Growth Simulation of Agriculturally Dominant Cities by Incorporating Multiple Drivers into a CA-based patch-generating Land Use Simulation Model: A Case Study in Siracusa, Italy

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Abstract:

Understanding the historical trajectory of land use and land cover (LULC) and predicting future alterations is essential to advancing the SDGs. Current researches on LULC in agriculture-dominated cities primarily focuses on the spatiotemporal pattern analysis of carbon storage changes, with relatively little attention given to LULC simulation studies. Moreover, most studies employing cellular automata (CA) models concentrate on urban centers, overlooking the specific sustainable development of agricultural cities. This paper selects Siracusa, Italy, as a case study, incorporating multiple drivers and constructing four development scenarios. The patch-generating land use simulation (PLUS) model is employed to predict the LULC for Siracusa by 2030 and to examine potential transformations under each scenario. Our findings show that 60% of the land in Siracusa is designated as cropland, predominantly situated in flat regions. Our simulation results reveal that urbanization and demographic growth are the main factors driving cropland conversion to urban areas. Different development scenarios exhibit significant variations in future land use structures; the cropland protection scenario emphasizes the stability and sustainability of agricultural development, whereas the economic development scenario highlights the substantial impact of urban and industrial expansion on agricultural land. These insights are instrumental for land use planning and policy-making in Siracusa and other agriculture-centric cities, providing a framework to guide urbanization while promoting agricultural sustainability.

1. Introduction

Agriculturally dominant global cities not only hold a significant position in agricultural production but also play a pivotal role in environmental sustainability and resource management. Current researches mainly address the spatiotemporal dynamics of carbon storage within these urban areas (Li et al., 2022), employ advanced high-resolution remote sensing and time series analytical methods to quantify farmland coverage (Yu et al., 2020), utilize Unmanned Aerial Vehicle (UAV) platforms and advanced sensor technologies to monitor and assess crop growth parameters, thereby enhancing the efficiency and management of viticulture production (D'urso et al., 2018), conduct land use and land cover (LULC) change studies, and evaluate soil erosion risks (Cheng et al., 2024). Nevertheless, studies on LULC simulation in agriculturally dominant cities remain relatively scarce.

LULC changes are among the most significant and observable transformations in our environment (Roy and Roy, 2010). LULC simulation serves as an essential instrument for analyzing land use patterns, aiding in urban planning and policymaking, and appraising the ecological effects of land utilization (Li et al., 2017). The intricacies of land use dynamics, coupled with policy shifts, market demand variability, and climate change, compound the challenge of accurately projecting LULC changes. By integrating remote sensing technology, geographic information systems (GIS), and predictive models, it is possible to achieve accurate forecasts of future land use changes. Accurate forecasts are crucial for devising comprehensive and precise land use planning and management schemes, which are essential for the sustainable development and resource management of agriculturally dominant cities.

Land use change research and simulation models are pivotal for predicting regional land pattern evolution and future developments. These models analyze land use changes under various scenarios, providing essential support for achieving diverse planning objectives within a region (Wu and Wang, 2024). Current models include Cellular Automata (CA) (Zhang et al., 2015), Artificial Neural Networks (ANN) (Mozaffaree Pour et al., 2022), CA-Markov models, the CLUE-S model (Conversion of Land Use and its Effects at Small Region Extent Model) (Akin et al., 2022), the FLUS model (Future Land-Use Simulation) (Liang et al., 2018), and the PLUS model (Patch-Generating Land Use Simulation Model). The PLUS model stands out for its ability to capture spatial heterogeneity through patch-based simulation, offering higher accuracy and dynamic updating capabilities compared to other CA-based models.

Despite the extensive research on urban expansion and urbanization processes (Yadav and Ghosh, 2021), studies on land use in agriculturally dominant cities remain limited. Taking Siracusa, Italy, as a case study, with its rich agricultural land and traditions, there is a need to focus on the preservation and optimal utilization of agricultural land. Developing scenarios constructed should prioritize cropland protection and ecological considerations, addressing the unique management and planning requirements of these areas. This scenario supports sustainable agricultural development and ecosystem restoration, contributing to environmental and social benefits for both urban and rural communities.

Our proposed methodology, based on the PLUS model, simulates LULC in agriculturally dominant cities by incorporating multiple drivers and constructing four development scenarios. We simulated land use changes in Siracusa for the year 2030 under different conditions. This study not only fills the research gap on land use changes in agriculturally dominant cities but also provides a sustainable land use management framework for Siracusa and similar cities. It ensures that land use policies are tailored to local needs and aligned with the SDGs, thereby offering valuable insights for future policymakers and researchers.

2. Study Area and Data

2.1 Study Area

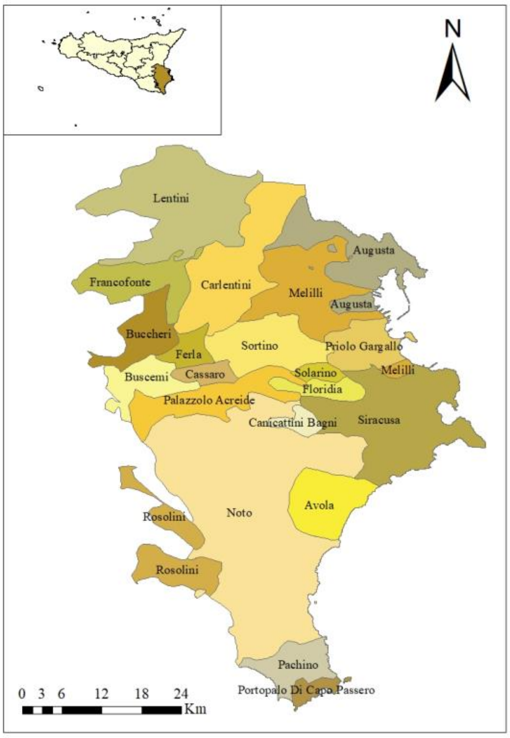

Figure 1. Study area

The study area is Siracusa, which is located at 36°41′-37°17′ north latitude and 14°51′-15°17′ east longitude. This province lies in the southeastern part of Sicily, in southwestern Italy (Fig. 1). It is bordered to the north and northwest by the province of Catania, to the west by the province of Ragusa, and to the east and south by the Ionian and Mediterranean Seas. Siracusa province comprises 21 cities, covering a total area of 2109 km^2.The gross domestic product (GDP) reached $49,280 in 2022 and the population stands at 383,604. Siracusa, Italy, is renowned for its agriculture and citrus industry. The region's fertile soil and favorable climate make it an ideal location for citrus cultivation. Cropland is predominantly found in the hilly areas, plains, and coastline of Siracusa, characterized by fertile soil and relatively flat terrain. This agricultural characteristic significantly influences the demand for land resources and future development requirements. Sustainable land management practices are necessary to ensure the continued production and growth of the citrus industry. The primary type of land use in this study area is cropland, and simulating the urban growth of Siracusa under multiple future scenarios is of great significance for agricultural distribution and sustainable development.

2.2 Data Sources and Processing

The publicly accessible land use production was retrieved for the experiment. Taking previous urban simulation studies into account, some driving forces are selected to explain the urban growth of Siracusa, encompassing socioeconomic, climatic, and environmental aspects. The specific data are shown in Table 1.

(1)The land use data in this study were sourced from the AGLC and created by (Tan et al., 2020) with a spatial resolution of 30 × 30 m . These data classify land use into six categories: cropland, forest land, grassland, water area, urban land, and other land. (2) The factors related to topographical and geographical conditions can constrain and impede continuous urban land expansion. The digital elevation model (DEM), aspect, and slope data for Siracusa in 2020, with a spatial resolution of 30 × 30 m, were obtained from Google Earth Engine. (3) The population data for 2021 and temperature data for 2020, both with a spatial resolution of 30 × 30 meters, were derived through the Google Earth Engine. (4) Proximity to railways, roads, waterways, places (towns, villages, and city blocks, etc.), and sites (bus stops, restaurants, pharmacies, etc.) are used as drivers for the PLUS model, all sourced from BBBike.

Category	Data	Year	Resolution	Source
Land use/cover data	LULC	2000-2015	30m	https://code.earthengine.google.com/asset=users/xxc/GLC_2000_2015
Climatic and environmental driver	DEM Aspect Slope Population Temperature	2020 2020 2020 2021 2020	30m	https://earthengine.google.com
Socioeconomic driver	Proximity to Waterways Proximity to Railways Proximity to Roads Proximity to Places Proximity to Sites	2024	30m	https://download.bbbike.org/osm

Table 1. Details of the dataset and data source information used in this study

3. Methodology

3.1 Fundamental Principles of the PLUS Model

The PLUS model was proposed to understand the drivers of land expansion and to enhance the simulation accuracy of landscape patterns, which contains two modules: (1) a rule-mining framework based on a land expansion analysis strategy (LEAS); and (2) a CA based on multi-type random patch seeds (CARS) (Liang et al., 2021). The general structure of the simulation framework of this study is illustrated in Figure 2. The LEAS identifies and samples the components of various land use expansions by comparing land use data from two distinct periods. It employs a random forest classification (RFC) algorithm to explore the relationships between the growth in each land use type and the multiple driving factors (Liang et al., 2021). The specific formula is as follows:

$$P_{j,k}^{d}(x) = \frac{\sum_{n=1}^{M} I(h_n(x)=d)}{M} \quad (1)$$

The value of d is either 0 or 1; a value of 1 indicates that there were other land use types that changed to land use type k, while 0 represents other transitions; x is a vector that consists of multiple driving factors; $I(.)$ is the indicative function of the decision tree set; $h_n(x)$ is the prediction type of the n −th decision tree for vector x; and M is the total count of decision trees(Liang et al., 2021).

The CARS module is a CA model that includes a patch-generation mechanism based on multi-type random seeds of land uses (Liang et al., 2021). During the simulation process, land use demands influence local land use competition through a self-adaptive coefficient, driving the land use quantity to meet future requirements. The PLUS model calculates the total probability through a multi-class random patch seeding mechanism based on descending thresholds, thereby simulating the evolution of patches for various land use types. This mechanism employs the Monte Carlo method to calculate the "seeds" that change the neighborhood effect for each land use type. The specific formula is as follows:

$$\Omega_{i,k}^{t} = \frac{con(c_i^{t-1}=k)}{n\times n-1} \times w_k \quad (2)$$

where $con(c_i^{t-1}=k)$ represents the total number of grid cells occupied by land use type k at the last iteration within the $n \times n$ window and w_k is the weight among the different land use types because there are different neighborhood effects for the different land use types. The default value of w_k is 1, but it can be defined by the model users (Liang et al., 2021). The self-adaptive method of $D_k\ t$ is as follows:

$$D_k^t = \begin{cases} D_k^{t-1} & if\ |G_k^{t-1}| \le |G_k^{t-2}| \\ D_k^{t-1} \times \frac{G_k^{t-2}}{G_k^{t-1}} & if\ 0 > G_k^{t-2} > G_k^{t-1} \\ D_k^{t-1} \times \frac{G_k^{t-1}}{G_k^{t-2}} & if\ G_k^{t-1} > G_k^{t-2} > 0 \end{cases} \quad (3)$$

where G_k^{t-1} and G_k^{t-2} are the differences between the current amount of, and future demand for, land use type k at the $t-1th$ and $t-2th$ iteration (Liang et al., 2021).

$$OP_{i,k}^{d=1,t} = \begin{cases} P_{i,k}^{d=1} \times (r \times u_k) \times D_k^t, if\ \Omega_{i,k}^t = 0\ and\ r < P_{i,k}^{d=1} \\ P_{i,k}^{d=1} \times \Omega_{i,k}^t \times D_k^t,\ all\ others \end{cases} \quad (4)$$

where r is a random value ranging from 0-1;$u_k$is the threshold to generate the new land use patches for land use type k, which is determined by the model users.

If a new land use type wins in a round of competition, a decreasing threshold $\tau$is employed to assess the candidate land use type c that was selected by the roulette wheel as follows:

$$If\ \sum_{k=1}^{N} |G_c^{t-1}| - \sum_{k=1}^{N} |G_c^{t}| < Step\ \ Then, l = l+1 \quad (5)$$

$$\begin{cases} Change\ \ P_{i,c}^{d=1} > \tau\ \ and\ TM_{k,c} = 1 \\ No\ change\ Pd_{i,c}^{d=1} \le \tau\ or\ TM_{k,c} \end{cases} \tau = \delta^l \times rl \quad (6)$$

where $Step$ is the step size of the PLUS model to approximate the land use demand; δ is the decay factor of decreasing threshold τ, which ranges from 0 to 1 and is set according to the expert; r is a normally distributed stochastic value with a mean of 1, ranging from 0 to 2; and l is the number of decay steps. $TM_{k,c}$ is the transition matrix that defines whether land use type k is allowed to convert to type c(Chen et al., 2021).

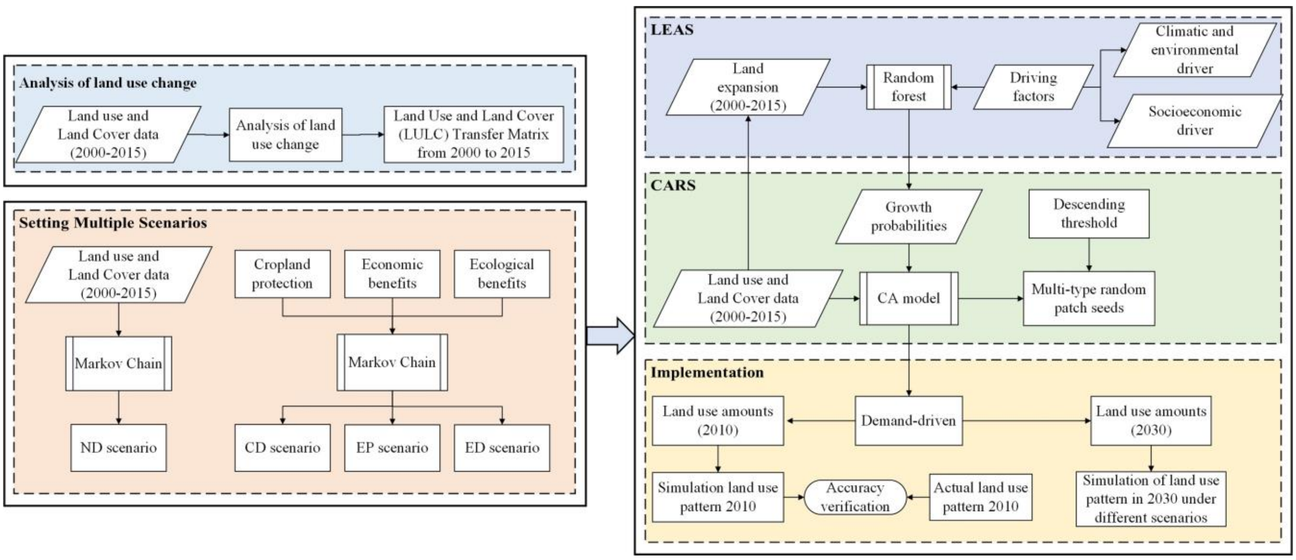

Figure 2. Schematic Diagram of this Research

3.2 Input Settings of the PLUS Model-driving Factors and Cost Matrix

Considering the unique natural geographical features and socioeconomic development of the study region, we selected 10 driving factors from natural, social, and economic perspectives (Table 1).

Specific conversion rules are established to reflect expectations and constraints on land use under different development scenarios, embodying scenario-specific land management strategies and objectives. In the natural development scenario, the conversion rules are as follows: 1) Land types other than grassland are not allowed to be converted to forest land; 2)

Grassland shall not be converted into cropland; 3) Water area cannot be converted into grassland or urban land; 4) Urban land is not allowed to be converted into cropland or water; 5) Other land types may not be converted into urban land. The transfer probability matrix serves as the basis for constructing and predicting land use change in PLUS model, detailing permissible land use conversions: The columns of the transfer matrix in Table 2 represent the current land use type, and the rows represent the future land use type. A value of 1 indicates conversion is allowed, while a value of 0 indicates conversion is not allowed.

ND	a	b	c	d	e	f
a	1	0	1	1	1	1
b	1	1	1	1	1	1
c	0	1	1	1	1	1
d	1	0	0	1	0	1
e	0	0	1	0	1	1
f	1	0	1	1	0	1

Table 2. Natural development scenario transition probability matrix

In this table, 1-conversion is allowed, 0-conversion is prohibited; a -Cropland, b -Forest land, c -Grassland, d -Water area, e -Urban land, f -Other land

3.3 Neighborhood Weight Setting of the PLUS Model and Markov Chain Simulation

The neighborhood weight parameter primarily reflects the expansion ability of different types of LULC. The parameter range is 0–1, with larger values indicating stronger expansion power. The total area of six LULC types from 2000 to 2015 was normalized to represent the neighborhood weight for each LULC type (Table 3).

LULC type	Cropland	Forest land	Grassland	Water area	Urban land	Other land
Weight	0.49	0.53	0.62	0.65	0.76	0.1

Table 3. Weight of neighborhood

This research employs the PLUS model to forecast and analyze the LULC for Siracusa in 2030. It primarily adopts a Markov chain approach for forecasting, and the formula is as follows:

$$S_{t+1} = S_t \times P \tag{7}$$

Where S_{t+1} denotes the state of an event in period $t+1$, which is the result of Markov chain prediction; S_t represents the state of an event in period t; and P is the transition probability matrix. Additionally, equation (2) is used to model the dynamic process of land use change:

$$X_{t,t+1} = f(X_t, N) \tag{8}$$

Where X is the set of discrete and finite time states of the f cell; represents cell change rule; $N$is the cell neighborhood;t and $t+1$ denote the consecutive time periods.

3.4 Construction of the Four Development Scenarios

Four widely-accepted scenarios are simulated for Siracusa's LULC in 2030: natural development (ND) cropland protection (CP) (Zhang et al., 2024), economic development (ED) and ecological protection (EP) (Meimei et al., 2023). This section specifies the parameter settings for land conversion rates under three distinct scenarios: cropland protection, economic development, and ecological protection. These settings, detailed in Table 4, modulate the transitions among various land types to strategically achieve desired developmental objectives.

Scenario	Conversion From	Conversion To	Percentage Change
CP	Cropland	Forestland	-30%
CP	Cropland	Grassland	-30%
CP	Cropland	Water Area	-20%
CP	Cropland	Urban Land	-60%
CP	Forest Land	Cropland	+20%
CP	Grassland	Cropland	+30%
ED	Cropland	Urban Land	+30%
ED	Forest Land	Urban Land	+30%
ED	Grassland	Urban Land	+30%
ED	Water Area	Urban Land	+10%
ED	Other Land	Urban Land	+60%
EP	Cropland	Urban Land	-30%
EP	Forest Land	Urban Land	-50%
EP	Grassland	Urban Land	-50%
EP	Water Area	Urban Land	-30%
EP	Cropland	Forest Land	+30%
EP	Forest Land	Water Area	-30%
EP	Grassland	Water Area	-20%
EP	Forest Land	Other Land	-10%
EP	Grassland	Other Land	-30%

Table 4. Parameter Settings for Land Conversion Rates

4. Results and Discussion

4.1 Land Use and Land Cover Transition Analysis for 2000-2015

According to Table 5, land use and land cover (LULC) in Siracusa remained relatively stable from 2000 to 2015. Cropland is widely distributed across the region, particularly in the southern and northern areas, accounting for 60% of the total land area. Over this 15-year span, the cropland area was reduced by 18.05 km^2, particularly near urban areas, largely due to urbanization and demographic growth driving the conversion of cropland into urban land. Simultaneously, forest cover saw a marginal decrease, while the areas of grassland and water remained largely unchanged. The total area of urban land continues to rise, particularly with the expansion of coastal areas, indicating sustained urban expansion driven by population growth and economic development. As shown in Table 5, from 2000 to 2015, the conversion of cropland to urban land was the most significant, amounting to 27.67 km^2. Approximately 517.35 km^2 of forest land remained unchanged, indicating that most of the forest was protected. A conversion of 0.45 km^2 from grassland to urban land occurred; very little water area was converted to other land use types. The total area of urban land increased by 24.91 km^2, primarily due to the transfer from cropland. Other land conversions mainly occurred between cropland and urban land, closely related to urban expansion and the alternating cultivation of crops.

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	Cropland	Forest land	Grassland	Water area	Urban land	Other land	2000Area
Cropland	1252.2265	2.3402	0.5236	0.3394	27.6745	0.0187	1283.1228
Forest land	8.9039	517.3502	0.1195	0.1922	0.6900	0.0032	527.2590
Grassland	0.1373	0.0208	140.9134	0.0110	0.4472	0.0052	141.5348
Water area	0.0473	0.0080	0.0003	20.5566	0.0833	0.0005	20.6959
Urban land	3.7654	0.1453	0.0316	0.0623	132.7880	0.0101	136.8028
Other land	0.0009	0.0000	0.0000	0.0000	0.0228	0.9691	0.9928
2015Area	1265.0812	519.8646	141.5884	21.1614	161.7058	1.0068	2110.4082

Table 5. Transfer matrix from 2000 to 2015

4.2 Comparative Analysis of Simulated and Real Land Use in 2010

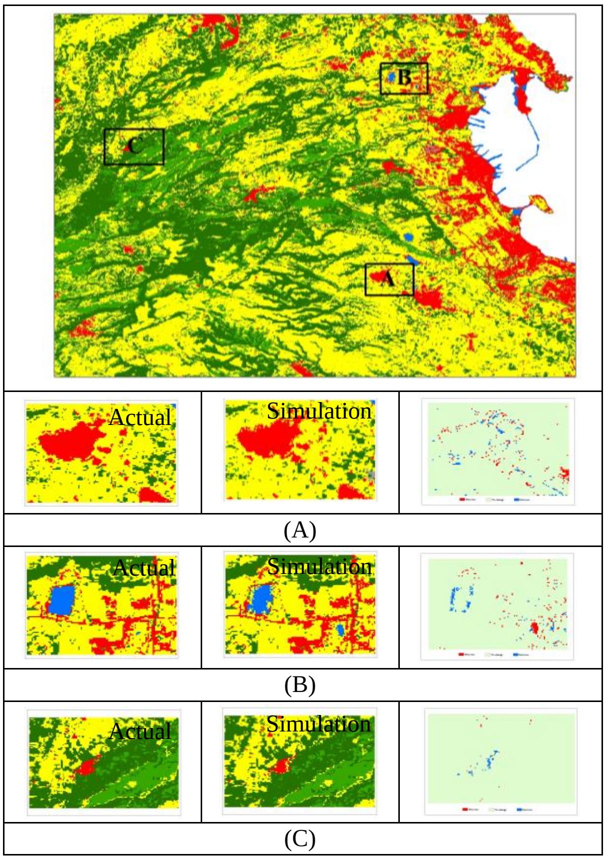

Figure 3. Spatial distribution difference between real and simulated cropland in 2010.

The PLUS simulations exhibit high accuracy, with an overall accuracy of 0.99 and a Kappa coefficient of 0.98. To intuitively contrasts the spatial distribution of actual land use in 2010 against PLUS model predictions, three validation regions with various LULC types in Siracusa were selected for presentation in Figure 3. Despite the results of the PLUS model simulating Siracusa LULC are relatively consistent, differences can be inferred from the enlarged results marked with A、B、C:

The spatial distribution discrepancies between actual and simulated land use types in 2010 are mainly found at the boundaries between different land use categories. In the comparative analysis of actual and simulated views of Area A, significant discrepancies were observed in urban land. In actual images, urban land primarily consists of a large, continuous area. Conversely, simulated images reveal a reduction in central urban land, with more dispersed and isolated buildings surrounding it. In the views of Area B, the simulated water area in 2010 is smaller than the actual area, with the main changes occurring at the boundaries between cropland and water area, where some water areas are simulated as cropland. In Area C, the distribution of forest land shows high consistency before and after simulation. However, in the 2010 simulation, a small portion of the urban land at the boundary with forest land is simulated as cropland. At the boundaries of cropland, soil quality exhibits significant variations, often due to differences in soil type, texture, and nutrient content, which directly affect crop growth conditions and rates (Mulat et al., 2021). In these areas, variations in soil quality may lead to differences in water supply. For instance, poor drainage or insufficient water supply might mislead the model to identify cropland as water areas. Furthermore, the boundaries of cropland are frequently influenced by human activities, which directly affect the distribution of soil structure and nutrients (Zhao and Yin, 2023). Consequently, these areas might be erroneously simulated as urban land. The land adjacent to water areas, influenced by humidity and moisture, may exhibit different soil qualities compared to other regions, potentially causing errors in the model's recognition of the boundaries between water area and cropland (Banjara et al., 2024).

4.3 Examination of Multi-Scenario Simulations Using the PLUS Model for 2030

As depicted in Figure 4, within the natural development scenario, cropland in Siracusa is predominantly situated in regions characterized by flat terrain and fertile soil. Here, the extent of cropland diminishes due to natural succession and the absence of policy intervention. These croplands are typically located in the agricultural belts on the urban periphery, renowned for producing high-quality crops. Forests and grasslands are primarily distributed in the eastern part of Siracusa, while water areas are concentrated in the north-central region. Urban land is predominantly situated in coastal areas. In the context of cropland protection, cropland in Siracusa constitutes a significant portion of the region, with a relatively continuous distribution, highlighting the stability and sustainability of agricultural development. Grasslands, serving as buffer zones between farmlands and forests, have the potential to maintain ecological balance and prevent land degradation. Urban land is more concentrated, and other land is scattered across areas unsuitable for agriculture or urban development.

In the economic development scenario, driven by demands for urbanization and industrialization, original agricultural lands are rezoned for residential and commercial areas, particularly in the southeastern coastal region. The development of transportation infrastructure around urban areas spurs the expansion of industrial parks and commercial facilities at the urban edge. In the ecological protection scenario, the Siracusa area prioritizes the preservation of its unique ecosystems and biodiversity. Continuous protective measures for forests and grasslands help maintain regional ecological balance and habitat integrity, while the protection of water bodies and wetlands not only sustains the health of water resources but also provides essential water supply for local agriculture, thereby supporting sustainable agricultural development.

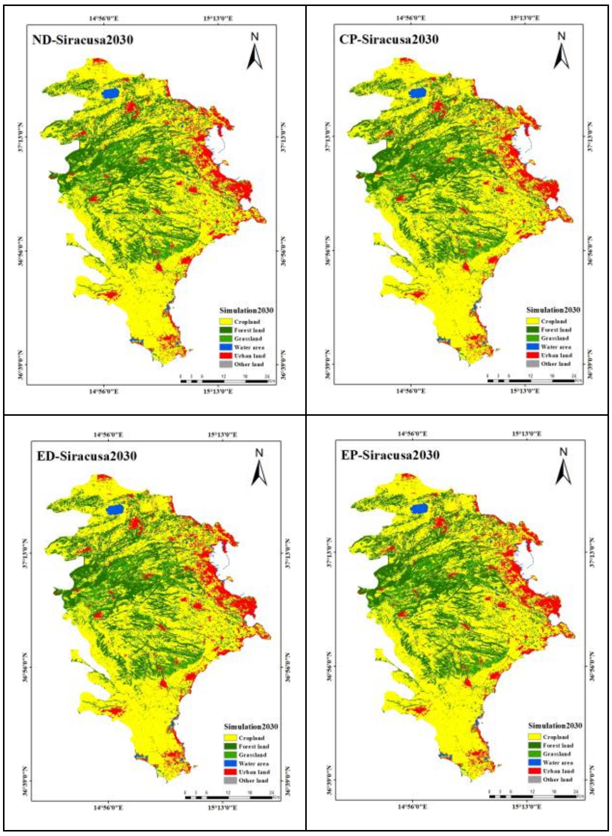

Figure 4. Land use and land cover maps for four development scenarios

In the natural development scenario, as illustrated in Figure5(A), cropland in Siracusa is primarily converted into urban land, likely driven by urban expansion and population growth. Despite Siracusa being predominantly agricultural, with cropland accounting for up to 60% of the land area, the minimal change in forest land area may indicate a process of natural ecological succession. Natural ecological succession involves long-term ecological changes, and the stability of forest cover demonstrates the region's emphasis on ecological conservation and biodiversity maintenance. Conversely, Figure 5(B) reveals that in the cropland protection scenario, the continuous decrease in cropland area has been effectively controlled, likely due to restrictions on non-agricultural land development, ensuring cropland is not illegally occupied or converted for construction purposes. Compared to other regions, Siracusa, a major agricultural province, views cropland protection as not only part of ecological conservation but also a crucial guarantee for the region's primary economic activities. The economic development scenario (Figure 5(C)) shows that the conversion of cropland into urban land significantly exceeds changes in other land types, highlighting the profound impact of urbanization and industrialization on the land use pattern of Siracusa, a major agricultural province. While the expansion of urban and industrial areas is essential for economic development, it also necessitates a balance to ensure the sustainability of agriculture and ecological health in Siracusa. Finally, Figure 5(D) indicates that in the ecological protection scenario, the focus of land use change from 2015 to 2030 is on the conversion and protection of grassland and water areas. For the predominantly agricultural Siracusa, this protection supports the region's agricultural ecological foundation, ensuring the basis for sustainable agricultural development.

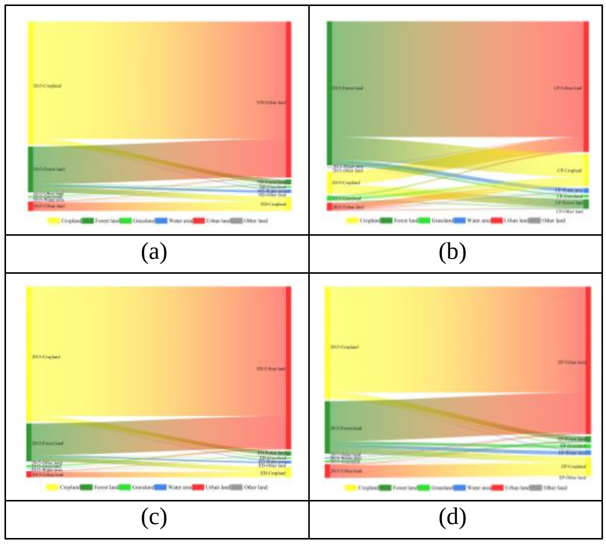

Figure 5. Land use change by scenario from 2015 to 2030:(a) natural development scenario, (b)cropland protection scenario, (c)economic development scenario, (d) ecological protection scenario.

5. Conclusions

The simulation of LULC in the Siracusa region has expanded the scope of research and simulations for agriculture-dominated cities. This study employs a multi-driver CA model to investigate land use changes in agriculture-dominated cities under various development scenarios, effectively capturing land use change trends in Siracusa under four development scenarios: natural development (ND), cropland protection (CP), economic development (ED) and ecological protection (EP). This approach not only deepens the understanding of land use dynamics in Siracusa, but also provides basis for land use planning and policy formulation.

Our results indicate that 60% of the land in Siracusa is designated as cropland, mainly located in flat regions. From 2000 to 2015, there were slight changes in land use types, primarily characterized by the conversion of cropland to urban land. The simulation outcomes demonstrate considerable variations in land use configurations under each scenario. The ND scenario reflects the results of natural succession, the CP scenario focuses on the stability and sustainability of agricultural practices, the ED scenario underscores the effects of urban and industrial sprawl on farmland, and the EP scenario is dedicated to conserving regional ecosystems and biodiversity. These findings provide a framework to guide urbanization while promoting agricultural sustainability.

Future research should further optimize model parameters and algorithms to enhance their applicability in complex geographical environments, address boundary deviations, and extend the application of these research findings to a broader range of agricultural cities. This would verify the model's universality and stability, providing more comprehensive scientific support for the sustainable development of agricultural cities globally.

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