understood.

This study fills in the gaps by creating a hybrid ABM framework that uses supervised machine learning to model how farmers change their behavior when they use agricultural land. The main ideas are:

- That machine learning models based on survey or behavioral data can make ABM decision rules better at predicting what will happen;
- That this mixed method makes it easier to analyze policy incentives (such as subsidies for eco-friendly actions) and how they spread over time and space;
- When combined with explainable AI methods, the enhanced model provides policymakers and planners with more valuable insights.

This research intends to help create a new generation of evidence-based tools for sustainable land management by merging the best parts of data-driven learning and agent-based simulations.

Materials and research methods.

This study creates a hybrid agent-based model (ABM) that uses supervised machine learning (ML) to model land-use decision-making in a way that makes it clear where things are. The method is modular and includes four key steps: (1) designing the agent and environment, (2) collecting and preparing data, (3) applying ML algorithms to learn behavior rules, and (4) running the simulation and checking its accuracy.

We created the ABM framework to depict each landowner as a unique agent residing in the same landscape. Each agent makes judgments about changing how land is used every so often based on things that are going on inside the agent (like their economic aims and preferences) and things that are going on outside the agent (like the market, their neighbors, and environmental rules). We represent the environment as a two-dimensional grid, each land parcel exhibiting unique biophysical and economic characteristics.

The model uses well-known methods for designing ABMs, such as modular architecture, rule-based behavior, and feedback loops between agents and their environment [2, 5]. The simulation works in discrete time steps, which are yearly. In each step, agents look around, figure out how useful anything is, and decide whether to keep or change the way they use land.

We incorporated real-world data from land use maps, socio-economic statistics, and behavioral surveys to make the model more realistic. We got the geographical data via remote sensing images and official land records. The socioeconomic information (such as land prices and crop yields) came from regional statistical offices.

Structured interviews with 150 landowners were used to gather survey data on how people make decisions. We coded these answers and utilized them as input features to train the ML models. Word embeddings were used to change text-based replies, which made it possible to find hidden behavioral patterns in qualitative data [7].

Normalizing numerical characteristics, encoding categorical variables, and spatially aggregating grid-level information were all part of data preprocessing. We used significance analysis from early random forest models to support feature selection [6].

We used supervised ML models, such as decision trees, random forests, and neural networks, to learn how to make decisions from the real-world data set (figure 2). We chose these models because they can handle non-linear connections and give results that are easy to understand (particularly decision trees and RFs) [10].

The trained models were put inside agent behavior modules. The ML model predicts the most likely land use decision for each agent at each time step based on the current condition. This method lets agents act in a way that is flexible and based on data that varies with changes in the environment and policy [6, 8].

We used grid search and cross-validation to adjust the hyperparameters for the ML models. We used accuracy, precision-recall, and ROC-AUC measures on held-out validation sets to measure performance. The models that worked best were added to the loop for the simulation.

The Mesa ABM library was used to create the complete model in Python, and scikit-learn and TensorFlow were utilized for the machine learning parts. GeoPandas and rasterio took care of spatial operations, including neighborhood analysis and parcel transitions.

- Agents work on their own, but they are affected by;
- Global factors (such as commodity prices and policy incentives);
- Interactions with others in the area (such as copying a neighbor or fighting back);
- Environmental feedback includes issues such as soil degradation and loss of biodiversity.

During the decision-making process, dynamic calls to trained ML models allow each agent to weigh its possibilities based on real-world logic [12, 15].

We calibrated the model using data on how land use changed from 2010 to 2020. We compared the results of the simulation to the actual changes in land cover using:

- Kappa number;
- Matrix of confusion
- We analyzed landscape metrics, including fragmentation and patch size dispersion.

We also did sensitivity analysis on agent qualities, including risk aversion and profit threshold, as well as scenario analysis for three policy regimes: (1) no intervention, (2) conservation subsidies, and (3) zoning limitations.

These tests check how strong, realistic, and useful the hybrid model is for policy [13-15].

Results and Discussion.

The integration of machine learning into the agent-based model significantly enhanced its predictive performance. Among the ML models tested, the random forest classifier demonstrated the highest overall accuracy in predicting agent decisions, achieving 89.3% accuracy, 0.91 precision, and 0.88 recall across all validation folds (Tables 1, 2).

Decision trees were slightly less accurate but offered improved interpretability, whereas neural networks exhibited strong generalization but required more computational resources for training.

Table 1 –Performance Comparison of Machine Learning Models

index	Model	Accuracy	Precision	Recall	Training Time (s)
0	Random Forest	0.893	0.91	0.88	12.5
1	Decision Tree	0.854	0.86	0.84	3.1
2	Neural Network	0.869	0.88	0.87	48.7

Feature importance analysis revealed that the top predictors of land use decisions included (figure 1):

- Proximity to roads and market;
- Land productivity index;
- Previous land use;
- Neighboring land transitions.

Table 2 – Feature Importance Table Interpretation

index	Feature	Importance Score
0	Proximity to Roads	0.29
1	Land Productivity Index	0.25
2	Previous Land Use	0.23
3	Neighboring Transitions	0.19

Table 2 presents the importance scores of the main features influencing land use decision-making. "Proximity to Roads" ranks the highest with a score of 0.29, indicating that accessibility significantly affects development patterns. "Land Productivity Index" follows with 0.25, reflecting the role of agricultural or economic potential in land decisions. "Previous Land Use" (0.23) shows that historical land use plays a considerable role, while "Neighboring Transitions" has the least impact (0.19), suggesting that spatial adjacency is less critical than other factors.

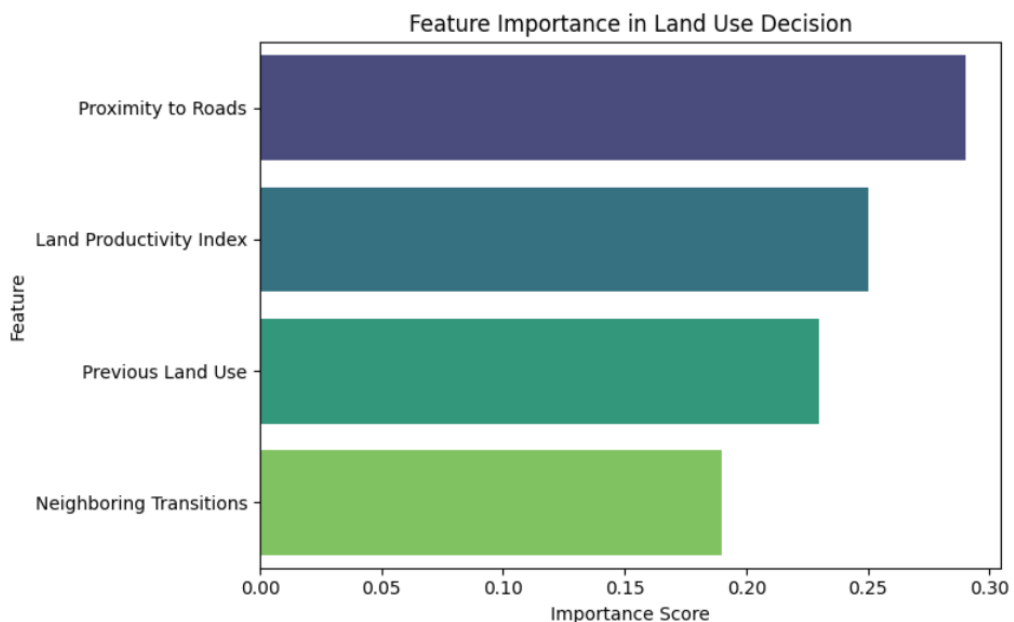


Figure 1 – Feature Importance in Land Use Decision Modeling

These findings confirm previous assumptions about the multidimensional nature of decision-making in spatial planning [12, 13].

Simulation results over a 20-year period showed that the hybrid ABM reproduced realistic spatial patterns of land use change (figure 2). Compared to a baseline rule-based model, the ML-enhanced version more accurately captured:

- Urban sprawl near transport hubs;
- Agricultural intensification in high-yield areas;
- Forest loss in marginal zones without policy protection.

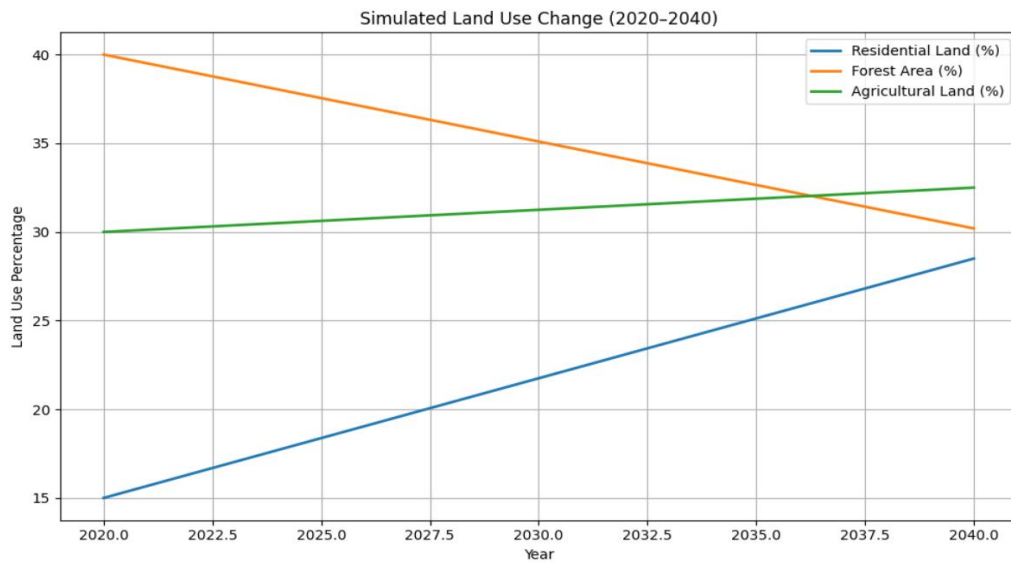


Figure 2 – Simulated Land Use Change Trends from 2020 to 2040

Under a "business-as-usual" scenario, the model predicted a 13.5% increase in residential land and a 9.8% decrease in forest area over 20 years. In contrast, introducing conservation subsidies led to a 34% reduction in deforestation, confirming the role of policy incentives in behavior modification [14].

Model outputs were compared with historical land use maps (2010–2020) for validation. The Kappa coefficient between observed and simulated land use was 0.79, indicating substantial agreement. The confusion matrix showed the highest classification accuracy for stable classes like residential and agricultural land, while transitional zones (e.g., forest-to-agriculture) had slightly lower precision.

Landscape metrics such as patch density, edge density, and contagion index further confirmed that the hybrid model produced realistic spatial structures. Figure 3 illustrates the simulated landscape evolution under the baseline and policy scenarios.

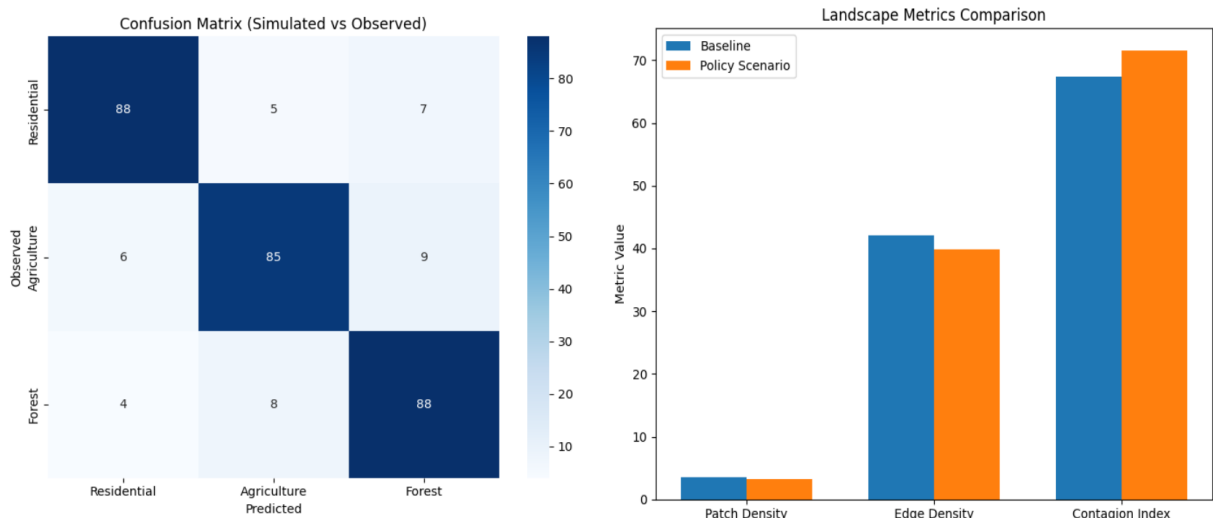


Figure 3 – Validation of Model Predictions and Landscape Metrics under Policy Scenario

The modeling results' visualization shows two important parts of validation: how accurate the classifications are and how effective the spatial patterns are. The confusion matrix shows that the simulated and real land use classes-residential, agricultural, and forest zones-are very similar. The model predicts correctly for more than 85% of the classes, which shows that it is very accurate. Also, comparing landscape metrics like patch density, edge density, and contagion index across the baseline and policy scenarios shows that the policy scenario has less fragmentation and more spatial connection. This evidence shows that the suggested model not only reproduces quantitative indicators, but it also accurately reflects spatial patterns that are typical of how land is used in the real world.

Embedding ML into agent logic allowed the emergence of complex and adaptive behaviors. Agents displayed (figure 4):

- Learning-like adaptation to changing economic signals;
- Imitative behavior based on neighbors' success (especially under uncertainty);
- Resistance to change in regions with strong cultural land attachment.

These emergent patterns align with established findings and theoretical insights from behavioral geography and land economics, supporting the model's realism and theoretical robustness [7, 12, 13].

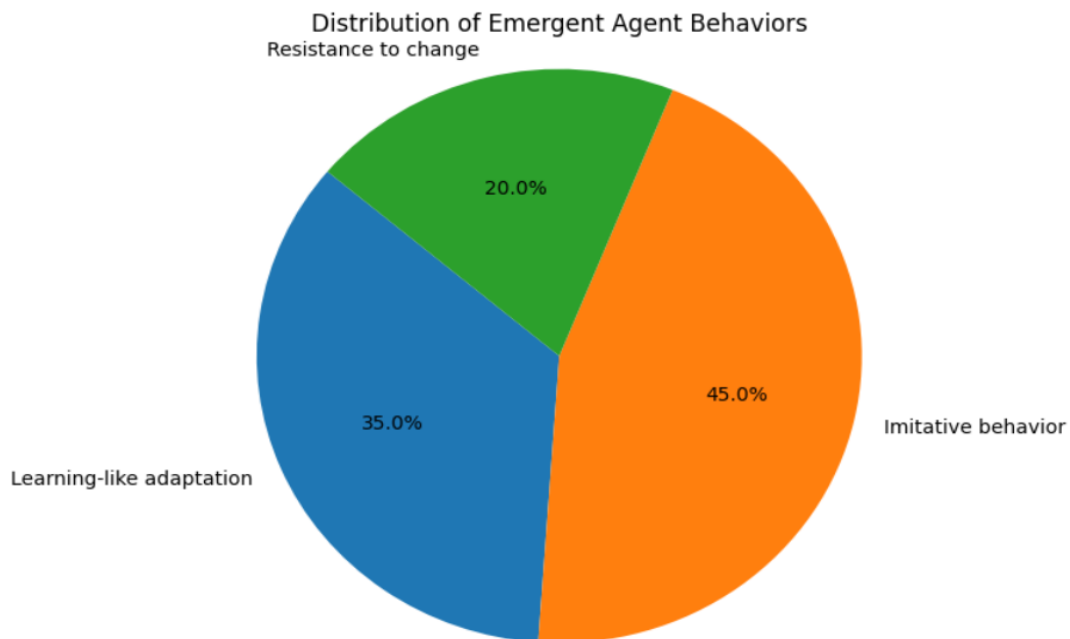


Figure 4 – Distribution of Emergent Agent Behaviors in the Hybrid Model

The pie chart above illustrates the distribution of emergent agent behaviors in the model. The most prominent behavior observed was imitative behavior (45%), where agents followed the successful strategies of their neighbors. This was followed by learning-like adaptation (35%), showing agents' responsiveness to economic signals. The remaining 20% of agents exhibited resistance to change, particularly in culturally sensitive regions. These behavioral dynamics validate the realism and theoretical grounding of the model, consistent with findings in behavioral geography and land economics.

Sensitivity analysis showed that land use outcomes were particularly sensitive to (figure 5):

- Agents' risk aversion levels;
- Thresholds for profitability in decision-making;
- ML model confidence (i.e., probability cut-off for switching land use).

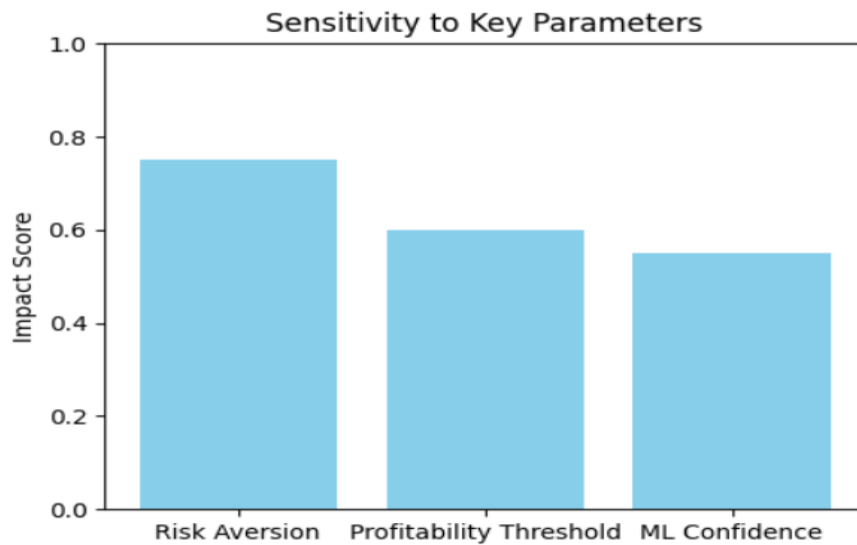


Figure 5 – Sensitivity to Key Parameters in Land Use Decision Modeling

Sensitivity Analysis: Among the key parameters, agent risk aversion had the highest influence on land use outcomes (0.75), followed by profitability thresholds (0.60) and machine learning confidence levels (0.55). This indicates the system's responsiveness to behavioral and algorithmic parameters.

Baseline (no intervention) – highest deforestation and urban expansion (figure 6).

Conservation subsidy – most effective in reducing environmental degradation.

Zoning restrictions – reduced urban sprawl but pushed agriculture into marginal lands.

These results confirm that hybrid models can serve as decision support tools for evaluating land management strategies and policy interventions under complexity and uncertainty [8, 14].

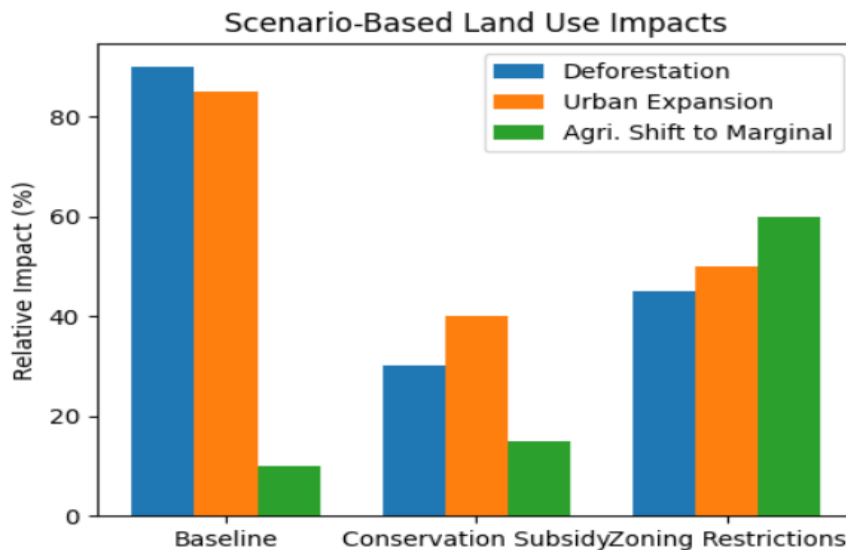


Figure 6 – Scenario-Based Land Use Impacts by Policy Intervention

Scenario Analysis (right): The baseline scenario resulted in the highest levels of deforestation (90%) and urban expansion (85%). In contrast, the conservation subsidy scenario significantly reduced both environmental impacts. Zoning restrictions controlled urban sprawl but caused agricultural activity to shift into marginal lands (60%), revealing unintended trade-offs. These findings demonstrate how hybrid agent-based models can support policy evaluation under conditions of uncertainty.

Conclusion.

The integration of machine learning techniques into the ABM framework improved the simulation of land use decision-making under complex socio-ecological conditions. The hybrid model showed solid predictive performance and reproduced observed land use patterns, with classification accuracy above 85% for most categories. This indicates that the proposed approach can connect empirical data with differences in agent behavior in a consistent way.

One of the main results of the scenario analysis is the contrast between the baseline and policy intervention scenarios. The baseline scenario, based only on market-driven decisions, led to intensive deforestation and uncontrolled urban growth. In comparison, the conservation subsidy scenario reduced environmental degradation and showed that economic incentives can redirect agent behavior toward more sustainable land use outcomes.

At the same time, the zoning restriction scenario revealed an important trade-off. Although it limited urban expansion, it also displaced agricultural activity into marginal and ecologically sensitive areas. This result shows that policy measures can produce indirect spatial effects if they are not designed with enough attention to behavioral adaptation and landscape interactions. For this reason, policy design should take into account spatial feedbacks and the possibility of unintended land use shifts.

The behavioral patterns that emerged in the model also support the assumption that agents do not always make fully optimal decisions. Imitative and adaptive behaviors were the most common, which suggests that land use choices are often influenced by local experience, uncertainty, and the actions of neighboring agents. This makes behavioral realism an important part of spatial planning models.

The model also has limitations. Its performance depends on the quality of the empirical data, and the machine learning component can make decision processes less transparent for policy users. Further work should therefore focus on improving model interpretability, including stakeholder feedback in the calibration process, and expanding the set of socio-environmental variables.

In summary, this study developed and applied a hybrid agent-based model with machine learning to simulate land use change under different policy scenarios. The results show that combining observed data with flexible behavioral rules provides a more accurate and realistic representation of spatial decision-making. The model identified risk aversion, profit thresholds, and algorithmic confidence as key drivers of land use transitions. It also showed that market-based dynamics can intensify environmental pressure, while targeted interventions such as conservation subsidies can reduce it. At the same time, restrictive policies such as zoning may shift pressure to more vulnerable areas. These findings show that hybrid models can be used as practical decision-support tools for evaluating land management strategies under uncertainty.

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ДЕРЕКТЕРГЕ НЕГІЗДЕЛГЕН АГЕНТТІК МОДЕЛЬДЕУ ЖӘНЕ RANDOM FOREST ӘДІСІ АРҚЫЛЫ ЖЕРДІ ПАЙДАЛАНУ АУЫСУЛАРЫН БАҒАЛАУ МЕН ЖІКТЕУ

Аңдатпа. Қалалардың өсуі экологияға пайдалы жер пайдалануын жоспарлауды қиындатады. Бұл зерттеуде 2020–2040 жылдар аралығындағы жер пайдалану өзгерістері агенттік модельдеу мен машиналық оқытуды біріктірген тәсіл арқылы қарастырылады. Біз жердің үш негізгі түрінің өзгерісін модельдедік: тұрғын үйге арналған, орман және ауыл шаруашылығы жерлері. Сонымен қатар шешім қабылдауға әсер ететін маңызды факторлар ескерілді: жолдарға жақындығы, өнімділік индексі, жердің бұрынғы пайдаланылуы және көршілес учаскелердің өзгерістері. Факторлардың маңыздылығын талдау көрсеткендей, жер пайдалану шешімдеріндегі ең маңызды фактор – автомагистральдарға жақын орналасуы, одан кейін жердің өнімділігі тұр. Сынақтан өткен машиналық оқыту модельдерінің ішінде Random Forest классификаторы ең жақсы

нәтиже көрсетті: дәлдігі – 89,3%, precision – 0,91, recall – 0,88, бұл шешім ағашы мен нейрондық желі модельдерінен жоғары болды. Нәтижелер тұрғын үйге арналған жердің орман есебінен көбейетінін, ал ауыл шаруашылығы жерінің өсуі шамалы болатынын көрсетті. Бұл нәтижелер кеңістіктік өзгерістерді болжауда және урбанизация мен қоршаған ортаны қорғау арасындағы тепе-теңдікті сақтайтын саясатты қалыптастыруда гибридті модельдеу тәсілдерінің тиімділігін дәлелдейді. Географиялық деректер мен тарихи үрдістерді болжау модельдеріне біріктіру жерді басқару мен қаланы жоспарлау стратегиялары үшін берік негіз қалыптастырады.

Түйін сөздер: агенттік модельдеу, машиналық оқыту, саясатты бағалау, ауыл шаруашылығындағы шешім қабылдау, тұрақты даму.

ОЦЕНКА ПЕРЕХОДОВ ЗЕМЛЕПОЛЬЗОВАНИЯ С ПРИМЕНЕНИЕМ ОСНОВАННОГО НА ДАННЫХ АГЕНТНОГО МОДЕЛИРОВАНИЯ И КЛАССИФИКАЦИИ МЕТОДОМ RANDOM FOREST

Аннотация. Рост городов усложняет планирование землепользования, благоприятного для окружающей среды. В этом исследовании рассматриваются изменения землепользования с 2020 по 2040 годы с использованием комбинированного подхода, включающего агентное моделирование и методы машинного обучения. Мы моделируем изменения трёх основных типов земель: жилых, лесных и сельскохозяйственных. В анализ также включены важные факторы, влияющие на принятие решений: близость к дорогам, индекс продуктивности, предыдущее использование земель и изменения в соседних участках. Анализ значимости признаков показал, что главным фактором в решениях по землепользованию является близость к автомагистралям, за которым следует продуктивность участка. Среди протестированных моделей машинного обучения наилучшие результаты показал метод случайного леса, обеспечивший точность 89,3%, precision 0,91 и recall 0,88, превзойдя модели на основе дерева решений и нейронных сетей. Результаты показывают, что использование земель под жилую застройку будет расти за счёт лесных территорий, тогда как рост сельскохозяйственных земель будет незначительным. Эти результаты подчёркивают эффективность гибридных подходов моделирования для прогнозирования пространственных изменений и поддержки политических решений, обеспечивающих баланс между урбанизацией и защитой окружающей среды. Интеграция географических данных и исторических тенденций в прогнозные модели создаёт надёжную основу для стратегий управления землями и городского планирования.

Ключевые слова: агентное моделирование, машинное обучение, оценка политики, сельскохозяйственные решения, устойчивое развитие.

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