

# SPATIO-TEMPORAL ANALYSIS OF BUILT-UP EXPANSION (BUA): THE CASE OF METROPOLITAN DAVAO'S THIRD CONGRESSIONAL DISTRICT

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## Abstract

The migration of individuals from rural regions to urban areas leads to a growing need for housing, infrastructure, and services, which drives social, economic, and environmental changes. This study uses Landsat Data to generate LULC maps across multiple timeframes. Utilizing satellite images acquired from the United States Geological Survey (USGS), the research employs various techniques, including image processing, classification and accuracy testing to analyze dynamic shifts in five land classes. The study's methodology involves using a Quantum Geographic Information System (QGIS) for LULC classification, vector layer intersection for refining results, and change detection through pivot tables and zonal statistics. The findings provide insights into spatial patterns and temporal trends within the district. The data indicates that forest areas consistently occupy most of the land, although gradual decline is observed, particularly between 2020 and 2023. Agricultural and barren lands show fluctuating trends, with agricultural land experiencing a notable decrease in specific years due to urbanization pressures. Built-up areas (BUA) have seen continuous growth, reflecting the district's shifts towards urban development, which can be linked to its proximity to the Central Business District (CBD), which leads to land conversion. The data underscores the need for sustainable land management practicing balance amidst pressures from rapid urban growth.

Keywords: Spatio-temporal analysis, BUA, GIS, Davao City, Philippines.

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## INTRODUCTION

Land use change is a shared global phenomenon driven by anthropogenic activities altering landscapes (Subedi et al. 2021). Accelerated urbanization creates significant global societal,

economic, cultural, and environmental changes. It continues to become a threat in rural and urban communities globally. It is driven by rapid economic growth (Wang et al. 2023), intensifies

the evolution of the regional land-use structure (Chen et al. 2021), and significant changes in land use patterns (Vaddiraju & Reshma 2022) and dramatically changed land cover globally (Zhou et al. 2021). LULC allows us to monitor and understand human-induced alterations and requires spatio-temporal evaluation involving analysis of historical satellite images (Velastegui-Montoya et al. 2023). Cities are engines of economic growth and development. The urban environment continues to expand at an unprecedented rate to meet the demands of increasing population and economic development (Nath et al. 2021). Data shows that >55% of the population lives in urban areas, and this is expected to grow to 68% by 2050 (Zhang et al. 2023), creating immense pressures on existing urban lands and resulting in numerous adverse impacts on the physical and social environment and end up with fast development of sprawl (Ghosh & Das 2018). Urbanization varies from country to country, causing significant environmental threats (Chatterjee & Majumdar 2021), altered landscape patterns and ecological functions (Zhou et al. 2018), and the provision of ecosystem services from multifunctional landscapes have contributed to human well-being (Zhang et al. 2017). Most studies focus on specific timeframes and often lack comprehensive analysis over an extended period. Moreover, analyzing LULC in multiple time frames with high-resolution data can provide a detailed understanding of the dynamics and drivers of LULC changes, which is essential for transitioning sustainable urban development. The objective of the study is (i) to determine the land use and land cover changes in the Third Congressional District of Davao City (TCDDC) from 2018-2023 and (ii) to analyze the trend of the land use and land cover changes of Davao City from 2018-2023.

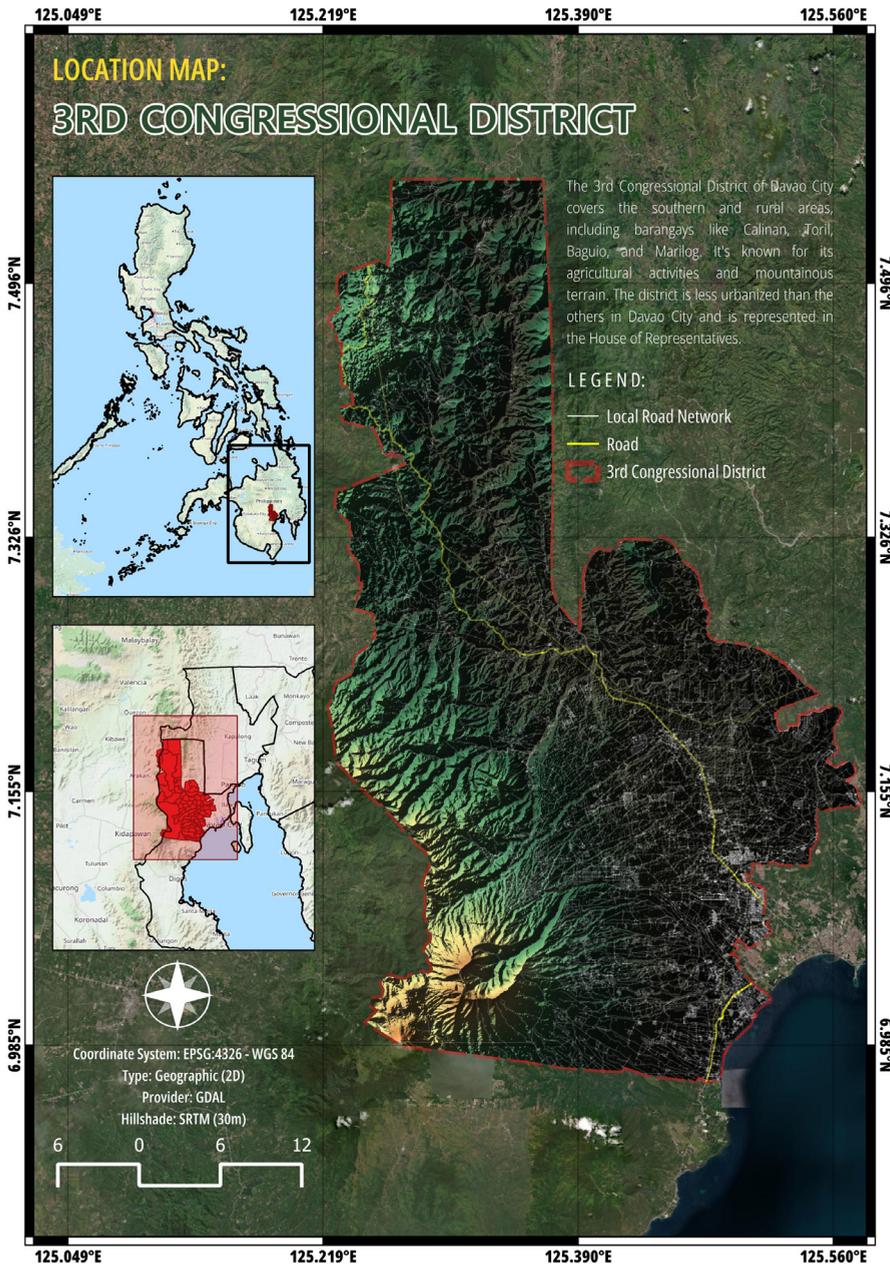
## MATERIAL AND METHODS

This study utilized a descriptive, quantitative, non-experimental design. The quantitative research approach analyzes geospatial data and derives changes, patterns and trends of urban dynamics (Seto & Kaufmann 2016). It also intends to describe and analyze urban dynamics concentrate on land use and land cover changes associated with built-up expansion (Grimmond & Oke 1999). One of the most advanced techniques for describing the sensory characteristics of products is quantitative descriptive analysis, which thoroughly explains key sensory characteristics (Cardoso & Bolini 2008). This study utilized various processes and techniques to assess the LULC changes and BUA from 2018-2023 in the TCDDC (Fig. 1). This includes data acquisition of satellite images, image processing, image reclassification, and change analysis. Satellite data of the TCDDC from the year 2018-2023 were obtained from ESRI Sentinel 2-Land Cover Explorer.

After extracting and accurately projecting the study area within QGIS, a detailed classification of the LULC data is conducted. This involved a systematic analysis of the study areas' geographic and environmental features, allowing for the identification and categorization of the data into five distinct LULC types. Each category was carefully defined to reflect the specific characteristics and patterns observed within the study area, ensuring a comprehensive understanding of the landscape dynamics. To estimate spatiotemporal changes and to compute land cover across from 2018 to 2023, a Semi-Automatic Classification Plugin (SCP) within QGIS developed by (Congedo 2024) has been utilized. The validation of the classified images is achieved through a critical accuracy assessment. Ground truth data collection is conducted, enabling a rigorous comparison between the classified results and actual land cover conditions. Statistical metrics, including overall accuracy and kappa coefficient, are employed for a robust evaluation of precision

(Rwanga & Ndambuki 2017). This post-processing tool generated five land cover change maps, each reflecting the variations over the specified time periods. Lastly, change detection

compares the classified images from different years to identify change areas, such as increases and decreases, trends, and patterns.



**Figure 1.** Map showing the location of the Third Congressional District of Davao City.

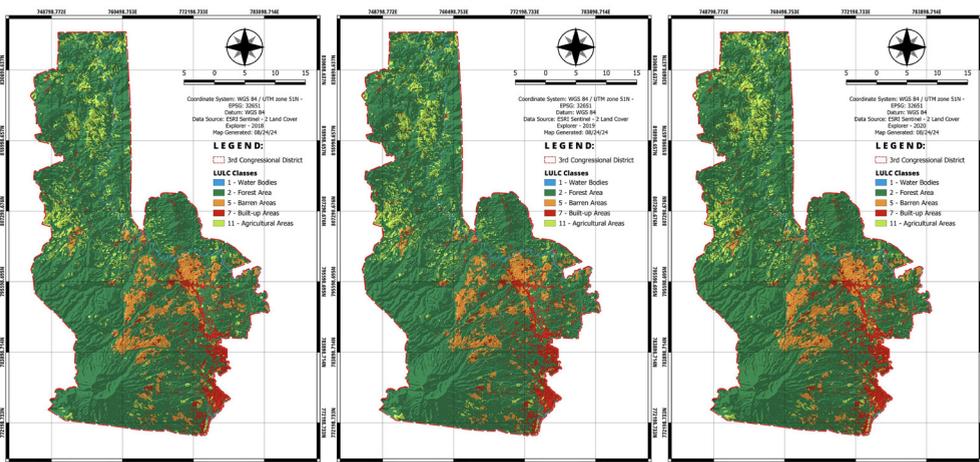
## RESULTS AND DISCUSSION

Presented in the Table 1 is the data on land use and land cover change (LULC) of the TCDDC (Fig. 2). From 2018, the forest is the highest total number of ha within the TCDDC, with 116,379.72 ha comprising 79.66% of the total land area, followed by agricultural with 11,168.71 ha or 7.64%, barren land with 10,302.40 or 7.05%, built-up with 7,275.09 or 4.98% and the least is water bodies with .76% or 974.77 ha of the total land area. This indicates that forest and other green vegetation cover most of the land area. The location of

the TCDDC is on the way out from the Central Business District (CBD), which is located within the suburban periphery, primarily engaging in the agriculture sector. According to Salvati et al. (2021), forests and green in surrounding cities have been considered vital components in urban ecosystems providing varied ecosystem services and increasing urban livability along megacities globally, and the understanding of the patterns of the natural forest expansion in rural regions under the influences of urbanization process, the so-called suburban countryside, and is crucial for integrated spatial planning (Barbati et al. 2012).

**Table 1.** Land use and land cover changes of the TCDDC 2018-2020.

LULC Classes	Year								
	2018			2019			2020		
	Area (ha)	%	% (-/+)	Area (ha)	%	% (-/+)	Area (ha)	%	% (-/+)
Water Bodies	974.77	.67	-	945.45	.65	-3.01	880.33	.60	-6.89
Forest	116379.72	79.66	-	117444.79	80.39	+92	113946.83	77.99	-2.98
Barren	10302.40	7.05	-	9151.23	6.26	-11.17	10906.27	7.46	+19.18
Built-Up	7275.09	4.98	-	8112.71	5.55	+11.51	8681.81	5.94	+7.01
Agricultural	11168.71	7.64	-	10446.51	7.15	-6.47	11685.45	8.00	11.86
Total	146100.70	100	-	146100.70	100		146100.70	100	



**Figure 2.** Map of land use and land cover change of the TCDDC 2018-2020.

Moreover, in 2019, the forests area had the highest number of hectares among the other land classes, covering 80.39% or 117,444.79 ha with an increase of .92% or 1,065.07 ha of the total land area, followed by agricultural with 7.15% or 10446.51 ha with a reduction of -6.47% or 722.20 ha, barren areas with 9,151.23 or 6.26% with a change of -11.17% or 1,151.71 ha, built-up with 8,112.71 or 5.5% with an increase of +.11.51% or 837.62 ha, and water bodies with .65% or 94.5.45 ha of the total land area with a reduction of -3.01% or 29.32 ha of the total land area. Although forest growth is increasing, BUA is also increasing, which can be associated with a significant increase in urban development expansion within the sub-urban district, which accounts for some of the land conversion within agricultural areas. For 2020, forest area is still dominant, accounting for 77.99% or 113,946.83 ha, with

an observed decrease in cover of -2.98% or a total of 3,497.96, followed by agricultural land, which covers 8% or 11,685.45 ha, indicating an increase of 11.86% or 1,238.94 ha, barren with 7.46% with the observed increase of +19.18% or 1,755.04 ha, built-up with 5.94% or 8,681.81 ha with recorded increase rate of +7.01% or 549.10 ha and the least is water bodies with .60% or 880.33 ha with an observed decrease rate of -6.89% which comprises 65.12 ha of the total land area. The decline in forest cover can be attributed to the increasing demand for agricultural land, where a notable increase in agriculture was recorded aside from the continued built-up expansion. This was supported by the results from the study of Quan et al. (2015) that built-up expansion is increasing at the expense of the cultivated land, woodland, and grassland, resulting in patches and irregular shapes.

**Table 2.** Land use and land cover changes of the TCDDC 2021-2023.

LULC Classes	Year								
	2021			2022			2023		
	Area (ha)	%	% (-/+)	Area (ha)	%	% (-/+)	Area (ha)	%	% (-/+)
Water Bodies	919.69	.63	4.47	1016.92	.65	+10.57	1038.01	.60	+2.07
Forest	116052.84	79.43	1.85	117077.65	80.39	+88	115876.24	77.99	-1.03
Barren	8358.55	5.72	-23.36	8271.32	6.26	+15	8581.96	7.46	+2.52
Built-Up	9629.48	6.59	+10.92	9746.30	5.55	+1.21	10726.09	5.94	+10.05
Agricultural	11140.13	7.62	-4.67	8888.50	7.17	-20.21	9878.39	8.00	+11.14
Total	146100.70	100		146100.70	100		146100.70	100	

Table 2 shows the data on LULC of the TCDDC from 2021 to 2023 (Fig. 3). For 2021, forest area remains the dominant land class, comprising 79.43% or 116,052.84 ha with an observed increase rate of +1.85% from the latter year, equivalent to 2,106.01 ha of the total land area. On the other hand, agriculture comprises 7.62% or 11,140.13 ha with a notable decrease rate of -4.67%, equivalent to 545.32 ha, followed

by built-up areas with 6.59% or 9,629.48 ha with an increase rate of +10.92% equivalent to 947.67 ha, barren lands with 5.72% or 8358.55 ha with reduction rate -23.36% or 603.87 ha, and the least is water bodies with 4.47% or 919.69 ha of the total land area with change rate of +4.47% comprises of about 39.36 ha. The decline in the barren lands and agricultural lands can be attributed to the substantial growth

in BUA, leading to land conversion as urban development expands to agricultural areas, and the conversion of barren lands into development areas boosts economic potential within the district. Van Vliet et al. (2015) cited that agricultural land is constantly changing and associated with varied development trajectories and societal demands.

For 2022, forests comprise the largest land class share with 80.39% of the total land area with 117,077.65 ha with an increased rate of +.88%, equivalent to 1,024.81 ha, followed by agricultural with 7.15% or 8888.50 has with a decrease rate of -20.21% amounting to 2,251.63 ha, barren lands with 6.26% or 8371.32 ha signifies increase rate of +.15% or 12.77 ha, built-up with 5.55% or 9,746.30 ha with change rate of +1.21% or 116.82 ha, and the least is water bodies which comprises the .65% of the total land area with 1,016.92 ha with increase rate of +10.57% or 97.23 ha. The highest observed decrease rate was in agriculture, which can be linked to the little to significant increase in water bodies, forests, and barren and built-up areas. However, the BUA remains the main threat of agricultural decline associated with intensified and continued urban expansion going to the suburban districts to accommodate demands for housing, infrastructure, and other economic and social services. It was supported by the results from the study of Frimpong and Molhenthin

(2021) that urban expansion was significantly towards the periphery of the sub-metropolitan zones, and the increasing built-up expansion has resulted in the conversion of croplands to accommodate the increasing demand for settlements and development associated to growing populations globally (Ke et al. 2018).

In 2023, although forest areas remain the most dominant class, which accounts for 77.89% of the total area of 115,876.24 ha, it recorded a decline rate of -1.03%, equivalent to 1,201.41 ha, followed by agricultural lands with 8% or 9,978.39 ha with an indication of the change rate of +11.14% equivalent to 989.89 ha, barren lands with 7.46% or 8,581.96 ha with the recorded change rate of +2.52% or 210.64 ha, built-up areas with 5.94% or 10,726.09 ha signifying increase rate of 10.05% or 979.79 ha, and the least is water bodies with .60% or 1,038.01 ha with change rate of +2.07 or 21.09 ha. It was observed that the decline in forest areas can be attributed to the increase in BUA and agricultural areas, which leads to the conversion of forest areas into production land for commercial and industrial use. Moreover, the study of Kindu et al. (2015) has confirmed that population growth, expansion of cultivated lands and settlements, livestock ranching, cutting of woody species for fuelwood, and charcoal-making are factors that drive LULC changes.

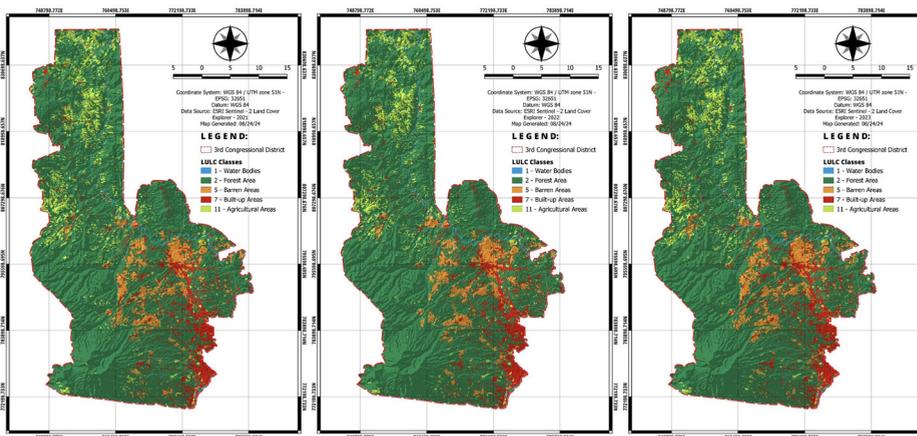


Figure 3. Map of land use and land cover change of the TCDDC from 2021-2023.

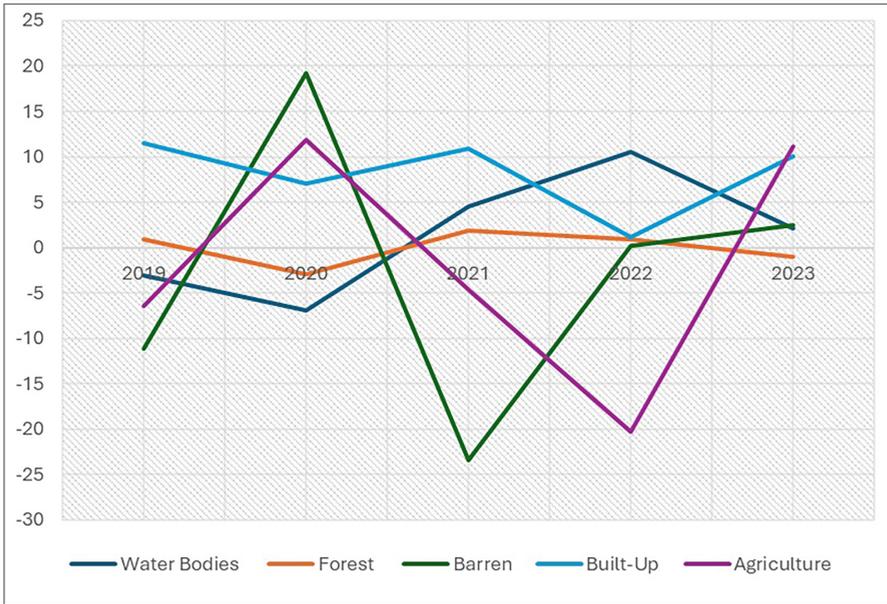
Presented in Table 3 is the data of the percent changes per year among various land classes and the graph of the trends of LULC change rates shown in Figure 4.

Results have revealed a decrease in agricultural, water bodies, and barren lands, but a significant increase in forest and BUA has been observed. Also, in 2020, water bodies and forests are experiencing declining rates, but an increased rate in barren, built-up, and agricultural lands was observed. In 2021, agriculture and barren land were experiencing a decline, but an increase in water bodies, forests, and BUA was observed. 2022 observed a notable increase in areas of water bodies, forests, barren, and BUA, but a significant decline in agricultural lands was observed. For 2023, forests decline while water bodies, barren, agriculture, and BUA continue to increase. This is evident in the trend that the changes in all land classes are dynamic with respect to time, but it is notable that among the land classes in the TCDDC, only BUA doesn't experience a decline based on the data analyzed. The study of Munthali et al. (2019) cited that most agricultural lands, forest lands, and water bodies were intensively converted into

built-up areas to give way for development intended for commercial, academic, and business purposes. This only signifies that the changes in other land classes can be attributed to the increasing BUA expansion that resulted in converting agricultural, water bodies, and forest areas within the congressional district into urban settlements and other urban uses. This means that the BUA expansion is happening within the study area, posing threats to other land classes. Although this area is in the sub-urban periphery, it has now become the new hub for development as CBD becomes congested and the pattern of urbanization is transitioning to the CBD going to the sub-urban peripheries, which were ideal for development considering less traffic and potentially less pollution as compared to those of present in the metropolitan central. From the study of Tuffour-Mills et al. (2020) have identified human activities drive considerable changes in LULC in forest areas, which caused significant implications for the long-term sustainability of urban and sub-urban forests, therefore recommends government intervention.

**Table 3.** Trends of land use and land cover changes in TCDDC 2019-2023.

LULC Classification	Percent Change in (hectares per year)				
	2019	2020	2021	2022	2023
Water Bodies	-3.01	-6.89	4.47	10.57	2.07
Forest	0.92	-2.98	1.85	0.88	-1.03
Barren	-11.17	19.18	-23.36	0.15	2.52
Built-Up	11.51	7.01	10.92	1.21	10.05
Agriculture	-6.47	11.86	-4.67	-20.21	11.14



**Figure 4.** Graph showing the percent change of land use and land cover classification of the TCDDC.

**Table 4.** Area-Based Error Matrix and Accuracy Testing of LULC changes in TCDDC in 2018.

Area-Based Error Matrix										
> Reference										
Classified	1	2	4	5	7	8	10	11	Area	Wi
1	0.0085	0	0	0	0.0016	0	0	0	149100	0.0101
2	0.0025	0.815	0	0	0.0135	0.0025	0	0.001	12302400	0.8345
4	0	0	0	0	0	0	0	0	600	0
5	0.004	0	0	0.0113	0.0065	0	0	0.0019	349700	0.0237
7	0.0003	0	0	0	0.0915	0	0	0	1353400	0.0918
8	0	0	0	0	0	0.002	0	0	29300	0.002
10	0	0.0002	0	0	0	0	0	0	3600	0.0002
11	0	0.017	0	0	0.0088	0.0011	0	0.0107	553900	0.0376
Total	0.0153	0.8323	0	0.0113	0.122	0.0056	0	0.0135	14742000	1
Estimated area	226000	12269100	0	165900	1798900	82400	0	199700	14742000	
SE	0.0002	0.0004	0	0.0002	0.0004	0.0002	0	0.0003		
SE area	3322.95	6470.38	0	2953.32	6247.06	2292.2	0	3909.66		

Area-Based Error Matrix										
> Reference										
Classified	1	2	4	5	7	8	10	11	Area	Wi
95% CI area	6512.98	12681.95	0	5788.5	12244.24	4492.7	0	7662.94		
PA [%]	55.3097	97.9232	nan	100	74.9903	35.5583	nan	78.7181		
UA [%]	83.8364	97.6582	0	47.4407	99.6749	100	0	28.3806		
Overall accuracy [%] = 93.88				CI = confidence interval						
Area unit = metre <sup>2</sup>				PA = producer's accuracy						
SE = standard error				UA = user's accuracy						

**Table 5.** Area-Based Error Matrix and Accuracy Testing of LULC Changes in TCDDC in 2023.

Area-Based Error Matrix										
> Reference										
V_Classified	1	2	4	5	7	10	11	Area	Wi	
1	0.0175	0	0	0	0	0	0	63500	0.0175	
2	0.0002	0.5356	0	0	0	0.0029	0.004	1971900	0.5427	
4	0.0002	0	0	0	0	0	0	600	0.0002	
5	0	0	0	0.0457	0.0245	0	0.0017	261200	0.0719	
7	0	0	0	0	0.3567	0	0	1296000	0.3567	
10	0	0	0	0	0	0.001	0	3500	0.001	
11	0	0	0	0	0	0	0.0102	36900	0.0102	
Total	0.0178	0.5356	0	0.0457	0.3812	0.0039	0.0158	3633600	1	
Estimated area	64800	1946200	0	165900	1385200	14000	57500	3633600		
SE	0.0001	0.0004	0	0.0007	0.0007	0.0003	0.0004			
SE area	264.53	1592.68	0	2460.74	2424.06	1021.99	1426.67			
95% CI area	518.49	3121.66	0	4823.06	4751.16	2003.1	2796.28			
PA [%]	97.9938	100	nan	100	93.5605	25	64.1739			
UA [%]	100	98.6967	0	63.5145	100	100	100			
Overall accuracy [%] = 96.65				CI = confidence interval						
Area unit = metre <sup>2</sup>				PA = producer's accuracy						
SE = standard error				UA = user's accuracy						

Table 4 and Table 5 are the computed area-based error matrix and accuracy testing of LULC changes in year 2018 and 2023 in TCDDC. The computed overall accuracy is 93.88% and 96.65% for 2018 and 2023 respectively. The acceptable accuracy level of remotely sensed data is within 85%. The computed accuracy of land change in TCDDC is considered good. This indicates that the LULC changes of the total area analyzed are correctly classified and mapped. Moreover, this means that a higher accuracy percentage implies the representation of real-world land use and cover types within the TCDDC.

## CONCLUSIONS

The land use and land cover (LULC) analysis in TCDDC from 2018-2023 has revealed dynamic changes over time highlighting shifts and changes in various land classes from 2018-2023 which can be attributed to various landscape transformations like urban development, agricultural expansion, deforestation and natural processes. Although forest areas consistently remained the largest land class, they experienced a gradual decline, especially in 2020 and 2023. The agricultural lands and barren areas also fluctuated, with notable reductions in agricultural lands in 2022, which can be linked to the continued expansion of built-up areas (BUA). Trends have shown that BUA consistently grew over the years, signifying ongoing urbanization and converting other land classes into urban settlements, including forests and agricultural lands. This expansion highlights the district's transition from a sub-urban periphery to a new hub for development, driven by the congestion in the Central Business District (CBD) and the demand for space in less congested, less polluted areas. The dynamic changes in LULC underscore the growing pressures on natural and agricultural land due to urban expansion, posing the district's challenges for sustainable land management.

## REFERENCES

- Barbati A., Corona P., Salvati L., Gasparella L. 2013. Natural forest expansion into suburban countryside: Gained ground for a green infrastructure? *Urban Forestry & Urban Greening* 12(1): 36–43. <https://doi.org/10.1016/j.ufug.2012.11.002>
- Cardoso J.M., Bolini H.M. 2008. Descriptive profile of peach nectar sweetened with sucrose and different sweeteners. *Journal of Sensory Studies* 23(6): 804–816. <https://doi.org/10.1111/j.1745-459X.2008.00167.x>
- Chen Y., Zeng Y., Li X. 2021. Urbanization and the evolution of regional land-use structures. *Journal of Urban Planning and Development* 147(3): 04021025. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000681](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000681)
- Chatterjee S., Majumdar S. 2021. Environmental threats from urbanization in different countries: A comparative study. *Environmental Science & Policy* 123: 34–45. <https://doi.org/10.1016/j.envsci.2021.04.012>
- Congedo L. 2024. Semi-Automatic Classification Plugin (SCP). QGIS. Retrieved from <https://fromgistors.blogspot.com/2013/07/semi-automatic-classification-plugin.html>
- Frimpong B.F., Molkenthin F. 2021. Tracking urban expansion using random forests for the classification of Landsat imagery (1986–2015) and predicting urban/built-up areas for 2025: A study of the Kumasi Metropolis, Ghana. *Land* 10(1): 44. <https://doi.org/10.3390/land10010044>
- Ghosh S., Das D. 2018. Urban sprawl and its impacts on the environment: a case study from a rapidly urbanizing city in India. *Cities* 82: 59–67. <https://doi.org/10.1016/j.cities.2018.05.005>

- Grimmond C.S.B., Oke T.R. 1999. Aerodynamic properties of urban areas derived from analysis of surface form. *Journal of Applied Meteorology* 38(9): 1262–1292. [https://doi.org/10.1175/1520-0450\(1999\)038<1262>2.0.CO;2](https://doi.org/10.1175/1520-0450(1999)038<1262>2.0.CO;2)
- Ke X., van Vliet J., Zhou T., Verburg P.H., Zheng W., Liu X. 2018. Direct and indirect loss of natural habitat due to built-up area expansion: A model-based analysis for the city of Wuhan, China. *Land Use Policy* 74: 231–239. <https://doi.org/10.1016/j.landusepol.2017.12.048>
- Kindu M., Schneider T., Teketay D., Knoke T. 2015. Drivers of land use/land cover changes in Munessa-Shashemene landscape of the south-central highlands of Ethiopia. *Environmental Monitoring and Assessment* 187(452). <https://doi.org/10.1007/s10661-015-4671-7>
- Munthali M.G., Davis N., Adeola A.M., Botai J.O., Kamwi J.M., Chisale H.L.W., Ori-moogunje O.O.I. 2019. Local perception of drivers of land-use and land-cover change dynamics across Dedza District, Central Malawi Region. *Sustainability* 11(832). <https://doi.org/10.3390/su11030832>
- Nath A., Ni-Meister W., Choudhury D. 2021. The impact of rapid urban expansion on ecosystems and biodiversity. *Urban Ecosystems* 24(2): 281–295. <https://doi.org/10.1007/s11252-020-01030-8>
- Quan B., Bai Y., Römkens M.J.M., Chang K.-T., Song H., Guo T., Lei S. 2015. Urban land expansion in Quanzhou City, China, 1995–2010. *Habitat International* 48: 131–139. <https://doi.org/10.1016/j.habitatint.2015.03.021>
- Rwanga S.S., Ndambuki J. M. 2017. Accuracy assessment of land use/land cover classification using remote sensing and GIS. *International Journal of Geosciences* 8(4): 611–622. <https://doi.org/10.4236/ijg.2017.84033>
- Salvati L., Ranalli F., Carlucci M., Ippolito A., Ferrara A., Corona P. 2017. Forest and the city: A multivariate analysis of peri-urban forest land cover patterns in 283 European metropolitan areas. *Ecological Indicators* 73: 369–377. <https://doi.org/10.1016/j.ecolind.2016.09.025>
- Seto K.C., Kaufmann R.K. 2003. Modeling the drivers of urban land use change in the Pearl River Delta, China: Integrating remote sensing with socioeconomic data. *Land Economics* 79(1): 106–121. <https://doi.org/10.2307/3147108>
- Subedi N.R. 2021. Measuring the impact of land use regulation on the land market in Nepal (Doctoral thesis). University of Southern Queensland. <https://doi.org/10.26192/q709x>
- van Vliet J., de Groot H.L.F., Rietveld P., Verburg P.H. 2015. Manifestations and underlying drivers of agricultural land use change in Europe. *Landscape and Urban Planning* 133: 24–36. <https://doi.org/10.1016/j.landurbplan.2014.09.001>
- Vaddiraju A.K., Reshma S. 2022. Changes in land use patterns due to urbanization in India. *Land Use Policy* 112: 105820. <https://doi.org/10.1016/j.landusepol.2021.105820>
- Velastegui-Montoya R., Escandon-Panchana M., Peña-Villacreses A., Herrera-Franco G. 2023. Spatio-temporal analysis of land use and land cover changes using satellite imagery. *Remote Sensing Applications: Society and Environment* 29: 100429. <https://doi.org/10.1016/j.rsase.2023.100429>

- Wang L., Wang Q., Liu Y., Sun Q., Guo Y., Song J. 2023. The effects of rapid economic growth on urbanization and societal changes. *Sustainable Cities and Society* 85: 104201. <https://doi.org/10.1016/j.scs.2022.104201>
- Zhang C., Gao C., Fan Z., Lan J., Zhao Y. 2017. The contribution of ecosystem services from multifunctional landscapes to human well-being. *Ecological Indicators* 74: 370–378. <https://doi.org/10.1016/j.ecolind.2016.11.025>
- Zhang J., Zhao Y., Liu Y., Pereira P. 2023. Urban population growth and its implications for sustainable urban development. *Population and Environment* 45: 123–137. <https://doi.org/10.1007/s11111-022-00403-7>
- Zhou Y., Chen Y., Tang Z., Mei X. 2021. Global land cover changes driven by urbanization: An analysis using remote sensing data. *Global Environmental Change* 66: 102206. <https://doi.org/10.1016/j.gloenvcha.2020.102206>
- Zhou Y., Tian Y., Jiang Y. 2018. The impact of urbanization on landscape patterns and ecological functions: A case study from China. *Landscapes and Urban Planning* 174: 74–84. <https://doi.org/10.1016/j.landurbplan.2018.03.014>

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