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ASSESSING URBAN GROWTH IN GREATER SURABAYA USING GOOGLE EARTH ENGINE: AN EVALUATION OF BUILT-UP AREA EXPANSION IN INDONESIAN SECONDARY CITIES

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Abstract: Urbanization in Indonesia's cities is increasing, leading to various impacts, including negative consequences due to insufficient investment in local public infrastructure. Urbanization assessment primarily relies on examining changes in built-up areas over the past decade. These changes serve as an indicator that can be effectively derived from remote sensing data. In our study, we applied remote sensing data from the Google Earth Engine (GEE) catalog to delve into the urbanization dynamics within Greater Surabaya area, Indonesia. We employed satellite imagery from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI TIRS) for 2012 and 2022. We used Support Vector Machine (SVM) classification techniques to construct precise urban expansion models. Our analysis revealed distinct urban expansion trends in Mojokerto and Sidoarjo, which contrast with the relatively stable urban development trends in northern Surabaya due to the construction of toll roads. The findings provide valuable inputs for urban management, necessitating targeted interventions and strategies to address the urbanization disparities between these two areas. It underscores the critical importance of resource allocation, infrastructure development, and urban planning initiatives, with a specific focus on Gresik, to ensure sustainable urban growth and mitigate potential challenges associated with rapid expansion.

Keywords: urbanization; built-up expansion; secondary city; GEE catalog; Greater Surabaya

1. Introduction

Cities in Indonesia are experiencing significant levels of urbanization. This phenomenon mirrors a global trend toward forming extensive mega-urban regions, where the traditional boundaries between rural and urban areas are becoming increasingly blurred. For instance,

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the development of Jakarta Metropolitan Area and Bandung Metropolitan Area exemplify this transformative shift in the urban landscape (Firman, 2009). As such, understanding the dynamics of urbanization in Indonesia is not merely an isolated concern, but it is intricately connected to broader worldwide urbanization trends. Individuals from rural areas are drawn to thriving urban centers by the prospect of enhanced employment opportunities, prompting them to relocate from their hometowns to improve their quality of life (Jones, 2016). This migration-driven urbanization profoundly impacts the development of cities in Indonesia. It has the potential to act as a driving force behind overall economic growth, a phenomenon extensively documented in the literature (Prasodjo, 2018).

In Indonesia, urbanization has various effects, including the proliferation of cities, the emergence of non-statutory towns, and the development of extended urban regions (Mardiansjah et al., 2021). As a result, development imbalances are not limited to the rural-urban divide, but also extend to the regional disparities between Java and non-Java regions, as well as between the western and eastern regions of Indonesia (Wilonoyudho et al., 2017). In addition, urban population growth is also often accompanied by adverse effects resulting from inadequate spending on local public infrastructure (Lewis, 2014). Consequently, it is essential to monitor urbanization, with one critical indicator being urban expansion.

Despite the existing research on global and national urbanization trends, there is a notable research gap that our study aims to address. While the effects of urbanization on city development and economic growth have been explored, there remains a need for a detailed examination of the specific spatial patterns and drivers of urban expansion within Greater Surabaya area, Indonesia. Our study seeks to bridge this gap by utilizing remote sensing data and advanced classification techniques to gain insights into the unique urbanization patterns in this region, with a particular focus on change detection and its implications for urban management. Our research contributes to the broader understanding of urbanization trends and provides valuable insights for policymakers and urban planners in Indonesia and beyond.

Remote sensing data can be a highly effective tool for measuring urbanization, allowing for accurate and comprehensive monitoring of urban expansion, land use changes, and other critical factors that shape city development (Hegazy & Kaloop, 2015; K & Angadi, 2021). The use of multi-temporal remotely sensed data enables the analysis of change detection at the urban footprint level in terms of monitoring of spatiotemporal dynamics and urbanization trends (Taubenböck et al., 2012). Furthermore, the capabilities of remote sensing technology have been continuously advancing with each new satellite launched, longer operational lifetimes, and increasingly higher spatial resolution (Belward & Skøien, 2015), which can contribute to a higher level of analysis accuracy. In addition, the development of artificial intelligence and cloud computing has facilitated the processing of remote sensing data considering more streamlined workflows, for example, using Google Earth Engine (GEE). GEE provides convenient access to high-performance computing for processing extensive geospatial datasets, even for individuals without programming expertise (Gorelick et al., 2017). As a result, there has been a steady rise in the utilization of GEE since 2017 (Amani et al., 2020).

The application of GEE for urbanization monitoring is not a new concept, as numerous similar studies have been conducted in various countries. In most of these studies, the focus lies on tracking land cover and land use changes from non-urban to urban areas. For instance, Aryal et al. (2023) employed GEE to examine urbanization in Kathmandu, Nepal. The study revealed a substantial increase of approximately 67 km^2 in built-up areas over a span of 20 years, resulting in the conversion of agricultural and forested land. Shetty et al. (2022) analyzed the impact of urbanization on climatic variables using GEE and observed a decline in forested areas along with an expansion of built-up areas within the study area. Similarly, Zurqani et al. (2019) utilized GEE to identify urbanization trends in the upstate region of South Carolina, revealing transformations from forested areas to newly developed lands, bare lands, and non-forested areas.

Given the similar developments occurring in Indonesia, it is crucial to conduct research on urbanization monitoring in the country. Therefore, our study has utilized remote sensing data from GEE to examine urbanization within secondary cities, specifically focusing on Greater Surabaya area. The region is undergoing significant development as its morphology transforms, leading to the creation of metropolitan areas like Jakarta Metropolitan Area and Bandung Metropolitan Area. Given its rapid growth and its strategic location, Greater Surabaya is an intriguing area to observe, especially considering the changing global and national politico-economic landscapes that have contributed to its development (Katherina & Indraprahasta, 2019).

The main objective of this study is to assess urban expansion in Greater Surabaya area using remote sensing data and the GEE platform. By analyzing changes in urbanization patterns and land use over a specific period, this research aims to provide valuable insights into the extent and dynamics of urban growth in secondary cities in Indonesia. The findings will contribute to a better understanding of the ongoing urbanization process in Greater Surabaya area and its implications for regional development, land management, and sustainable urban planning. This research also highlights the significance of utilizing remote sensing and GEE as effective tools for monitoring and analyzing urban expansion, which can support evidence-based decision-making and inform policies for future urban development in the country.

2. Materials and methods

2.1. Study area

The study area is centered in Greater Surabaya region, locally referred to as Gerbangkertosusila, which is an acronym derived from the names of its constituent cities: Gresik, Bangkalan, Mojokerto, Surabaya, Sidoarjo, and Lamongan (Figure 1). This region holds immense significance as it falls under Indonesia's national strategic areas category, signifying its critical role in expediting macro-level development initiatives. These initiatives encompass a wide range of projects, including establishing arterial and toll road systems, continuously enhancing the Suramadu Bridge area, and improving regional seaports (Pamungkas et al., 2016). However, it is essential to note that despite its strategic importance, Greater Surabaya area is not exempt from ongoing urbanization challenges, as alluded to in the Introduction. The rapid urbanization trend observed in Indonesia and globally has a profound impact on these challenges. As an area that drives economic activity within East Java Province and at the national level, Greater Surabaya region faces complex urbanization problems that warrant closer examination (Santoso et al., 2022).

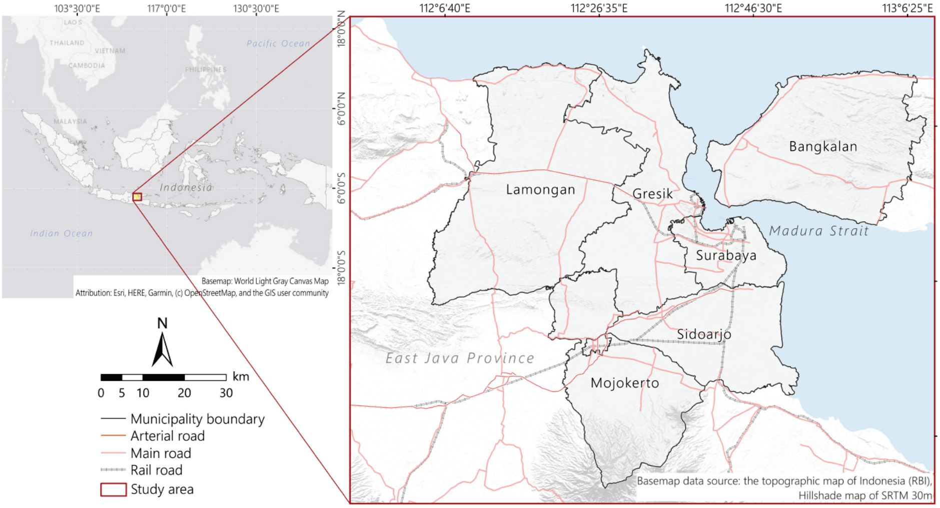

Figure 1. Study area.

2.2. Data

The satellite Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI TIRS) (Google Earth Engine, 2023) were used in this study to build urban agglomeration models. Landsat 7 ETM+ was used for urban mapping in 2012, along with Landsat 8 OLI TIRS for mapping urban conditions in 2022. These two satellites have similar specifications (Roy et al., 2016), but Landsat 8 OLI TIRS, as the most recent generation, has advantages in terms of band numbers and wavelength range. These classifications were based on the composite data derived from bands 742 of Landsat 7 and 432 of Landsat 8. However, at all wavelengths except thermal and panchromatic waves, they have the same spatial resolution of 30 m. The image scenes used in this research were LE07_119065, LE07_118065, LC08_119065, and LC08_118065 with average cloud cover on Landsat 7 imagery of 31.92% and Landsat 8 of 40.48%. This research used Landsat 7 data with the time range from 2012-01-01 to 2012-12-31 and Landsat 8 with the time range from 2022-01-01 to 2022-12-31.

2.3. Methods

Data processing was divided into three phases: pre-processing, processing, and post-processing. GEE was used for these phases, which include several functions that use the JavaScript programming language, such as ImageCollection, CloudRemoval, GapFilling, and ImageComposite (Figure 2). These commands were used to retrieve all available images for the recording year chosen for this study, to perform cloud removal, to fill in gaps caused by damage to the recording system, and to merge images in the form of composite bands. Due to the damage to the acquisition system, Landsat 7 ETM+ required a GapFilling process in addition to the Scan Line Error (SLE) correction process. Composite images provided data for training and validation.

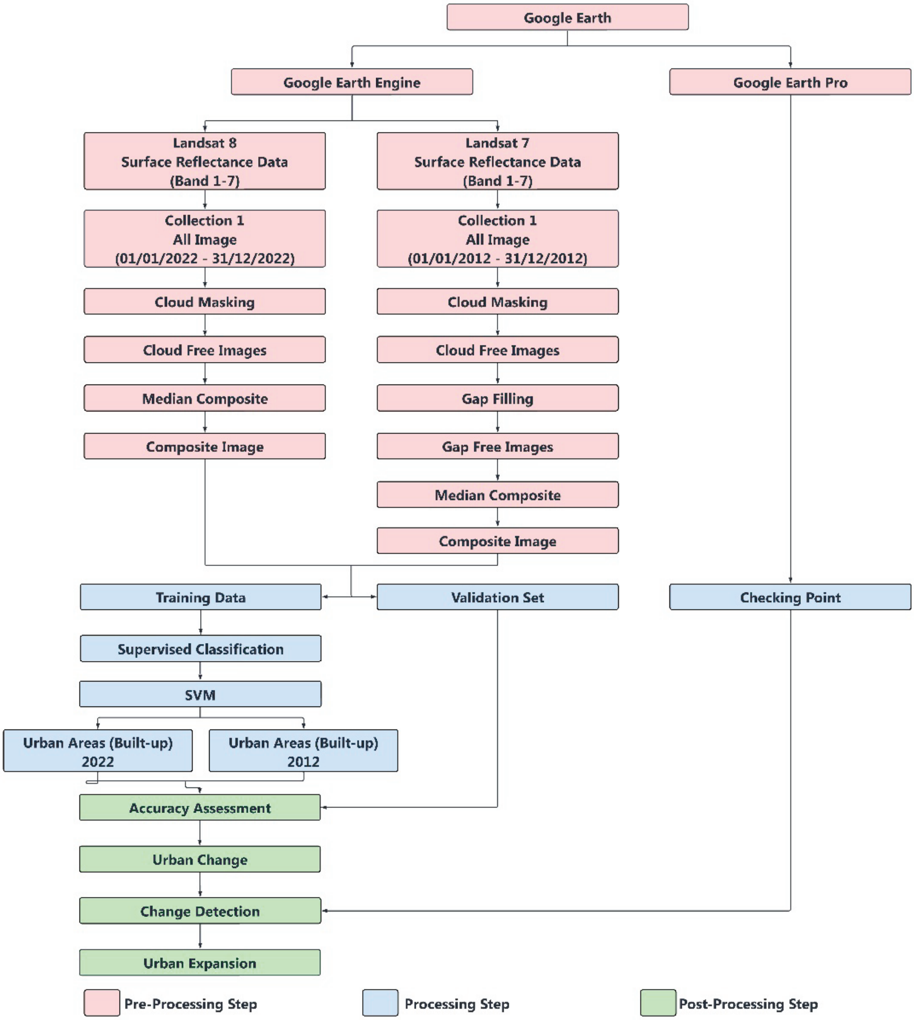

Figure 2. Research process flowchart.

The research utilized training data derived from point and polygon samples. A total of 6,278 samples were employed for training purposes, selected based on the density of built-up areas in the region. The choice between polygon and point for training data depended on the extent of built-up areas. Larger areas favored polygon data, while rarer built-up areas were represented by point data. This approach aimed to enhance the precision of classification results and yield more detailed outcomes. We use stratified sampling as it considers different types (polygon and point samples) based on the density of built-up areas, ensuring that each stratum is adequately represented. Simultaneously, purposive sampling is employed since the selection of samples is purposeful and driven by specific criteria related to the built-up areas. This combination enables a more tailored and precise sampling strategy that considers the region's unique characteristics (Stehman & Foody, 2019).

The training data were used to construct a classification scheme that is based on the Support Vector Machine (SVM) method (Rijal et al., 2023). SVM is a non-parametric supervised machine learning technique based on kernels that are used for image classification and commonly gives consistent results, especially for urban area classification compared to other machine learning algorithms and any traditional classifier such as maximum likelihood and minimum distance (Elhamdouni et al., 2022). The selection of kernel is crucial in SVM because it will highly influence the results. In this study, we used Linear kernel to reach promising mapping accuracy (Razaque et al., 2021).

The accuracy testing in this research employed a clustered random sampling technique, stratified by city areas. Within each city area, 50 test points were designated for urban class and additional 50 points for non-urban class. The overall sample size for accuracy assessment comprised 600 points encompassing both urban and non-urban classes. The evaluation method employed was the confusion matrix, providing comprehensive accuracy figures to gauge the final outcomes of the conducted accuracy tests. The accuracy of the model was represented by the Cohen's Kappa (K) that was calculated from the confusion matrix (Wicaksono & Lazuardi, 2018). Beyond evaluating the accuracy of data classification, the study also assessed the accuracy of urban expansion. For this purpose, 100 sample points were allocated for the whole study area. Change detection was confirmed by a Google Earth (2024) which can display urban conditions from time to time.

3. Results

3.1. Classification results

The research yielded two distinct classifications within the study area, categorized explicitly as built-up and non-built-up areas. Within the research context, objects falling under the classification of built-up areas encompass various structures, such as residential zones, industrial facilities, and other physical constructions intended to support diverse human activities. Conversely, objects classified as non-built-up areas encompass fields, agricultural lands, plantations, forests, vacant lots, and bodies of water.

Implementing the Support Vector Machine (SVM) algorithm for classifying built-up and non-built-up areas revealed a noteworthy trend across all cities within the study area between 2012 and 2022 (Figure 3). The findings underscore a significant expansion in the extent of residential and industrial zones, with Sidoarjo exhibiting the most substantial increase in built-up area compared to other regions.

One significant finding in this study is the major change from built-up to non-built-up areas, especially in the Bangkalan area. Land cover changes usually include shift from non-urban to urban areas, which makes this finding distinctive. An accuracy assessment demonstrates that the classification results for 2012 were less precise than those for 2022 (Figure 4). The transformation of Bangkalan from a built-up area to a non-built-up area can be attributed primarily to suboptimal visualization of Landsat 7 images for analyzing built areas in the region. Furthermore, in 2012, Bangkalan featured vacant land that, when observed through Landsat 7 imagery, resembled built-up areas. To mitigate this issue, we harnessed the composite data from band 742 in Landsat 7 to enhance the accuracy of the 2012 classification results.

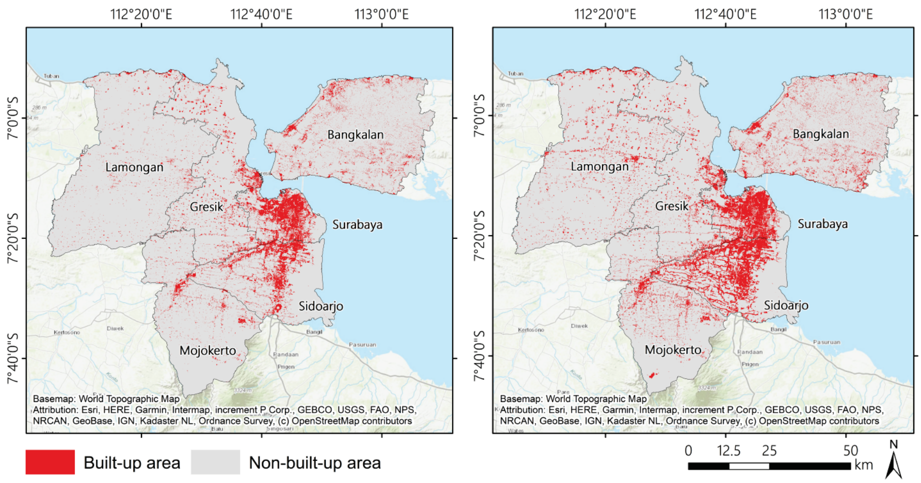

Figure 3. Non built-up area and built-up area classification results: (left) in 2012 and (right) in 2022.

Figure 4 illustrates the confusion matrix used to assess the accuracy of classification results in 2012 and 2022. In the accuracy testing stage of this research, a total of 300 sample points were used for the built-up class and additional 300 sample points for the non-built-up class. The confusion matrix presents the accuracy values of producers and users from two periods of observation data; even K accuracy values show differences between 2012 and 2022.

Classified Data 2012	Reference Data 2012: Non built-up area	Built-up area	Total	User Accuracy
Non built-up area	296	4	**300**	98.67
Bulit-up area	55	245	**300**	81.67
Total	**351**	**249**	**600**	
Producer Accuracy	84.33	98.39		

Cohen's Kappa	
	Po:0.9017
	Pe:0.5000
	K:0.8033

Classified Data 2022	Reference Data 2022: Non built-up area	Built-up area	Total	User Accuracy
Non built-up area	294	6	**300**	98.00
Bulit-up area	19	281	**300**	93.67
Total	**313**	**287**	**600**	
Producer Accuracy	93.93	97.91		

Cohen's Kappa	
	Po:0.9583
	Pe:0.5000
	K:0.9167

Figure 4. Built-up area and non-built-up area classification results: (left) in 2012 and (right) in 2022.

After examining the accuracy Figure 4, there is a clear difference: the accuracy of the built-up area classification in 2012 is much lower than the accuracy achieved in 2022. This difference is primarily due to the superior visual quality of the region. Landsat 8 imagery is different from Landsat 7 imagery. As a result, this difference in image quality significantly affects the overall accuracy value, and data from 2022 show higher overall accuracy when compared to the value obtained in 2012.

3.2. Change detection results

Figure 5 depicts an indication of urban change in the study area. Urban expansion is represented by red color on the map, while, yellow, and orange are the existing built-up areas in 2012 and 2022. The figure clearly illustrates that Sidoarjo has a dominant red color, showing a sizeable urban expansion toward the south of Surabaya. In contrast, the northern region of Surabaya has a slightly red color distribution, which indicates relatively lower urban expansion than the opposite region. These results highlight Sidoarjo as the region experiencing the most significant urban expansion, while Gresik is relatively stable in urban development.

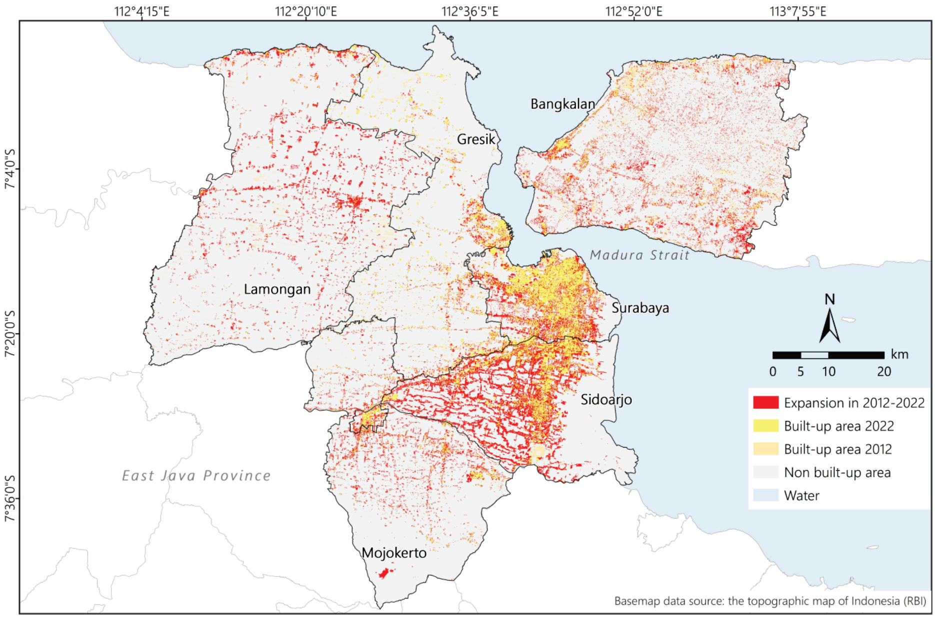

Figure 5. Urban expansion in Greater Surabaya during 2012–2022.

Table 1 provides support for those findings by presenting the area changes of each region. According to the table, sthe total changed area amounted to 278.16 km^2. Sidoarjo and Bangkalan have had the most significant changes, while Gresik has had the least. Significant changes have been observed in urban areas bordering Surabaya in the last decade. In terms of distribution, it was evident that the spread pattern occurred south of Surabaya, where the most apparent expansion occurred in Sidoarjo area (Figure 5).

Table 1. The transformation of urban areas in each city and regency in Greater Surabaya

	Surabaya	Sidoarjo	Mojokerto	Lamongan	Gresik	Bangkalan
Area change (km^2)	34.43	97.31	28.66	47.36	16.06	51.96
Ratio of each region (%)	10.44	13.48	11.75	2.69	1.53	3.97

Meanwhile, out of 100 test points used to analyze the accuracy of change detection, 70 points truly experienced changes based on historical images from Google Earth (2024). Thus, it can be concluded that the accuracy of the resulting change detection was 70%. This result was quite satisfactory and can represent the quality of the generated model. Based on the accuracy test conducted, most of the changes observed were from bare land to industrial areas. Another portion involved the expansion of residential areas, although the quantity was not substantial.

4. Discussion

4.1. Urban expansion patterns in Greater Surabaya

Our research findings highlight significant urban growth and expansion in Greater Surabaya region from 2012 to 2022. This expansion pattern predominantly extends southward from Surabaya and aligns with infrastructure development initiatives, notably arterial and toll roads, particularly in the Java region. These changes have significant implications for land use in Greater Surabaya, with various land conversion patterns observed in urban areas. In Sidoarjo, the transformation primarily involves a shift from agricultural land to industrial zones or factories. However, coastal areas in Bangkalan have undergone conversion to built-up areas, encompassing buildings, settlements, and ports. It underscores the impact of coastal development and the utilization of available land for infrastructure and economic activities. It signifies a transition from agriculture-based activities to industrialization and emphasizes these areas' crucial role in accommodating economic growth and attracting development investments (Grabowski & Self, 2020; Rustiadi et al., 2021).

The observed urban growth in Greater Surabaya raises questions about regional disparities in Indonesia. Although Jakarta Metropolitan Area and Bandung Metropolitan Area have traditionally served as hubs for urban development and economic growth (Dorodjatoen, 2009; Firman, 2009), the emergence of secondary cities like Surabaya signals a potential shift in the regional landscape. Meanwhile, as the regional economic center, Surabaya exhibits relatively minor changes in the city expansion. This could be attributed to the pre-existing urban development and limited available land for further expansion within the city. Consequently, the growth focus in Surabaya may center on redevelopment and densification, as opposed to outward expansion. Conversely, the Sidoarjo area, with its larger land area and potentially greater land availability, is noticing substantial urban growth. At the same time, it stresses the potential for further economic development and urbanization in these regions.

4.2. The implications and challenges of its expansion

These results highlight the dynamic nature of urbanization in Greater Surabaya area and indicate the spatial distribution of urban growth across different administrative units. Urban growth in that region is not limited to the main urban center of Surabaya but extends to neighboring cities and regencies, creating an interconnected and integrated metropolitan region. A metropolitan area has traditionally been the focus of urban development and economic growth; the emergence of secondary cities such as Surabaya indicates a potential shift in the regional landscape (Santoso et al., 2022). However, it is crucial to ensure that urban development is not concentrated solely in specific regions, exacerbating existing disparities. Policy interventions and targeted investments should be implemented to promote balanced urban development across different regions in Indonesia, reducing regional disparities and fostering inclusive growth. The identified changes from croplands to factory areas and settlement development highlight the importance of planning and providing infrastructure to support industrial activities, housing needs, and transportation networks (Kuller et al., 2022).

The rapid urban growth observed in Greater Surabaya area poses several implications and challenges. It is crucial to consider the environmental and ecological implications of urban expansion. First, it raises concerns about the pressure on natural resources and the environment, as urban expansion often leads to the conversion of agricultural land, loss of biodiversity, and increased pollution (Rustiadi et al., 2021). It is important to strike a balance between urban development and environmental conservation, preserving green spaces, promoting sustainable land use practices, and mitigating the adverse impacts of urbanization on natural resources, biodiversity, and ecosystems (Kapucu et al., 2021).

Furthermore, expanding urban areas necessitates providing adequate infrastructure and public services to meet the population's growing demands. Ensuring access to clean water, sanitation facilities, transportation networks, and healthcare services becomes increasingly vital in sustaining the quality of life for residents (Zeng et al., 2022). This research underlines that infrastructure planning should apply an approach that considers the long-term implications of urban growth to create sustainable and resilient urban environments.

Finally, the disparities in urban growth among different cities and regencies within Greater Surabaya area underscore the broader global challenge of balancing regional development. While some areas experience rapid growth, others may need to catch up, leading to regional inequalities (Kim et al., 2020). Policy interventions must promote inclusive and equitable development across the entire region, considering factors such as infrastructure investment and social services provision.

5. Conclusion

In conclusion, our study has provided compelling evidence of the substantial urban growth and expansion within Greater Surabaya area over the studied decade. We have identified critical implications of these urbanization patterns, including the discernible influence of coastal development, the transformation of croplands and ponds into built-up areas, and the varying degrees of development concentration observed across different regions within the area. These findings collectively highlight the importance of leveraging remote sensing and GEE as robust and reliable tools for monitoring and analyzing urban expansion. Moreover, they underscore the need for continuous research and monitoring efforts dedicated to comprehensive understanding of urbanization dynamics in Indonesia. Such endeavors are essential for addressing development imbalances and fostering sustainable urban growth nationwide.

Ultimately, this research contributes to a better understanding of the ongoing urbanization process in secondary cities in Greater Surabaya, Indonesia. It provides valuable evidence-based insights that can inform decision-making and guide the formulation of policies for future urban development in the country. By embracing these findings and integrating them into urban planning and management strategies, Indonesia can work toward achieving more balanced and sustainable urbanization, ensuring a prosperous future for all its regions.

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References

Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., Moghaddam, S. H. A., Mahdavi, S., Ghahremanloo, M., Parsian, S., Wu, Q., & Brisco, B. (2020). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 5326–5350. https://doi.org/10.1109/JSTARS.2020.3021052

Aryal, A., Bhatta, K. P., Adhikari, S., & Baral, H. (2023). Scrutinizing Urbanization in Kathmandu Using Google Earth Engine Together with Proximity-Based Scenario Modelling. *Land*, *12*(1), Article 25. https://doi.org/10.3390/land12010025

Belward, A. S. & Skøien, J. O. (2015). Who launched what, when and why; trends in global land-cover observation capacity from civilian earth observation satellites. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 115–128. https://doi.org/10.1016/j.isprsjprs.2014.03.009

Dorodjatoen, A. M. H. (2009). The Emergence of Jakarta-Bandung Mega-Urban Region and Its Future Challenges. *Journal of Regional and City Planning*, *20*(1), 15–33. https://www.researchgate.net/publication/302957191_THE_EMERGENCE_OF_JAKARTA-BANDUNG_MEGA-URBAN_REGION_AND_ITS_FUTURE_CHALLENGES

Elhamdouni, D., Arioua, A., & Karaoui, I. (2022). Monitoring urban expansion using SVM classification approach in Khenifra city (Morocco). *Modeling Earth Systems and Environment*, *8*(1), 293–298. https://doi.org/10.1007/s40808-021-01092-w

Firman, T. (2009). The continuity and change in mega-urbanization in Indonesia: A survey of Jakarta-Bandung Region (JBR) development. *Habitat International*, *33*(4), 327–339. https://doi.org/10.1016/j.habitatint.2008.08.005

Google Earth. (2024). Google Earth Pro 7.3.6.9750 (64-bit). https://earth.google.com/intl/earth/

Google Earth Engine. (2023). *Earth Engine Data Catalog*: USGS Landsat 7 and Landsat 8 Level 2, Collection 2, Tier 1 [Data Set]. https://developers.google.com/earth-engine/datasets/catalog/landsat

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Grabowski, R. & Self, S. (2020). Industrialization and deindustrialization in Indonesia. *Asia & the Pacific Policy Studies*, *7*(1), 95–111. https://doi.org/https://doi.org/10.1002/app5.295

Hegazy, I. R. & Kaloop, M. R. (2015). Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. *International Journal of Sustainable Built Environment*, *4*, 117–124. https://doi.org/10.1016/j.ijsbe.2015.02.005

Jones, G. W. (2016). Migration and Urbanization in China, India and Indonesia: an Overview. In C. Guilmoto & G. Jones (Eds), *Contemporary Demographic Transformations in China, India and Indonesia* (pp. 271–276). Springer. https://doi.org/10.1007/978-3-319-24783-0_17

K, D. & Angadi, D. P. (2021). Urban expansion quantification from remote sensing data for sustainable land-use planning in Mangaluru, India. *Remote Sensing Applications: Society and Environment*, *23, Article* 100602. https://doi.org/10.1016/j.rsase.2021.100602

Kapucu, N., Ge 'Gurt,' Y., Martín, Y., & Williamson, Z. (2021). Urban resilience for building a sustainable and safe environment. *Urban Governance*, *1*(1), 10–16. https://doi.org/https://doi.org/10.1016/j.ugj.2021.09.001

Katherina, L. K. & Indraprahasta, G. S. (2019). Urbanization Pattern in Indonesia's Secondary Cities: Greater Surabaya and Its Path toward a Megacity. *IOP Conference Series: Earth and Environmental Science*, *338*(1), Article 012018. https://doi.org/10.1088/1755-1315/338/1/012018

Kim, K., Mungsunti, A., Sumner, A., & Yusuf, A. (2020). *Structural Transformation and Inclusive Growth. Kuznets' 'developer's dilemma' in Indonesia. (*WIDER Working Paper 2020/31). UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2020/788-0

Kuller, M., Farrelly, M., Marthanty, D. R., Deletic, A., & Bach, P. M. (2022). Planning support systems for strategic implementation of nature-based solutions in the global south: Current role and future potential in Indonesia. *Cities*, *126*, Article 103693. https://doi.org/10.1016/j.cities.2022.103693

Lewis, B. D. (2014). Urbanization and Economic Growth in Indonesia: Good News, Bad News and (Possible) Local Government Mitigation. *Regional Studies*, *48*(1), 192–207. https://doi.org/10.1080/00343404.2012.748980

Mardiansjah, F. H., Rahayu, P., & Rukmana, D. (2021). New Patterns of Urbanization in Indonesia: Emergence of Non-statutory Towns and New Extended Urban Regions. *Environment and Urbanization ASIA*, *12*(1), 11–26. https://doi.org/10.1177/0975425321990384

Pamungkas, A., Rini, E. F., & Cahyo, P. N. (2016). Instruments for Development Controls in Gerbangkertosusila. *Journal of Regional and City Planning*, *27*(3), 236–250. https://doi.org/10.5614/jrcp.2016.27.3.5

Prasodjo, I. (2018). Dampak urbanisasi bagi pembangunan manusia 2010-2016 Studi kasus: Jakarta, Surabaya, Medan [The Impact of Urbanization on Human Development 2010-2016 Case Study: Jakarta, Surabaya, and Medan]. *Jurnal Ekonomi*, *23*(3), 305–318. https://doi.org/10.24912/je.v23i3.415

Razaque, A., Ben Haj Frej, M., Almi'ani, M., Alotaibi, M., & Alotaibi, B. (2021). Improved Support Vector Machine Enabled Radial Basis Function and Linear Variants for Remote Sensing Image Classification. *Sensors*, *21*(13), Article 4431. https://doi.org/10.3390/s21134431

Rijal, S. S., Pham, T. D., Noer'Aulia, S., Putera, M. I., & Saintilan, N. (2023). Mapping Mangrove Above-Ground Carbon Using Multi-Source Remote Sensing Data and Machine Learning Approach in Loh Buaya, Komodo National Park, Indonesia. *Forests*, *14*(1), Article 94. https://doi.org/10.3390/f14010094

Roy, D. P., Kovalskyy, V., Zhang, H. K., Vermote, E. F., Yan, L., Kumar, S. S., & Egorov, A. (2016). Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Remote Sensing of Environment*, *185*, 57–70. https://doi.org/10.1016/j.rse.2015.12.024

Rustiadi, E., Pravitasari, A. E., Setiawan, Y., Mulya, S. P., Pribadi, D. O., & Tsutsumida, N. (2021). Impact of continuous Jakarta megacity urban expansion on the formation of the Jakarta-Bandung conurbation over the rice farm regions. *Cities*, *111*, Article 103000. https://doi.org/10.1016/j.cities.2020.103000

Santoso, E. B., Aulia, B. U., & Desiana, T. A. (2022). Ecological Footprint Scenario Based on Dynamic System Model in Gerbangkertosusila Region. *International Review for Spatial Planning and Sustainable Development*, *10*(1), 99–116. https://doi.org/10.14246/irspsd.10.1_99

Shetty, A., Umesh, P., & Shetty, A. (2022). An exploratory analysis of urbanization effects on climatic variables: a study using Google Earth Engine. *Modeling Earth Systems and Environment*, *8*, 1363–1378. https://doi.org/10.1007/s40808-021-01157-w

Stehman, S. V. & Foody, G. M. (2019). Key issues in rigorous accuracy assessment of land cover products. *Remote Sensing Environment*, *231,* Article 111199. https://doi.org/10.1016/j.rse.2019.05.018

Taubenböck, H., Esch, T., Felbier, A., Wiesner, M., Roth, A., & Dech, S. (2012). Monitoring urbanization in mega cities from space. *Remote Sensing of Environment*, *117*, 162–176. https://doi.org/10.1016/j.rse.2011.09.015

Wicaksono, P. & Lazuardi, W. (2018). Assessment of PlanetScope images for benthic habitat and seagrass species mapping in a complex optically shallow water environment. *International Journal of Remote Sensing*, *39*(17), 5739–5765. https://doi.org/10.1080/01431161.2018.1506951

Wilonoyudho, S., Rijanta, R., Keban, Y. T., & Setiawan, B. (2017). Urbanization and regional imbalances in Indonesia. *Indonesian Journal of Geography*, *49*(2), 125–132. https://doi.org/10.22146/ijg.13039

Zeng, X., Yu, Y., Yang, S., Lv, Y., & Sarker, M. N. (2022). Urban Resilience for Urban Sustainability: Concepts, Dimensions, and Perspectives. *Sustainability, 14*(5), Article 2481. https://doi.org/10.3390/su14052481

Zurqani, H. A., Post, C. J., Mikhailova, E. A., & Allen, J. S. (2019). Mapping Urbanization Trends in a Forested Landscape Using Google Earth Engine. *Remote Sensing in Earth Systems Sciences*, *2*, 173–182. https://doi.org/10.1007/s41976-019-00020-y