Spatiotemporal on Built-Up Area and Population towards Urban Sprawl in Malang City using Google Earth Engine

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A B S T R A C T

Malang City is the second most populous city in East Java after Surabaya City. In addition, development in Malang City in recent years has also impacted changes in land use and land cover. The methods used in this research are 1) built-up area index EBBI, NDBI, and UI of Malang City from 2019 to 2023, 2) dasymetric density, 3) distance measurement, and 4) gradient direction. The results of the calculation of the built-up area index show that UI has an average kappa accuracy of 0.75, which is higher than the other two indices. In 2019-2020, the built-up area of Malang City decreased, while in 2021-2023. There was an increase in the built-up area. This condition is caused by large-scale social restrictions that cause a decrease in development in various sectors. The development of urban sprawl in Malang City in 2019-2023 leads to the north, namely, in the Districts of Lowokwaru and Blimbing. The correlation test shows that the total population variable has a strong correlation with the urban sprawl (density) variable based on five district in Malang City.

Kata Kunci:

Google Earth Engine

Lahan Terbangun

Indeks Kota

Pemekaran Kota

A B S T R A K

Kota Malang merupakan kota terpadat kedua di Jawa Timur setelah Kota Surabaya. Selain itu, pembangunan di Kota Malang dalam beberapa tahun terakhir juga berdampak pada perubahan penggunaan lahan dan tutupan lahan. Metode yang digunakan dalam penelitian ini adalah 1) indeks area terbangun EBBI, NDBI, dan UI Kota Malang tahun 2019-2023, 2) kepadatan dasimetrik, 3) pengukuran jarak, dan 4) arah gradien. Hasil perhitungan indeks area terbangun menunjukkan bahwa UI memiliki rata-rata akurasi kappa sebesar 0,75, yang lebih tinggi dari dua indeks lainnya. Pada tahun 2019-2020 area terbangun Kota Malang mengalami penurunan, sedangkan pada tahun 2021-2023 terjadi peningkatan luas area terbangun. Kondisi ini disebabkan oleh adanya pembatasan sosial berskala besar yang menyebabkan penurunan pembangunan di berbagai sektor. Perkembangan urban sprawl di Kota Malang pada tahun 2019-2023 mengarah ke arah utara, yaitu di Kecamatan Lowokwaru dan Blimbing. Hasil uji korelasi menunjukkan bahwa variabel jumlah penduduk memiliki korelasi yang kuat dengan variabel urban sprawl (kepadatan) berdasarkan lima kecamatan di Kota Malang.

Introduction

The development of urban centers is a process of urban growth (Dadras et al., 2015). The development of a city in each region can be caused by dynamic growth. Urbanization is the process of population influx from outside the city into one of the causes of urban development (Sithole et al., 2024). Urbanization plays a vital role in the dimensions of contemporary change (Li & Chen, 2018). Urbanization can be considered as a process of infiltration of urban values into rural life systems (Giyarsih, 2010). Rapid urbanization has significant environmental impacts, including increased land surface temperature, decreased groundwater levels, changes in land use and land cover, and conversion of agricultural land (Ahmadi et al., 2023; Astuty & Wibowo,). Urbanization supported by rapid growth rates is one of the challenges for the government (Rasul et al., 2018). By 2050, 2/3 of the world's population will live in urban areas, and 90% of developing cities will experience an increase in population (UN HABITAT, 2024). From this, it will form an urban expansion that can cause urban sprawl (Mun et al., 2024). Urban sprawl in Western countries usually arises from wealthy city dwellers moving to suburban areas. An influx of people from villages to cities in search of jobs and better living standards drives urban sprawl in Asian countries. The higher the population increase, the more vacant land and agricultural land will turn into built-up areas as a sign of an economic area (Astuti et al., 2022).

This research focuses on Malang City, which is the second most populous city in East Java after Surabaya City and has a population density of 7,617 people/km2 in 2022. The development of Malang City leads to the development of Malang Raya as well as urban development and surrounding areas that form core and satellite cities, based on the 2010-2030 RTRW document (Agustina & Herwangi, 2023). The high flow of urbanization in Malang City is supported by the number of universities, attractive tourist destinations, and cool weather, making Malang City an overseas place. The construction of the Malang to Pandaan toll road has caused urban sprawl to emerge in suburban areas as a result of population growth and large-scale road facilities. Urban sprawl is the expansion of the city into the surrounding area (Akbar, 2021). From 2018 to 2022, Malang City experienced an increase in development through eight infrastructures. The eight infrastructure developments are Kedungkandang Bridge, Tunggulmas Bridge, Malang Creative Center (MCC), Islamic Center Malang City, Kayutangan Heritage Area, Revitalization of 16 People's Markets in Malang City, Sanitary Landfill TPA Supit Urang Malang City and Miniblok Office (Tugumalang, 2023). The existence of this development will undoubtedly have an impact on land changes in Malang City.

Information on the characteristics of urban areas can be obtained through remote sensing platforms. The spectral index is an excellent approach to distinguishing the type of land cover (Rasul et al., 2018). Here are some literature studies of built-up land index research: (As-Syakur et al., 2012) introduced a new index in mapping built-up and vacant land areas using Index-based Built-up Index (IBI) in Denpasar with Landsat ETM+ imagery, Normalized Difference Built-up Index (NDBI), and Enhanced Built-up and Bareness Index (EBBI) index. The results showed that the accuracy of EBBI is higher than that of other indices, so it is effectively used in mapping vacant and built-up land areas in urban areas. (Kebede et al., 2022) examined the performance of urban indices including Normalized Built-up Area Index (NBAI), New Built-up Index (NBI), Normalized Difference Built-up Index (NDBI), Built-up Area Extraction Index (BAEI), Band Ratio for Built-up Area (BRBA), Modified Built-up Index (MBI), and Urban Index (UI) in the classification and detection of impervious surface changes using Sentinel-2A MSI imagery. The study showed that the Urban Index (UI) and Normalized Difference Built-up Index (NDBI) indices can be used to analyze built-up land and non-built-up land. (Hidayati et al., 2017) mapped built-up land using a semi-automatic segmentation approach that combines NDBI and Normalized Difference Vegetation Index (NDVI) methods and the Normalized Difference Built-up Index (NDBI) index in extracting built-up land in urban areas. (Rosyadi & Azahra, 2020) mapped building density in Bandung City with a regression model using Landsat 8 imagery to determine urban sprawl. The objectives of this research are:

1. To analyse the accuracy of the spectral index
2. To analyze the change of built-up area in Malang City.
3. To analyze the urban sprawl of Malang City.

4. To analyze the relationship between built-up area, population, and urban sprawl in Malang City

Methods

1. Study Area

Malang City is located at an altitude of 445-526 meters above sea level with an area of 111.077 km2. Malang City is located at coordinates 112.060-112.070 East Longitude and 7.060-8.020 South Latitude. Singosari borders Malang City and Karangploso district to the north, Pakis and Tumpang district to the east, Tajinan and Pakisaji district to the south, and Wagir and Dau district to the west (BPS Kota Malang, 2023).The study area can be seen in Figure 1.

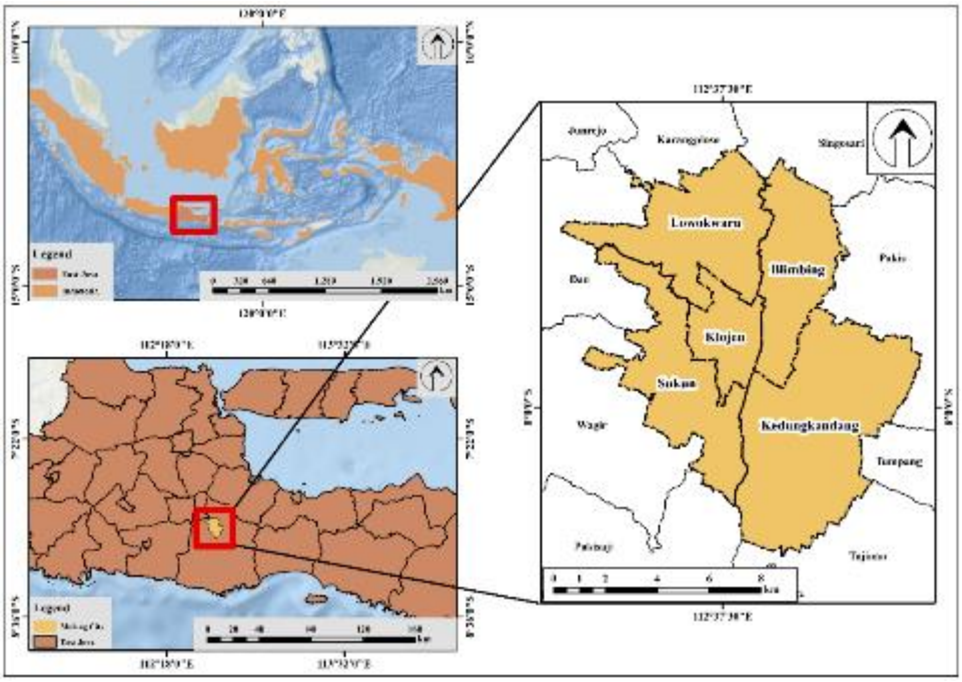

Figure 1. The study area of Malang City

2. Data

This research is an explanatory study that uses a quantitative approach, utilizing remote sensing technology and geographic information systems (González et al., 2024; Purwanti et al). The rapid development of technology, especially in Geographic Information System (GIS) will provide convenience for its users (Al Farikhi et al., 2023). It uses secondary data obtained from several sources presented in Table 1.

Table 1. Data source

No.	Description	Source	Data types
1.	Landsat 8 OLI/TIRS TOA Malang City 2019-2023	Catalog Google Earth Engine	Raster
2.	Administrative boundaries of Malang City	Dinas PUPR-PKP Malang City	Polygon
3.	Map of EBBI, NDBI and, UI 2019-2023	Data processing results of Landsat 8 OLI/TIRS TOA Collection 2 images in Google Earth Engine	Raster
4.	Built-up Area 2019-2023	Conversion result of UI index processing to polygon	Polygon
5.	Dasimetric density 2019-2023	Built-up area from UI index calculation and population data of Malang City	Polygon
6.	Population of Malang City 2019-2023	Population Profile of Malang City GIS Map Dukcapil Kemendagri	Tabular Tabular
7.	Cardinal buffers 2019-2023	Analysis of the direction of built-up area in each cardinal direction	Polygon

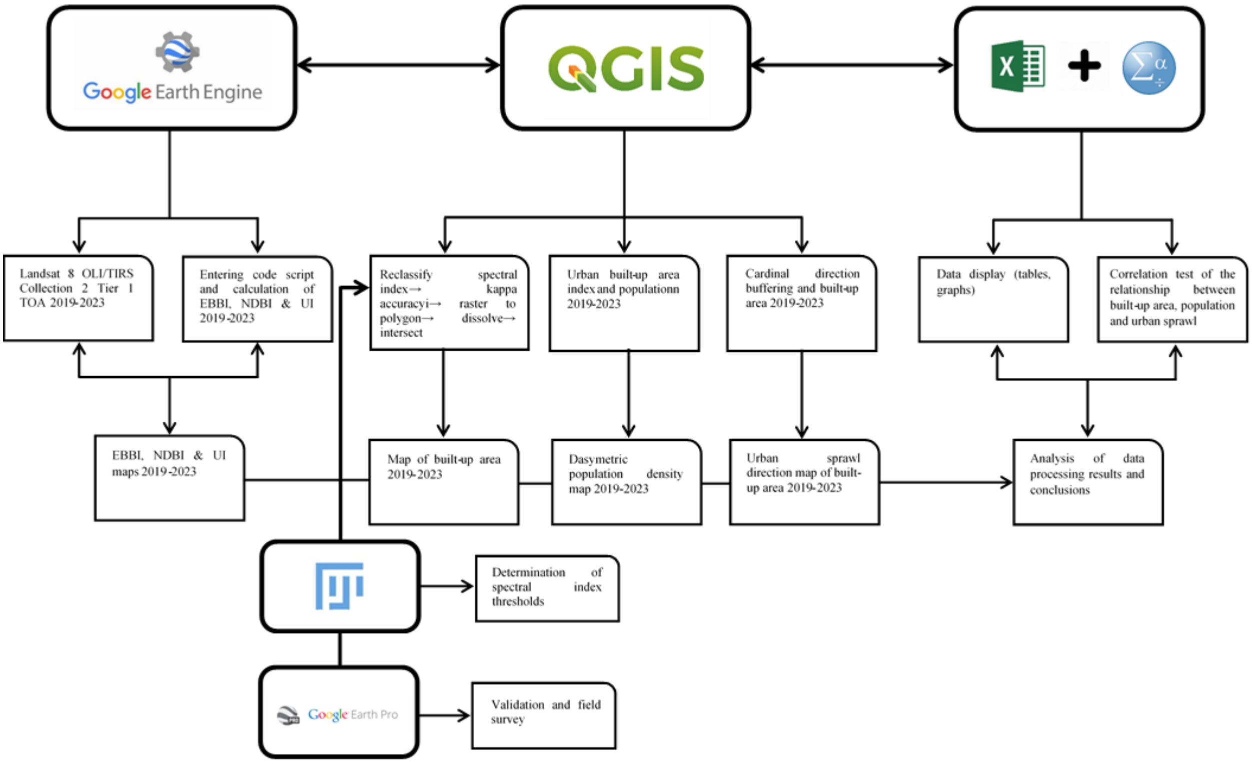

Figure 2. Diagram flow chart

Data processing is divided into 3, namely: 1.) Google Earth engine for the calculation of the built-up land index. 2.) QGIS for accuracy processing with a confusion matrix, calculating the built-up land area from the index results, dasymetric density calculation, buffer zone gradient direction 3.) Excel and SPSS are used for data display in the form of tables, graphs, and other statistical correlation tests. The research work steps are presented in Figure 2.

3. Spectral Index

Urban land consists of non-built land and built land. Built-up land is used for industry, trade, services, housing, and offices, while non-built-up land is used for urban activities such as open space, transportation, recreation, and cemeteries. Unbuilt land is used for non-city activities such as agriculture, plantations, natural resource mining, and water areas. The land use component consists of commercial, roads, residential, public land, industry, and vacant land (Sajow et al., 2016). Urban land analysis can use several spatial indices to detect built-up land. The built-up land indices used are:

1) The Enhanced Built-up and Bareness Index (EBBI).
2) Normalized Difference Built-up Index (NDBI).
3) Urban Index (UI).

The following is the mathematical calculation of these indices.

$$EBBI = \frac{SWIR1 - NIR}{10\sqrt{SWIR1 + TIRS1}} \quad (1)$$

(As-Syakur et al., 2012)

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (2)$$

(Azhari, 2020)

$$UI = \left[\frac{B7 - B4}{B7 + B4} + 1\right] \times 100 \quad (3)$$

(Kawamura, 1996)

The calculation and acquisition of the built-up land index was carried out on the Google Earth Engine Platform (Astuti et al., 2022). Google Earth Engine is a cloud computing-based remote sensing data processing platform that can process data quickly, especially temporally (Bessinger et al., 2022), so it does not require ample storage (Ganjirad & Bagheri, 2024). The selection of Landsat 8 OLI/TIRS TOA image recording date is based on cloud cover (Min et al., 2023), May to August has little cloud cover. Validation of the results of the calculation of the built-up land index using kappa accuracy. For the calculation of kappa accuracy, the method used is the confusion matrix, which is a table of actual classification information along with the predictions (results) of field checks (Hidayati et al., 2017).

4. Dasymetric Density

disaggregation of spatial data into finer units of analysis (Wan et al., 2023). The resulting data will help separate population locations(Cockx & Canters, 2015; Requia et al., 2018). In dasymetric mapping, it is assumed that the entire population within each census unit will be concentrated in the area it occupies. In intelligent dasymetric mapping, population growth is assessed based on LULC type (Cartagena-Colón et al., 2022).LULC data will provide information about where people live, which will be used as the basis for detailed population mapping (Su et al., 2010).

5. Distance

Remote sensing data can be used to measure urban growth (Sun et al., 2007). Distance in this study is used to determine the outermost building from the extraction of the built-up land index to Malang City Square. The result of this distance calculation will be one of the variables to measure urban sprawl in Malang City. The distance calculation is carried out on the Google Earth Pro application, which has a high image resolution, making it easier to detect buildings based on the results of the built-up land index extraction processing.

6. Gradient Direction

Gradient direction is used to determine the trend of built-up land area. The first is to create a buffer zone with an interval of 2 km from Malang City Square; the next is to create eight cardinal directions with an interval of 45o. The two data will intersect each other and produce the built-up land area of several segment zones (Cao et al., 2019). These results will be used to analyze the direction of urban sprawl.

Result and Discussion

The calculation of the built-up land index was done through Google Earth Engine, which will be in the form of raster data. The Fiji ImageJ application was used to determine the threshold of this research (Schindelin et al., 2012). Fiji ImageJ is an image image processing application based on image or color base. In the Fiji ImageJ application, the threshold used is the Otsu threshold (Level Otsu, 1979). The Otsu threshold is a threshold that minimizes the intra-class variance, which is the sum of the weighted variances of the two classes, namely built-up land and non-built-up land. Table 2 shows the Otsu threshold for the built-up land index in Malang City from 2019 to 2023. The threshold is used for the reclassification process.

Table 2. Threshold spectral index

No.	Years	Spectral Index		
		EBBI	**NDBI**	**UI**
1.	2019	-0.14	-0.17	-0.37
2.	2020	-0.15	-0.17	-0.37
3.	2021	-0.15	-0.17	-0.37
4.	2022	-0.10	-0.13	-0.32
5.	2023	-0.07	-0.11	-0.28

Accuracy Assessment of Spectral Index

Test the accuracy of built-up area (BUA) and non-built-up area (Non BUA) using a confusion matrix (Danih Lesmana & Mataburu, 2022) to determine the accuracy of the maps field validation through Google Earth Pro and field survey. The validation data is used to calculate kappa accuracy. Table 3, the UI index has a higher level of accuracy than the other two indices, with an average kappa accuracy of 0,75.

Table 3. Kappa accuracy

No,	Index	Years	Kappa	$\bar{X}$
1	EBBI	2019	0,70	0,74
		2020	0,82	
		2021	0,72	
		2022	0,69	
		2023	0,76	
2	NDBI	2019	0,77	0,74
		2020	0,76	
		2021	0,76	
		2022	0,67	
		2023	0,74	
3	UI	2019	0,79	0,75
		2020	0,77	
		2021	0,75	
		2022	0,69	
		2023	0,77	

Description:

Non BUA : Non Built-up Area
BUA : Built-up Area
EBBI : Enhanced Built-up and Bareness Index
NDBI : Normalized Difference Built-up Index
UI : Urban Index

The results of kappa accuracy show that UI is highly accurate compared to the other two indices. Then, further processing is carried out to determine the extent of the built-up land class and the non-built-up land class. The processing was carried out in the QGIS application by converting raster data to a polygon. The graph in Figure 6 shows the area of built-up and non-built-up area. The graph shows that the area of built-up land in Malang City has increased while the area of non-built-up land has decreased.

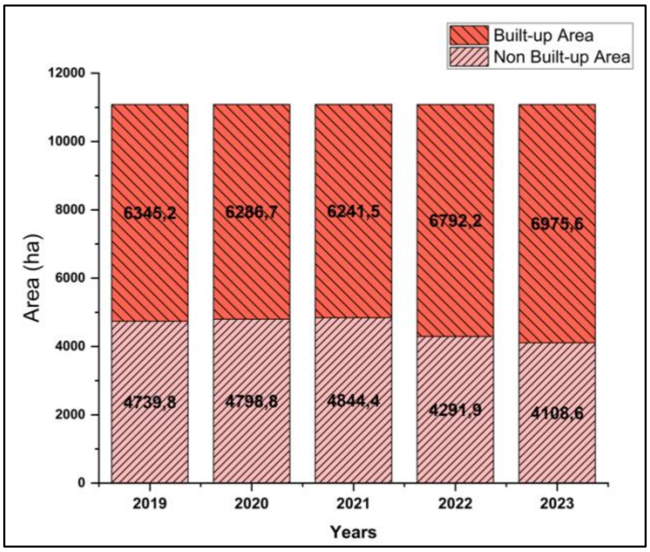

Figure 3. Built-up area and non built-up area

Trend Built-up Area

Figure 4 is the area of built-up land in the district; in 2019-2020, the area of built-up land in the five district has decreased; in 2022-2023, the area of built-up land has increased. Lowokwaru district will always experience an increase in built-up land from 2020 to 2023. The most significant increase in the Kedungkandang district was 366 ha in 2022 and 131.5 ha in 2023. Sukun district also experienced an increase of 85.2 ha in 2022 and 54 ha in 2023.

Spatially, the distribution map of built-up land can be seen in Figure 5. The Kedungkandang sub-district is the area that has experienced the most changes in the land that has been built up in Malang City. This can be seen through the distribution of built-up land on the map, which has increased every year. Klojen sub-district tends to have no change in built-up land because the area is full of buildings and there is no vacant land. Blimbing, Lowokwaru, and Sukun sub-districts experienced less significant changes than those in the Kedungkandang sub-district.

The direction of urban sprawl development in Malang City is to create an 8-way buffer zone according to the winds that will intersect with the built-up land area. From this process, the built-up land area in each buffer zone will be generated. Figure 6 shows the direction of urban sprawl development in Malang City. The north direction is the direction that always experiences an increase in built-up land area. The district in this direction are Lowokwaru and Blimbing. The increase in built-up area in the Lowokwaru district is supported by the number of universities built in the area and its proximity to Batu City, which is a tourist city with a cool climate, resulting in high development. The Blimbing district is close to the Malang-Pandaan toll road, has high accessibility, and is close to Surabaya, resulting in high community mobility.

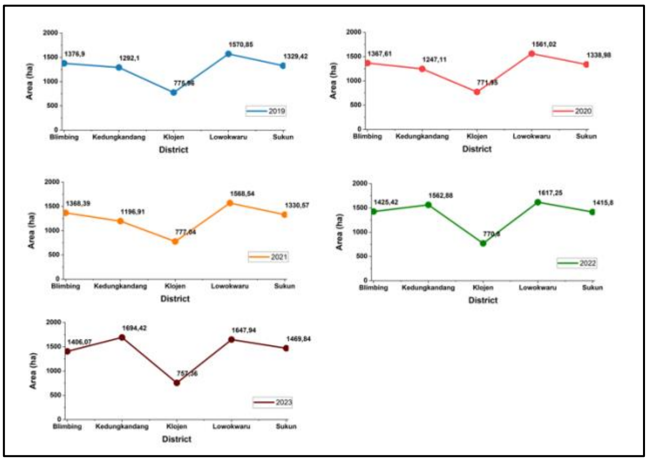

Figure 4. Distribution of built-up area in Malang City

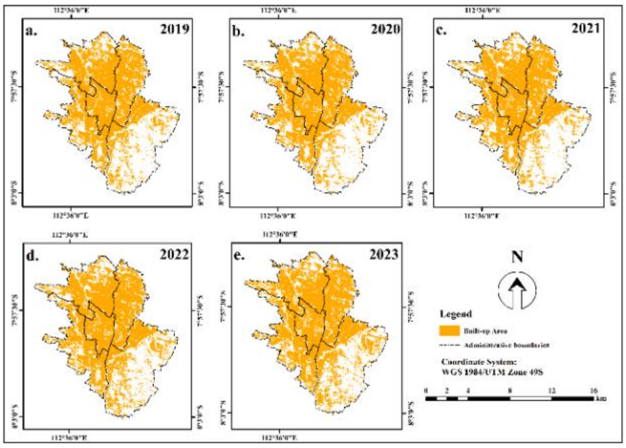

Figure 5. Spatial distribution of built-up area: a.) 2019, b.) 2020, c.) 2021, d.) 2022, e.) 2023

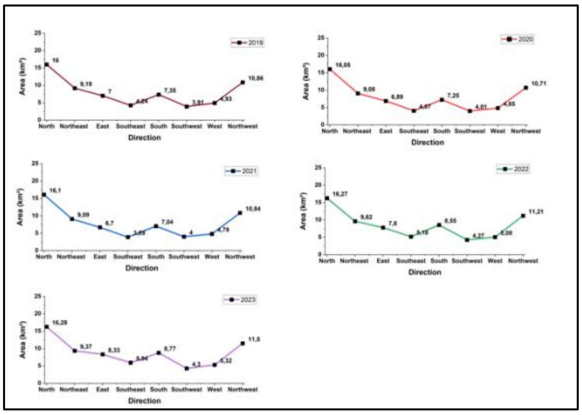

Figure 6. Distribution direction of built-up area

This decrease was caused by the COVID-19 pandemic that occurred in 2019, which made the government make efforts to suppress the spread of COVID-19 through physical, social, and lockdown distancing (Galvin et al., 2020; Toharudin et al., 2020). The lockdown has a significant negative impact on the economy in the industrial, tourism, and transportation sectors (Mandal & Pal, 2020). Partial lockdown schemes have been implemented in Indonesia through large-scale social restrictions, restrictions on micro-scale community activities, and local social restrictions. Malang City conducted large-scale social restrictions from May 17 to May 30, 2020

(Purwanto et al., 2022)These activity restrictions have reduced community activities, so development has also decreased. The years 2020-2021 are the initial and transition years of large-scale social restrictions, so the area of built-up land in these years has decreased, and in 2022-2023, it has increased. In 2022, the area of built-up land increased by 551.4 ha from 2021.

Urban Sprawl

The development of urban sprawl in this study uses dasymetric density analysis and the distance of the outermost building from Malang City Square. The data used in urban sprawl analysis are population, density, and distance. The population of Malang City was obtained through the Malang City Population Profile Book from 2020 to 2023; for 2023, it was obtained through the GIS Map of Dukcapil Kemedagri. Table 5 shows the total population of Malang City in 2019-2023. Kedungkandang district has the highest population, while Klojen district has the lowest population.

Table 4. Population of Malang City 2019-2023

No.	Distric	2019	2020	2021	2022	2023
1.	Klojen	111053	111313	110796	100257	100712
2.	Lowokwaru	179013	180418	181445	168439	170149
3.	Blimbing	202514	203211	203380	189534	190799
4.	Sukun	214650	216055	216918	202682	204970
5.	Kedungkandang	220055	222742	225337	210211	214157

The population density of Malang City is obtained from the dasymetric method, which uses data on the area of built-up land with the total population. Both data will be made into a raster with a grid size of 50 x 50 meters. The raster data that has been processed will then be calculated by dividing the population and the number of pixels of built-up land. Table 6 shows the results of the population density processing using the dasymetric method. Klojen district has a high density, and Lowokwaru district has a low density.

Table 5. Dasymetric density 2019-2023

No.	Distric	2019	2020	2021	2022	2023
1.	Klojen	31,88	31,93	31,88	28,79	29,89
2.	Lowokwaru	22,04	21,89	22,51	20,36	20,46
3.	Blimbing	30,36	30,49	30,42	28,92	28,59
4.	Sukun	28,37	28,83	29,84	27,09	26,93
5.	Kedungkandang	22,81	24,19	24,12	22,66	22,66

Distance is used to measure the outermost building from Malang City Square. The outermost building is seen through the distribution of built-up land, which is then checked using Google Earth Pro to find the boundaries and measure the distance between the building and Malang City Square. Table 7 is the result of measuring the distance of outermost buildings in Malang City in 2019-2023. Lowokwaru district is the district with the farthest building from Malang City Square.

Table 6. Distance outer building from Malang City Square 2019-2023

No.	Distric	2019	2020	2021	2022	2023
1.	Klojen	3,73	3,74	3,75	3,76	3,74
2.	Lowokwaru	8,27	7,91	7,88	7,89	7,90
3.	Blimbing	7,72	7,72	7,77	7,70	7,71
4.	Sukun	6,77	6,63	6,76	6,76	6,75
5.	kedungkandang	7,57	7,73	7,72	7,79	7,65

Correlation between Built-up Area and Population towards Urban Sprawl

Relationship measurement is done using inferential statistics. Inferential statistics are divided into two categories: parametric and non-parametric. This study uses non-parametric inferential statistics. For statistical tests using non-parametric inferential statistics, you can use Kendall Tau or Spearman. Because the research data scale is in the form of ratio or scale data with the results of non-normal data distribution, the non-parametric statistic used is Spearman. In determining the correlation, what needs to be considered is the significance value and the correlation coefficient (r) which aims to see how strong the relationship is. Table 8 shows the correlation between the research variables.

Table 7. Correlation value in each district

No.	District	X1, X2	X1, X3	X1, X4	X2, X3	X2, X4	X3, X4
1.	Blimbing	r = 0,90	r = -0,80	r = 0,98	r = -0,94	r = -0,60	r = -0,87
		p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05
2.	Kedungkandang	r = 0,90	r = -0,04	r = -0,20	r = -1,00	r = -0,10	r =1,00
		p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05
3.	Klojen	r = 0,90	r = -0,50	r = -0,67	r = -0,60	r = -0,36	r =1,00
		p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05
4.	Lowokwaru	r = 0,90	r = -0,80	r = -0,10	r = -0,90	r = -0,20	r =0,10
		p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05
5.	Sukun	r = 0,80	r = -0,80	r =-0,10	r = -1,00	r =0,46	r = -0,46
		p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05	p < 0,05

The results of the correlation test showed that the population and density variables in the five sub-districts are the variables that have the strongest correlation value of 0.90 in the Blimbing, Kedungkandang, Klojen, and Lowokwaru sub-districts and 0.80 in Sukun sub-district with a positive relationship direction, so that as the population increases, the density will also increase. The correlation between built-up land represented by the urban index and population in Blimbing, Lowokwaru, and Sukun sub-districts has a strong correlation value of -0.80 with a negative direction. Blimbing sub-districts have a correlation between population and distance of 0.98, which is a positive relationship, while the other sub-districts have a weak correlation. Blimbing, Kedungkandang, Lowokwaru, and Sukun sub-districts have a strong correlation between density and urban index of -0.94, -1.00, -0.90, -1.00, while the Klojen sub-district has a weak correlation. For the correlation of density and distance, all five sub-districts have a weak correlation. The correlation between the urban index and distance in Blimbing, Kedungkandang, and Klojen sub-districts has a strong correlation of -0.87, 1.00, and 1.00. The correlation test between the variables of built-up land, population, and urban sprawl represented by density and distance gave quite diverse results from five sub-districts in Malang City. The population and density variables have the strongest correlation relationship in the five sub-districts. The variables of built-up land (UI) and density also have a strong correlation, and the variables of built-up land (UI) and urban sprawl (distance) also have a strong correlation.

Conclusion

The urban index has a higher kappa accuracy than the other two indices, so it is used to calculate the area of built-up land in Malang City. The calculation results show that the area of built-up land in Malang City has increased in 2021-2023, while non-built-up land has decreased in 2021-2023. The Kedungkandang district has the highest increase in built-up land. The direction of urban sprawl development in Malang City in 2019-2023 is to the north, namely towards Lowokwaru and Blimbing District, where the three district are education centers and close to tourist attractions in Batu City (Lowokwaru District), close to the Malang-Pandaan toll road (Blimbing District) so as to facilitate access to community mobility. The results of the correlation test show that the population variable with urban sprawl (density) has a strong correlation in five district.

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