

Simulating land use changes and environmental implications of transportation development in Barru Regency using cellular automata

Mukti Ali¹, Yuni Andiyani Basri^{2*}, Haerani³

¹ Department of Urban and Regional Planning, Faculty of Engineering, Hasanuddin University, Makassar, Indonesia

² Department Regional Planning and Development Planning, Graduate School, Hasanuddin University, Makassar, Indonesia

³ Department of Agricultural Technology, Faculty of Agriculture, Hasanuddin University, Makassar, Indonesia

* Corresponding author's e-mail: yuniandiya@gmail.com

ABSTRACT

The expansion of transportation infrastructure often induces significant changes in land use patterns within adjacent areas, accompanied by ecological impacts on natural landscapes and environmental sustainability. This study aims to project anticipated land use changes surrounding the construction zone of the Takkalasi-Bainange-Lawo road in Barru Regency, Indonesia, using the cellular automata (CA) approach integrated with geographic information systems (GIS). The simulation results reveal substantial land use transformations over the next two decades, including the conversion of six land use categories such as rice fields, mixed gardens, upland fields, and residential and industrial zones. Projections indicate a reduction in agricultural land, particularly rice fields, which also support local ecosystems, by approximately 6.2 hectares from 2023 to 2043, driven by increasing demands for residential and industrial development. Conversely, industrial zones are expected to expand significantly, with land converted from other categories such as rice fields and mixed gardens, potentially affecting biodiversity and ecological balance. This study provides critical insights for sustainable land use planning by addressing environmental impacts and the requirements of transportation infrastructure development.

Keywords: land use changes, cellular automata (CA), transportation infrastructure development, geographic information system.

INTRODUCTION

Infrastructure development and population growth in a region significantly impact the increasing demand for land (Ghatak & Mookherjee, 2014). The development of transportation corridors enhances regional accessibility, attracts concentrations of new growth centers, and alters land prices. Consequently, the structure, type, and intensity of land use are subject to change (Badoe & Miller, 2000; Kasraian et al., 2016; Shaw & Xin, 2003; Xiao et al., 2024). According to the “patch-corridor-matrix” theory, transportation corridors are viewed as specialised pathways that traverse the matrix of natural landscapes, creating new patches (Xiao et al., 2024). This alters

connectivity and edge effects between patches, modifying the existing landscape patterns (Jaeger et al., 2008; Xiao et al., 2024).

The dynamics of development, alongside rapid population growth due to migration and urbanisation, create a gap between land demand and the limited availability of land resources. This scenario drives land-use competition, subsequently affecting regional development and land-use changes (Wenbo et al., 2024). Land use planning must involve allocating existing land use and formulating future land-use patterns, considering physical, social, cultural, and economic dimensions (Alemu et al., 2024; Jiang et al., 2024). These dynamics intensify the pressure on spatial utilisation and land use, particularly in regions with strategic locations

or significant economic value (Csomós et al., 2024). Increased land competition results in various issues and conflicts related to spatial utilisation (Qin et al., 2024). The results of the study indicate that infrastructure development and the increased demand for housing often lead to the sacrifice of rice fields, resulting in a reduction of agricultural land (Ge et al., 2024). The continued conversion of agricultural land for non-agricultural purposes threatens food security and could lead to a food crisis (Nguyen et al., 2016). Land degradation has numerous adverse effects, including environmental damage, declining environmental quality, and destruction of natural resources (Mamat et al., 2016; Purwanto & Andrasmo, 2021), reduced land carrying capacity, loss of ecosystem productivity, vegetation composition shifts, and the loss of rural livelihoods (Purwanto & Andrasmo, 2021).

Many research have examined the socio-economic impacts of road development on communities. Infrastructure development influences socio-economic transformation differently across various regions (Sun et al., 2024). Some areas may retain their original attributes, including agricultural zones, while others evolve into new urban centres (von Groß et al., 2024). The expansion of agricultural activities and practices around road construction zones drives land cover and land-use changes (Sun et al., 2024). These changes are often irreversible, as demonstrated by the transformation of forested areas into urban spaces, such as settlements, which are difficult to revert to their original forest state due to factors such as geography, politics, funding, and advancements in science and technology (Jiang et al., 2024).

Land-use projection is essential for spatial planning, natural resource management, and environmental change mitigation (Aidi & Maulana, 2020; Geng et al., 2022; Lin et al., 2023; Molineiro-Parejo et al., 2023). Techniques for forecasting land cover and land-use change are diverse and continue to evolve with advancements in technology and science (Geng et al., 2022). Cellular automata (CA) methodology is one of the most commonly used approaches for exploring regional spatial dynamics (Chen & Dong, 2024). Cellular automata (CA) is a mathematical framework utilised to model complex systems that evolve dynamically through simple local rules (Barreira-González et al., 2015). Cellular automata (CA) is applied in geospatial analysis to predict land cover and land-use changes by considering the

interactions of grid cells (Lin et al., 2023; Molineiro-Parejo et al., 2023).

Barru Regency, where the Takkalasi-Bainange-Lawo primary collector road is being developed, is primarily located within the administrative areas of Takkalasi Subdistrict and Kamiri Village in Balusu Subdistrict. Initial land use in the development area was predominantly protected forest, which has since been re-designated as land for other uses. Furthermore, much of the land bordering the road is classified as production forest, community forest, or protected forest. Infrastructure development often leads to land-use changes in adjacent areas (Xiao et al., 2024).

This research project aims to model anticipated land-use changes in the Takkalasi-Bainange-Lawo road development zone by utilising the cellular automata (CA) framework as a spatial analysis technique based on geographic information systems (GIS). This simulation provides insights into the potential evolution of land use along the proposed road, highlighting factors influencing these shifting patterns (Al-Darwish et al., 2018; Ma et al., 2024). The technique offers a comprehensive understanding to improve spatial planning and land management, ensuring that infrastructure development maximises benefits while minimising adverse environmental and community impact (Chen & Dong, 2024).

MATERIAL AND METHODS

The research was conducted at the Balusu Subdistrict of Barru Regency, Indonesia, where the Takkalasi-Bainange-Lawo road development was situated. Balusu Subdistrict covers an expanse of 11.321,9 hectares and consists of six villages: Takkalasi, Lampoko, Balusu, Kamiri, Binuang, and Madello (Badan Pusat Statistik Kabupaten Barru, 2024). The spatial location of the research area is presented in Figure 1.

The projection simulation for land use change employs the cellular automata method alongside Landuse Sim software. The cellular automata approach includes all elements organised as cells, where all variables in shapefile format are converted into 10×10 rasters and then transformed into ASCII data to model land use change (Jamaluddin & Parung, 2024; Pratomoatmojo, 2018). Land use change modelling has three phases: preparation, simulation, and visualisation. The QGIS application is employed during the data

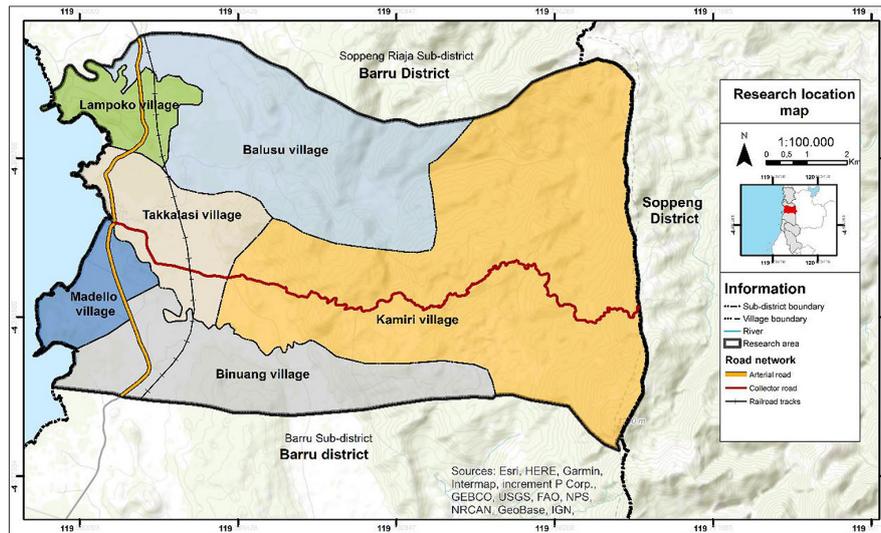


Figure 1. Map of the research area

preparation and data visualisation phases. The data simulation phase utilises the LanduseSim application. The modelling approach begins with identifying driving factors, creating an initial potential transition map, establishing a neighbourhood filter, developing transition rules, and conducting simulations (Pratomoatmojo, 2018).

$$LU_{i,x,y}^{t+1} = f(LU_{x,y}^t, TP_{i,x,y}, G_{i,x,y}, C_{i,x,y}, E_{i,x,y}, Z_{i,x,y}, TS) \quad (1)$$

where: $LU_{i,x,y}^{t+1}$ – the new growth of land use cs at time t+1 on certain cell (x,y), $f(LU_{x,y}^t)$ – the state of the previous land use class before simulated on certain cell (x,y), $TP_{i,x,y}$ – transition potential map of land use cs on certain cell (x,y), $G_{i,x,y}$ – number of expected cell growth from land use cs at the time t+1, $C_{i,x,y}$ – the growth constraints of land can be represented by specific land uses that cannot be converted into land use type i or zones designated for protection or conservation. Constraint areas are typically used to represent specific land uses that cannot be transformed into land use type i, $E_{i,x,y}$ – the elasticity of change for a specific land use to be converted into land use type I, $Z_{i,x,y}$ – zoning systems, such as land use plans, disaster-prone areas, and promoted growth zones, TS – the time step of the cellular automata (CA) iteration.

The preparation phase entails establishing the files and analytical parameters and generating and transforming accessible maps that will proficiently

facilitate the land use growth study. The preparatory step guarantees that all pertinent spatial data and driving variables required for the LanduseSim simulation are accessible and adequately formatted (Al-Darwish et al., 2018; Pratomoatmojo, 2018).

The driving factors used in this study were adapted from those employed in previous research and derived from various references relevant to the characteristics of the study area. The driving factors utilised in this research are detailed in Table 1. These parameters were subsequently employed to generate buffer maps for assessing land use according to their impact and spatial distribution within the research area. An analytical hierarchy process (AHP) was performed with ten participants, comprising academics, practitioners, and members from the Barru Regency Government in Indonesia using the Expert SA application (Jamaluddin & Parung, 2024; Pratomoatmojo, 2018). This procedure evaluates the driving factors and generates final weights that indicate the relative significance of each element in facilitating land-use change (Jamaluddin & Parung, 2024).

In addition to the driving factors, constraint data must be prepared for the simulation (Jamaluddin & Parung, 2024). Constraints consist of spatial planning policy regulations that apply to the study area, which limit land use changes (Jamaluddin & Parung, 2024; Padiyatu et al., 2023). The constraints used in this study include the designation of forest areas, slope gradients, sustainable agricultural land for food production, coastal and river buffer zones, and flood-prone

Table 1. Driving factors reference

Driving factors	Previously studies
Distance to arterial roads	(Al-Darwish et al., 2018; Lin et al., 2023; Rakuasa et al., 2022; Yue et al., 2024)
Distance to collector roads	(Al-Darwish et al., 2018; Lin et al., 2023; Paddiyatu et al., 2023; Rakuasa et al., 2022; Yue et al., 2024)
Distance to local roads	(Lin et al., 2023; Paddiyatu et al., 2023; Rakuasa et al., 2022; Yue et al., 2024)
Distance to railway stations	(Lin et al., 2023)
Distance to built-up areas	(Al-Darwish et al., 2018; Paddiyatu et al., 2023)
Distance to economic centers	(Al-Darwish et al., 2018; Lin et al., 2023; Molinero-Parejo et al., 2023)
Distance to tourist attractions	(Yue et al., 2024)
Distance to facilities	(Molinero-Parejo et al., 2023)

disaster areas (Jamaluddin & Parung, 2024; Lin et al., 2023; Molinero-Parejo et al., 2023).

The subsequent stage entails modifying the cell dimensions to forecast land expansion. The Landuse Sim application offers two cell size options: 3×3 cells and 5×5 cells. The assessment of cell size seeks to ascertain the growth rate. The growth rate in the Landuse Sim system can be ascertained through two methodologies: the trend-based approach and the target-based approach (Jamaluddin & Parung, 2024; (Bris et al., 2021). The neighborhood filter to be used is 5×5 based on the use of a small cell size, which requires a wider neighbourhood impact to produce more cohesive results (Pratomoatmojo, 2018).

The next step is to formulate transition regulations. Jamaluddin and Parung (2024) identify five fundamental guidelines to be established in the LanduseSim process. The regulations encompass the allocation of codes to each land use category, the incorporation of the previously developed suitability map, the identification of growth cell quantities, the establishment of dynamic variables, and the specification of conversion probability values (Paddiyatu et al., 2023). Upon the establishment of transition rules, the Landuse Sim simulation can be initiated by entering the necessary parameters, including the projection date, the initial land use map, the transition rule set, environmental filters, and the time step (Al-Darwish et al., 2018; Pratomoatmojo, 2018). An analysis was conducted to assess the development of an area based on land use by examining the land use change trends in the village areas based on the projected shifts in land use. These trends can be classified into urban land use and rural land use patterns (Jia et al., 2024; Sari & Santoso, 2017). The criterion for urban land use is the percentage of agricultural land use, including rice fields, dry land gardens, shrubs, mangroves, ponds, and forests, which

ranges from >0% to 25%. In contrast, the criterion for rural land use is characterized by agricultural land use percentages ranging from >75% to 100% (Sari & Santoso, 2017).

RESULT

Land use in 2023

The research area is categorized into 11 distinct land uses: fields, mixed gardens, shrubs, forests, ponds, paddy fields, rivers, mangroves, settlements, industry, and commerce and services. Forests represent the predominant land use in the eastern section of the research area. The spatial distribution of these land use types is illustrated in Figure 2.

The land use data in Table 2 indicate that the study area is predominantly characterised by natural environments, such as forests and shrublands, with a smaller proportion of land allocated for human activities, including settlements and commercial areas. Forests represent the most prominent land use type, covering 54,8% of the total area, highlighting the dominance of forested regions. Shrub rank second in land use, accounting for 13,5% of the total area, typically comprising unmanaged or minimally managed areas. In contrast, other land uses, including residential areas, commercial and service zones, industrial activities, and mangrove ecosystems, occupy significantly smaller portions of the total area.

Driving factors and constraint

In this research, the regulations identified as constraints consist of five types of rules, including the designation of forest areas, the regulation of sustainable food agricultural land use, slope

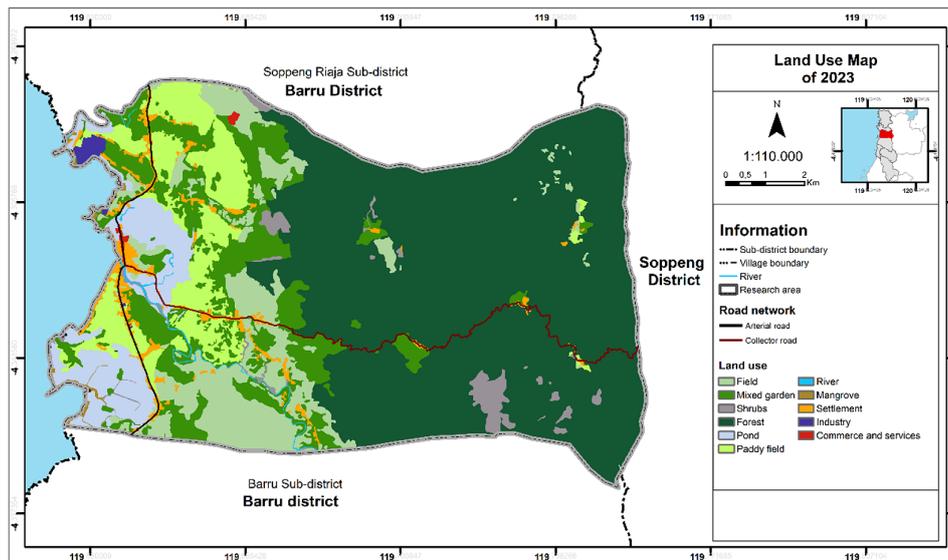


Figure 2. Land use in the research area in 2023

Table 2. Land use area in 2023

Landuse	Area	
	(ha)	(%)
Field	1.206,7	10,7
Mixed garden	1.528,1	13,5
Shrubs	233,3	2,1
Forest	6.199,2	54,8
Pond	676,7	6,0
Paddy field	1.012,4	8,9
River	42,9	0,4
Mangrove	59,9	0,5
Settlement	295,2	2,6
Industry	43,0	0,4
Commerce and services	24,4	0,2
Total	11.321,9	100

gradient, coastal and river setbacks, and disaster-prone areas. The results and discussion may be presented separately, or in one combined section, and may optionally be divided into headed subsections.

The forest area regulations in the study region consist of two types: protected forest areas and production forest areas. The slope classification in the study area is divided into five categories: flat (0–8%), gentle (8–15%), moderately steep (15–25%), steep (25–45%), and very steep (>45%). Disaster-prone areas, based on InaRISK data, include flood-prone zones, which are categorized into three levels of vulnerability: high, medium, and low. Constraints, such as sustainable food agricultural regulations and coastal and river buffer

zones, are considered unclassified. The five spatial datasets were overlaid to create a single constraint map encompassing these regulations. The constraint factor map is shown in Figure 3.

The results of the AHP Analysis show a consistency ratio (CR) value of 0.009. The CR value indicates that the resulting weights are considered consistent enough and can be used for further analysis. The resulting weight values are presented in the Table 3.

The distance map in Figure 4 shows the range of the drivers. The blue color on the map indicates that the area is getting closer to the driving factor. Meanwhile, the red color indicates that the area is farther away from the driving factor. The

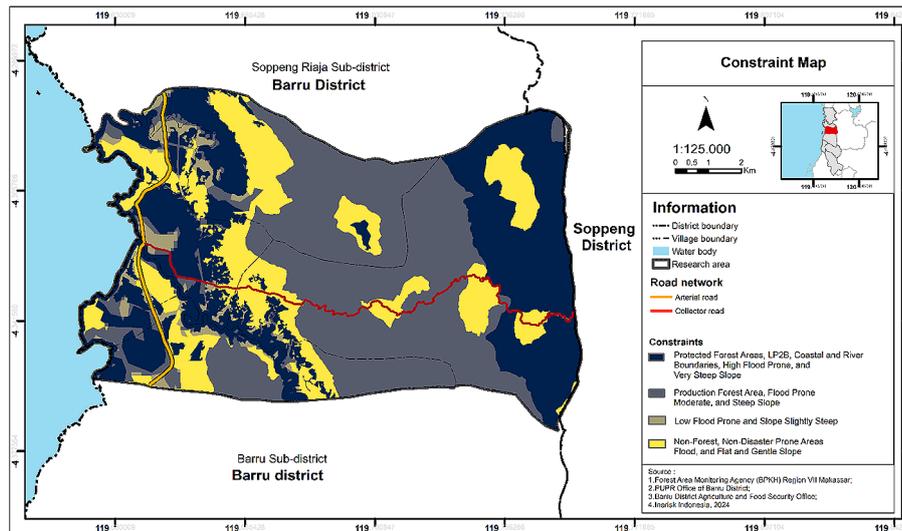


Figure 3. Constraints map

Table 3. Weight value of driving factors

Driving factors	Weight value
Arterial road	0,2384
Collector road	0,1343
Local road	0,0464
Train station	0,1041
Built-up land	0,1656
Economic center	0,1782
Tourism objects	0,0602
Facilities	0,0728

yellow color on the map shows the area that is between the closest area and the farthest area from the driving factor.

Simulation result

The simulation of projected land-use changes in the study area over the next 20 years reveals variations in the extent of several land-use types.

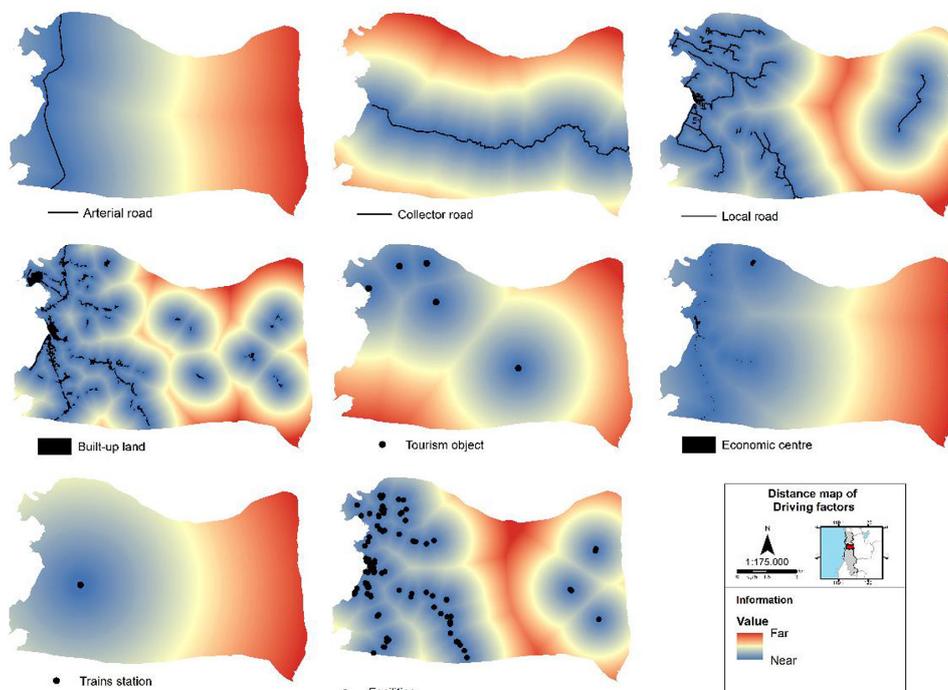


Figure 4. Distance map of driving factors: (a) distance to arterial road, (b) distance to collector road, (c) distance to local road, (d) distance to built-up land, (e) distance to trains station, (f) distance to tourism object, (g) distance to economic centre, (h) distance to facilities

Six of the 11 land-use categories experienced changes, while five remained unchanged. The six changed land-use types include upland fields, mixed gardens, paddy fields, settlements, industry, commerce, and services. Meanwhile, the five stable land-use types are shrubs, forests, ponds, rivers, and mangroves. The projected land use for the years 2023 to 2043 can be seen in Figure 5.

According to the land-use area data presented in Table 4 to 5, upland fields experienced a slight annual decline, decreasing from 1.206,7 hectares in 2023 to 1.200,5 hectares in 2043. This indicates a gradual land conversion driven by the increasing demand for settlements, industry, commerce, and services. Similarly, mixed gardens underwent a conversion of 76,6 hectares into settlements, industry, commerce and services. Ponds also experienced a land-use shift, with 0,3 hectares converted into settlements and industrial areas. Paddy fields were similarly affected, with 12,5 hectares converted into settlements, industry, commerce and services.

Settlements are another land-use type that changed. Settlement areas are projected to convert 31,5 hectares into industrial areas and 0,5 hectares into commerce and services areas. However, this does not result in a reduction in the total settlement area by 2043. Instead, the settlement area increases due to conversions from other land uses into new settlement areas, reaching 328,2 hectares. Commerce and services land experienced a slight decline in 2023, primarily due to conversions into settlement and industrial areas. While commerce and services areas also gained some land from conversions of other uses, the total gain did not offset the losses, resulting in a net decrease in area. Industrial land use stands out as the only category that did not convert into other land uses. Instead, it experienced significant expansion through conversions from other land types, including paddy fields, upland fields, mixed gardens, settlements, and commerce and services areas. Initially covering 43 hectares, industrial land gained an additional

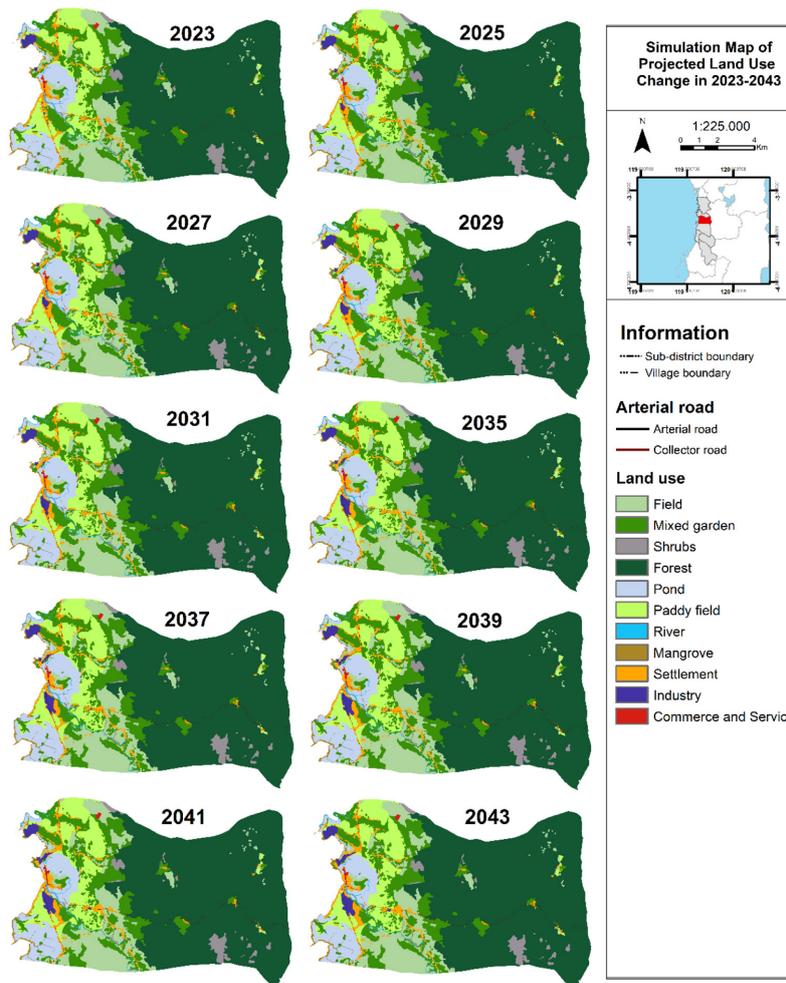


Figure 5. Map of simulation results in 2023–2043

Table 4. Land use change in 2023 and 2043

Landuse	Area (Ha)						
	Field	Mixed garden	Shrubs	Forest	Pond	Paddy field	River
Field	1.191,6	0	0	0	0	0	0
Mixed garden	0	1.451,5	0	0	0	0	0
Shrubs	0	0	233,3	0	0	0	0
Forest	0	0	0	6199,2	0	0	0
Pond	0	0	0	0	676,4	0	0
Paddy field	0	0	0	0	0	1.000	0
River	0	0	0	0	0	0	42,9
Mangrove	0	0	0	0	0	0	0
Settlement	0	0	0	0	0	0	0
Industry	0	0	0	0	0	0	0
Commerce and services	0	0	0	0	0	0	0
Grand total in 2043	1.191,6	1.451,5	233,3	6.199,2	676,4	1.000	42,9

Table 5. Land use change in 2023–2043 (continued)

Landuse	Area (ha)					Grand total in 2023
	River	Mangrove	Settlement	Industry	Commerce and services	
Field	0	0	10,9	4,0	0,2	1.206,7
Mixed garden	0	0	49,4	26,1	1,1	1.528,1
Shrubs	0	0	0	0	0	233,3
Forest	0	0	0	0	0	6.199,2
Pond	0	0	0,3	0	0	676,7
Paddy field	0	0	4,2	8,1	0,2	1.012,4
River	42,9	0	0	0	0	42,9
Mangrove	0	59,9	0	0	0	59,9
Settlement	0	0	263,2	31,5	0,5	295,2
Industry	0	0	0	43	0	43
Commerce and services	0	0	0,1	2	22,3	24,4
Grand total in 2043	42,9	59,9	328,2	114,6	24,3	11.321,9

71,7 hectares from these conversions, resulting in 114,6 hectares by 2043. The graph depicting changes in land use area from 2023 to 2043 is presented in Figure 6.

In Figure 7, which illustrates land-use maps for 2023 and 2043, three distinct zones show notable land-use changes. Zone 1 is the area that shows the conversion of fields, mixed gardens, and settlements into industrial land. Additionally, there is a noticeable expansion of settlement areas, converting mixed garden land. In Zone 2, industrial land is shown to expand further in this area by converting mixed gardens, settlements, commerce and services areas, and paddy fields. The growth in Zone 2 is attributed to the presence of pre-existing industrial land in 2023, similar to Zone 1. In contrast to zones 1 and 2, zone 3 shows

industrial land development in an area where no industrial land existed in 2023. However, the scale and extent of this development are smaller than in zones 1 and 2. The industrial land in Zone 3 expands by converting settlements, mixed gardens, and paddy fields. Settlement growth is also evident in this zone, primarily through the conversion of mixed gardens and paddy fields.

Based on the projected land-use changes in 2043, patterns of land-use tendencies can be observed across the villages within the study area.

Table 6 reveals that all villages within the study area fall under rural land use. This classification is evident from the percentage of agricultural land in all villages, which exceeds 75%. Ranked by the highest rate of agricultural land, Kamiri exhibits the most prominent rural land-use pattern,

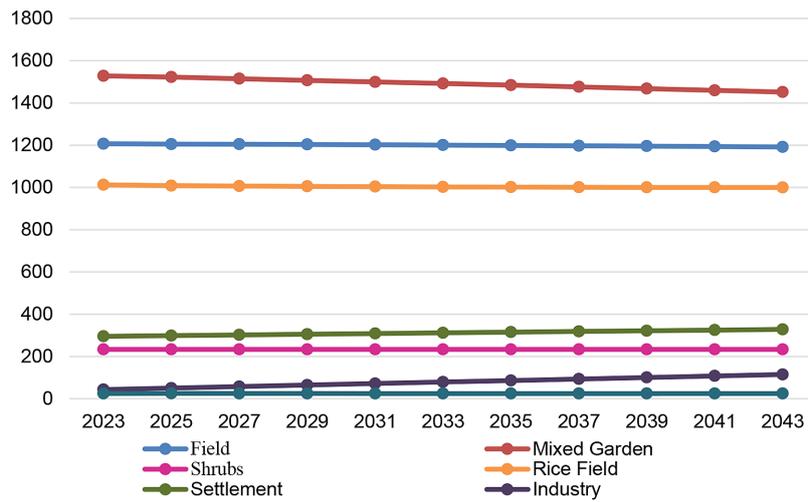


Figure 6. Land-use changes in the research area in 2023–2043

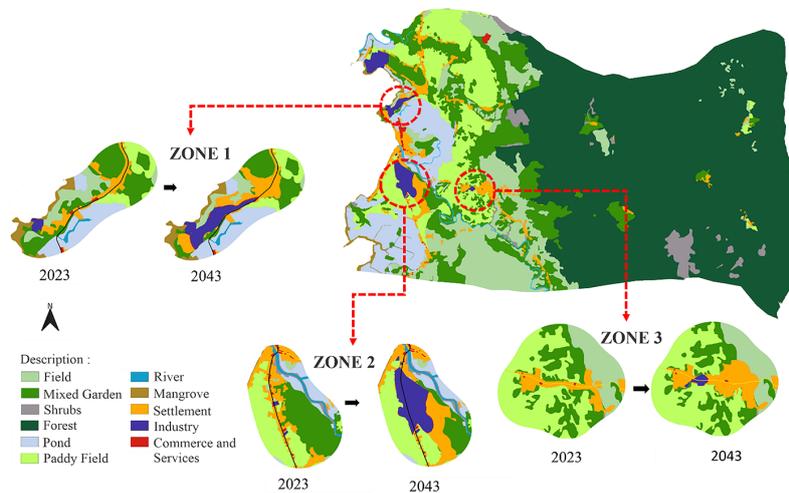


Figure 7. Three zones of land use change in the study area

Table 6. Land use pattern trend in 2043

Land classified	Landuse	Land use area in 2043(Ha)					
		Balusu	Binuang	Kamiri	Lampoko	Madello	Takkalasi
Agriculture	Field	249	595	226,9	26,8	1,7	92.2
	Mixed garden	425	261,8	306,3	160,3	74,9	223.1
	Shrub	63, 1	23,7	128	2,3	9,7	6.6
	Forest	1296,5	411,4	4461,1	0	0,3	29.9
	Pond	0,5	192,2	0	40,2	166,3	277.2
	Paddy field	403,9	22,4	41,8	134,1	159,3	238.5
	Mangrove	0	13,9	0	13,7	21,3	11.1
Total		2438,0	1520,2	5164,1	377,4	433,5	878,7
Percentage		98,1 %	97,7%	99%	80%	76,6%	89,2%
Non-Agriculture	Settlement	40,8	33,6	50,8	54,1	75,7	73.1
	Industry	0	0	0	39,4	54,7	20.6
	Commerce and services	7,4	1,6	0	0,9	2,1	12.3
Total		48,2	35,2	50,8	94,3	132,5	106
Percentage		1,9%	2,3%	1%	20%	23,4%	10,8%

followed by Balusu and, in third place, Binuang. The extensive areas of forest, fields, and mixed gardens in these three villages contribute to their solid rural land-use characteristics compared to the other three villages. Meanwhile, Madello, Lampoko, and Takkalasi also tend toward rural land-use patterns. However, when considering the percentage of non-agricultural land, these three areas demonstrate the potential to transition into urban land-use patterns in the future.

DISCUSSION

Based on the projected land use changes around the Takkalasi-Bainange-Lawo road development area, it can be observed that, over the next 20 years, no significant land use conversion is expected, particularly within the Takkalasi-Bainange-Lawo corridor. This finding supports the principle of “everything remains unchanged,” as proposed by Liu et al. (2024), is also applicable to the study area. Although no significant changes are anticipated, it is still possible that more substantial land use changes may occur beyond the 20-year period. Driving factors such as the development of new transportation routes or the planning of new activity centers within the study area, aimed at maximizing the functionality of the Takkalasi-Bainange-Lawo road, could serve as new catalysts for more significant land use changes.

The analysis of the influence level of each driving factor on land use change shows that arterial roads are the primary factor in land use changes, which aligns with the projection results. Three zones exhibit land use changes, two of which are located within the arterial road corridor. The third zone is situated within the collector road corridor, which in this case refers to the Takkalasi-Bainange-Lawo road. However, the land use changes observed are not solely attributable to the availability of road networks, but also due to factors such as proximity to economic centers and the presence of built-up land. A comparison between the 2023 and 2043 maps clearly indicates that land use changes are beginning to occur in areas where built-up land already exists, subsequently expanding by converting the surrounding land uses.

Land uses such as rivers, mangroves, shrubs, ponds, and forest areas have not experienced any land use changes. This is due to spatial planning regulations that prohibit land conversion in these areas, as they serve

protective functions. Additionally, the slope gradient in these areas is categorized as moderately steep to steep, which further restricts development. Similarly, rice fields have not undergone significant land use conversion due to regulations aimed at the protection of sustainable rice land. Under these regulations, certain rice fields are designated as protected areas. The protection of forest and rice land ensures food security and promotes harmonious development between ecological and economic aspects (Liu et al., 2024).

CONCLUSIONS

This research predicts land-use changes around the Takkalasi-Bainange-Lawo road development in Barru Regency for 2023–2043, using the cellular automata (CA) methodology through the LanduseSim program. The analysis reveals significant changes in six land use categories, influenced by proximity to infrastructure and economic centres, while protected areas show stability due to spatial policies. The findings emphasise the need for adjustments in spatial planning policies in the study area to accommodate anticipated changes, incorporate environmental mitigation techniques, and ensure the sustainability of agricultural and conservation zones to support overall sustainability. The results highlight that the presence of the Takkalasi Bainange Lawo collector road should be viewed as a crucial economic infrastructure, particularly by utilising the Takkalasi-Bainange-Lawo road as a strategic connector to enhance inter-regional connectivity. Addressing the ecological impacts of land conversion and the ecosystem restoration of degraded areas, especially ponds and affected agricultural lands, is a critical step. Furthermore, the potential for land conflicts can be reduced through an inclusive and transparent approach between the government, local communities, and business stakeholders.

To improve the imbalanced and inadequate land planning, rational allocation of land resources, optimization of the functional layout of production spaces, residential areas, and ecological zones, as well as the development of optimal urban and agricultural land planning and layout schemes, are necessary. This research provides valuable insights for sustainable spatial planning and infrastructure development.

Acknowledgements

The authors would like to express their sincere gratitude to the informants for their participation in this research. We also extend our heartfelt thanks to the editor and the anonymous reviewers for their in-depth feedback, which greatly contributed to enhancing the quality of this study.

REFERENCES

- Aidi, M. N., & Maulana, S. I. (2020). a Spatial Model for Predicting the Occurrences of Deforestation in the Island of Sumatra, Indonesia. *Journal of Sustainability Science and Management*, 15(6), 75–84. <https://doi.org/10.46754/jbsd.2020.08.007>
- Al-Darwish, Y., Ayad, H., Taha, D., & Saadallah, D. (2018). Predicting the future urban growth and its impacts on the surrounding environment using urban simulation models: Case study of Ibb city – Yemen. *Alexandria Engineering Journal*, 57(4), 2887–2895. <https://doi.org/10.1016/j.aej.2017.10.009>
- Alemu, M., Warkineh, B., Lulekal, E., & Asfaw, Z. (2024). Analysis of land use land cover change dynamics in Habru District, Amhara Region, Ethiopia. *Heliyon*, 10(19), e38971. <https://doi.org/10.1016/j.heliyon.2024.e38971>
- Badoe, D. A., & Miller, E. J. (2000). Transportation–land-use interaction: empirical findings in North America, and their implications for modeling. *Transportation Research Part D: Transport and Environment*, 5(4), 235–263. [https://doi.org/10.1016/S1361-9209\(99\)00036-X](https://doi.org/10.1016/S1361-9209(99)00036-X)
- Barreira-González, P., Gómez-Delgado, M., & Aguilera-Benavente, F. (2015). From raster to vector cellular automata models: A new approach to simulate urban growth with the help of graph theory. *Computers, Environment and Urban Systems*, 54, 119–131. <https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2015.07.004>
- Bris, A., Wang, T. Y. H., Zatzick, C. D., Miller, D. J. P., Fern, M. J., Cardinal, L. B., Gregoire, D. A., Shepherd, D. A., Westphal, J. D., Shani, G., Troster, C., Van Quaquebeke, N., Lanaj, K., Hollenbeck, J. R., Ilgen, D. R., Barnes, C. M., Harmon, S. J., Feldman, E. R., DesJardine, M. R., ... Sangiorgi, F. (2021). Knights, raiders, and targets - the impact of the hostile takeover - coffee, Jc, Lowenstein, L, Roseackerman, S. *Journal Of Banking & Finance*, 37(1).
- Chen, Z., & Dong, H. (2024). Exploring urban and agricultural land use planning. *Results in Engineering*, 24(October), 103093. <https://doi.org/10.1016/j.rineng.2024.103093>
- Csomós, G., Szalai, Á., & Farkas, J. Z. (2024). A sacrifice for the greater good? On the main drivers of excessive land take and land use change in Hungary. *Land Use Policy*, 147(September), 0–2. <https://doi.org/10.1016/j.landusepol.2024.107352>
- Ge, K., Wang, Y., Liu, X., Ke, S., Jiang, X., & Lu, X. (2024). Impacts and threshold effects of urban–rural integration on the transition of arable land use functions. *Ecological Indicators*, 166(July), 112595. <https://doi.org/10.1016/j.ecolind.2024.112595>
- Geng, J., Shen, S., Cheng, C., & Dai, K. (2022). A hybrid spatiotemporal convolution-based cellular automata model (ST-CA) for land-use/cover change simulation. *International Journal of Applied Earth Observation and Geoinformation*, 110(April), 102789. <https://doi.org/10.1016/j.jag.2022.102789>
- Ghatak, M., & Mookherjee, D. (2014). Land acquisition for industrialization and compensation of displaced farmers. *Journal of Development Economics*, 110, 303–312. <https://doi.org/10.1016/J.JDEVECO.2013.01.001>
- Jaeger, J. A. G., Bertiller, R., Schwick, C., Müller, K., Steinmeier, C., Ewald, K. C., & Ghazoul, J. (2008). Implementing landscape fragmentation as an indicator in the swiss monitoring system of sustainable development (Monet). *Journal of Environmental Management*, 88(4), 737–751. <https://doi.org/10.1016/J.JENVMAN.2007.03.043>
- Jamaluddin, A. A., & Parung, H. (2024). *Implementation of Aerropolis Concept in the Development of the Areas Around Sultan Hasanuddin International Airport*. X(X), 1–11.
- Jia, K., Huang, X., Qiao, W., & Zhong, S. (2024). Unpacking divergent rural-urban land use dynamics in county urbanization: A comparative socio-spatial analytics approach. *Cities*, 154, 105343. <https://doi.org/10.1016/J.CITIES.2024.105343>
- Jiang, Y., Long, H., Tang, Y. ting, & Deng, W. (2024). Deciphering how promoting land consolidation for village revitalization in rural China: A comparison study. *Journal of Rural Studies*, 110, 103349. <https://doi.org/10.1016/J.JRURSTUD.2024.103349>
- Kasraian, D., Maat, K., Stead, D., & van Wee, B. (2016). Long-term impacts of transport infrastructure networks on land-use change: an international review of empirical studies. *Transport Reviews*, 36(6), 772–792. <https://doi.org/10.1080/01441647.2016.1168887>
- Lin, J., Li, X., Wen, Y., & He, P. (2023). Modeling urban land-use changes using a landscape-driven patch-based cellular automaton (LP-CA). *Cities*, 132(August 2021), 103906. <https://doi.org/10.1016/j.cities.2022.103906>
- Liu, J., Liu, B., Wu, L., Miao, H., Liu, J., Jiang, K., Ding, H., Gao, W., & Liu, T. (2024). Prediction of land use for the next 30 years using the PLUS model’s multi-scenario simulation in Guizhou Province, China. *Scientific Reports*, 14(1), 1–12. <https://doi.org/10.1038/s41598-024-56111-4>

- doi.org/10.1038/s41598-024-64014-7
19. Ma, S., Wang, G., Xu, C., Zhang, X., Zhao, Y., & Cai, Y. (2024). Does the optimal land use pattern for cross-regional cooperation change at different stages of urbanization? Evidence from the trade-off between urban growth scenarios and SDGs indicators. *Applied Geography*, *167*, 103294. <https://doi.org/10.1016/J.APGEOG.2024.103294>
 20. Mamat, L., Basri, N. E. A., Zain, S. M., & Rahmah, E. (2016). Environmental sustainability indicators as impact tracker: A review. *Journal of Sustainability Science and Management*, *11*(1), 29–42.
 21. Molinero-Parejo, R., Aguilera-Benavente, F., Gómez-Delgado, M., & Shurupov, N. (2023). Combining a land parcel cellular automata (LP-CA) model with participatory approaches in the simulation of disruptive future scenarios of urban land use change. *Computers, Environment and Urban Systems*, *99*(March 2022). <https://doi.org/10.1016/j.compenvurbsys.2022.101895>
 22. Nguyen, T. H. T., Tran, V. T., Bui, Q. T., Man, Q. H., & Walter, T. de V. (2016). Socio-economic effects of agricultural land conversion for urban development: Case study of Hanoi, Vietnam. *Land Use Policy*, *54*, 583–592. <https://doi.org/10.1016/J.LANDUSEPOL.2016.02.032>
 23. Paddyatu, N., Umar, F., Zainuddin, S., & Arista, M. A. Y. (2023). Model Perkembangan Permukiman Berbasis Cellular Automata di Kabupaten Takalar. *Jurnal Pembangunan Wilayah Dan Kota*, *19*(3), 409–421. <https://doi.org/10.14710/pwk.v19i3.45639>
 24. Pratomoatmojo, N. A. (2018). LanduseSim Algorithm: Land use change modelling by means of cellular automata and Geographic Information System. *IOP Conference Series: Earth and Environmental Science*, *202*(1), 0–12. <https://doi.org/10.1088/1755-1315/202/1/012020>
 25. Purwanto, A., & Andrasmo, D. (2021). Land capability evaluation of former bauxite mining land for land use planning by integrating remote sensing and geographic information system in Sanggau West Kalimantan Indonesia. *Journal of Sustainability Science and Management*, *16*(6), 214–227. <https://doi.org/10.46754/jssm.2021.08.019>
 26. Qin, S., Wang, C., & Yan, Y. (2024). Identification of conflict and its evolution between land use and land suitability during urban expansion: A case of Guangzhou, China. *Ecological Frontiers*. <https://doi.org/10.1016/J.ECOFRO.2024.08.006>
 27. Rakuasa, H., Salakory, M., & Latue, P. C. (2022). Analisis Dan prediksi perubahan tutupan lahan menggunakan model celular automata-Markov Chain Di Das Wae Ruhu Kota Ambon. *Jurnal Tanah Dan Sumberdaya Lahan*, *9*(2), 285–295. <https://doi.org/10.21776/ub.jtstl.2022.009.2.9>
 28. Sari, K. D. R., & Santoso, E. B. (2017). Analisis Keterkaitan Wilayah Peri Urban di Kabupaten Gresik dengan Wilayah Desa-Kota di Sekitarnya. *Jurnal Teknik ITS*, *6*(2), 2–7. <https://doi.org/10.12962/j23373539.v6i2.24971>
 29. Shaw, S. L., & Xin, X. (2003). Integrated land use and transportation interaction: a temporal GIS exploratory data analysis approach. *Journal of Transport Geography*, *11*(2), 103–115. [https://doi.org/10.1016/S0966-6923\(02\)00070-4](https://doi.org/10.1016/S0966-6923(02)00070-4)
 30. Sun, P., Linghu, L., & Zhang, M. (2024). Relationship between regional economic development and its associated land use changes: A case study of Shaanxi province in China. *World Development Sustainability*, *4*(September 2023), 100122. <https://doi.org/10.1016/j.wds.2023.100122>
 31. von Groß, V., Sibhatu, K. T., Knohl, A., Qaim, M., Veldkamp, E., Hölscher, D., Zemp, D. C., Corre, M. D., Grass, I., Fiedler, S., Stiegler, C., Irawan, B., Sundawati, L., Husmann, K., & Paul, C. (2024). Transformation scenarios towards multifunctional landscapes: A multi-criteria land-use allocation model applied to Jambi Province, Indonesia. *Journal of Environmental Management*, *356*, 120710. <https://doi.org/10.1016/J.JENVMAN.2024.120710>
 32. Wenbo, X., Hengzhou, X., Xiaoyan, L., Hua, Q., & Ziyao, W. (2024). Ecosystem services response to future land use/cover change (LUCC) under multiple scenarios: A case study of the Beijing-Tianjin-Hebei (BTH) region, China. *Technological Forecasting and Social Change*, *205*, 123525. <https://doi.org/10.1016/J.TECHFORE.2024.123525>
 33. Xiao, C., Wang, Y., Yan, M., & Chiwiukem Chiaka, J. (2024). Impact of cross-border transportation corridors on changes of land use and landscape pattern: A case study of the China-Laos railway. *Landscape and Urban Planning*, *241*, 104924. <https://doi.org/10.1016/J.LANDURBPLAN.2023.104924>
 34. Yue, W., Qin, C., Su, M., Teng, Y., & Xu, C. (2024). Environmental and Sustainability Indicators Simulation and prediction of land use change in Dongguan of China based on ANN cellular automata - Markov chain model. *Environmental and Sustainability Indicators*, *22*(July 2023), 100355. <https://doi.org/10.1016/j.indic.2024.100355>
 35. Zhang, Z., & Li, J. (2022). Spatial suitability and multi-scenarios for land use: Simulation and policy insights from the production-living-ecological perspective. *Land Use Policy*, *119*, 106219. <https://doi.org/10.1016/J.LANDUSEPOL.2022.106219>
 36. Zong, S., Xu, S., Jiang, X., & Song, C. (2024). Identification and dynamic evolution of land use conflict potentials in China, 2000–2020. *Ecological Indicators*, *166*(July), 112340. <https://doi.org/10.1016/j.ecolind.2024.112340>