Assessing urban growth through morphological spatial pattern analysis in cloud computing platform

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Abstract

Purpose – This study aims to quantify and analyse the dynamics of land use and land cover (LULC) changes over three decades in the rapidly urbanizing city of Abha, Saudi Arabia, and to assess urban growth using Morphological Spatial Pattern Analysis (MSPA).

Design/methodology/approach – Using the Support Vector Machine (SVM) classification in Google Earth Engine, changes in land use in Abha between 1990 and 2020 are accurately assessed. This method leverages cloud computing to enhance the efficiency and accuracy of big data analysis. Additionally, MSPA was employed in Google Colab to analyse urban growth patterns.

Findings – The study demonstrates significant expansion of urban areas in Abha, growing from 62.46 km^2 in 1990 to 271.45 km^2 in 2020, while aquatic habitats decreased from 1.36 km^2 to 0.52 km^2. MSPA revealed a notable increase in urban core areas from 41.66 km^2 in 2001 to 194.97 km^2 in 2021, showcasing the nuanced dynamics of urban sprawl and densification.

Originality/value – The novelty of this study lies in its integrated approach, combining LULC and MSPA analyses within a cloud computing framework to capture the dynamics of city and environment. The insights from this study are poised to influence policy and planning decisions, particularly in fostering sustainable urban environments that accommodate growth while preserving natural habitats. This approach is crucial for devising strategies that can adapt to and mitigate the environmental impacts of urban expansion.

Keywords Urban sprawl, Fragmentation analysis, Bootstrapping trend analysis, Cloud computing

Paper type Research paper

1. Introduction

Urbanisation, a defining phenomenon of the 21st century, is having a profound impact on landscapes, economies and societies worldwide (Li *et al.*, 2021). The United Nations reports that urban areas will absorb the growth of the world's population. By 2050, almost 68% of the world's population is expected to live in urban areas (United Nations, Department of Economic and Social Affairs, Population Division, 2018). This rapid expansion of cities, particularly in developing countries, brings with it significant challenges, including environmental degradation, loss of arable land and increased pressure on infrastructure and services (Liu *et al.*, 2021; Zhang *et al.*, 2022; Khan *et al.*, 2021; Sarker *et al.*, 2021). In Saudi Arabia, the rate of urbanisation is emblematic of this global trend, with cities such as Riyadh

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and Jeddah experiencing rapid growth (Alharbi, 2018). The Kingdom's urban population increased from 86% in 2010 to over 83% in 2020, reflecting a significant urban transformation (AlQadhi *et al.*, 2021; Mallick *et al.*, 2022).

Quantifying urban growth is not just a statistical exercise, but a critical component of effective urban planning and the promotion of sustainable development (Clifton *et al.*, 2008). As cities expand and evolve, understanding the nuances of land use and land cover change (LULC) is essential (Azizi *et al.*, 2022). These changes, indicative of urban expansion, environmental change and anthropogenic impacts, require careful and dynamic analysis to ensure the resilience and sustainability of urban environments (Fang *et al.*, 2022; Krivoguz, 2024). Conventional methods of LULC analysis, such as manual interpretation of satellite imagery or simple automatic classification techniques, often lack the precision and depth required to capture the complex and multi-layered nature of urban growth (Talukdar *et al.*, 2020). They struggle to accurately represent the rapid and often non-linear changes in the urban environment, which can lead to oversimplifications when assessing urban expansion and its environmental and socio-economic consequences (Versluis and Rogan, 2010). This inadequacy stems from their limited ability to process the vast and diverse datasets generated by modern remote sensing technologies (Talukdar *et al.*, 2021). This leads to a gap between the scale of urban change and the analytical capacity of these traditional methods.

In response to these limitations, Morphological Spatial Pattern Analysis (MSPA) has emerged as a powerful analytical tool in the field of urban research (Lian and Feng, 2022; Zhang *et al.*, 2023). MSPA goes beyond the capabilities of traditional LULC analysis by providing a detailed and structured approach to deciphering the spatial patterns of urban growth (Wang and Banzhaf, 2018). It provides a granular examination of the urban landscape and categorises the land into different morphological elements such as core areas, edges, bridges, bifurcations, loops and isolated patches (Kaminski *et al.*, 2021; Qiao *et al.*, 2023). Understanding the geometry and configuration of urban spaces is crucial, enabling a more thorough analysis of urban sprawl, fragmentation, and densification processes, as noted by Reis *et al.* (2016). MSPA identifies core areas as the most consolidated and stable urban zones, typically characterized by high building density and scarce green spaces (Zhang *et al.*, 2024). Conversely, peripheral areas act as transition zones where urban development intersects with natural or semi-natural landscapes, making them essential for studying the urban-rural interface and the spread of urbanization into natural habitats (Liu *et al.*, 2024a, b). These transition zones, as outlined by MSPA, reveal the dynamics of urban change by displaying areas of new development, the potential for urban expansion, and spaces susceptible to urbanization pressures (Li *et al.*, 2024). MSPA's capability to dissect urban landscapes into these distinct components allows urban planners and researchers to gauge urbanization intensity, monitor urban sprawl progression, and pinpoint areas of significant ecological value or vulnerability (Jiang *et al.*, 2024). This intricate classification aids in evaluating current urban forms and projecting future urbanization patterns, thereby enhancing strategic planning and decision-making processes (Ding *et al.*, 2024). MSPA's insights into the spatial organization and morphological changes of urban areas make it a vital tool in pursuing sustainable urban management and crafting a balance between development needs and environmental protection, as Bosch *et al.* (2019) suggest. The advent of cloud computing has revolutionised the field of remote sensing and spatial analysis, offering unprecedented opportunities for managing and analysing large data sets (Amani *et al.*, 2020). Cloud-based platforms such as Google Earth Engine have democratised access to vast stores of satellite imagery and computational resources, enabling researchers and planners to conduct detailed LULC analysis with greater efficiency and accuracy (Lin *et al.*, 2013; Parente *et al.*, 2019). This technological shift has facilitated the integration of MSPA into cloud computing environments and improved the ability to monitor and analyse urban growth on a global scale (Canedoli *et al.*, 2018).

Despite significant advancements in urban research, notable gaps persist, particularly in the integration of comprehensive Land Use and Land Cover (LULC) analysis with Morphological Spatial Pattern Analysis (MSPA) within the realm of cloud computing to tackle the complexities of urban growth dynamics. This is especially relevant for rapidly urbanizing cities in the Middle East, such as Abha, Saudi Arabia, where there is a limited understanding of urban form evolution. Research is also scant on the socio-economic and environmental repercussions of urbanization in these areas, characterized by a distinctive interplay between natural habitats and urban expansion. This study aims to bridge these research gaps by employing Support Vector Machine (SVM) classification within the Google Earth Engine to analyse LULC changes in Abha City over a 30-year period, utilizing cloud computing to enhance data processing and analytical efficiency. Furthermore, the study will implement MSPA in Google Colab to quantitatively and qualitatively assess urban growth and morphological transformations, thereby providing a holistic view of the urbanization process. The novelty of this research lies in its methodological integration, combining advanced LULC classification techniques with MSPA to furnish a nuanced and dynamic understanding of urban and environmental transformations. This innovative approach contributes significantly to the scholarly discourse and aligns with the strategic goals of Saudi Vision 2030, offering practical insights for sustainable urban planning and environmental management in the region.

2. Materials and methods

2.1 Study area

Abha and Khamis Mushait, situated in Saudi Arabia's Asir province, were chosen as the focal points for this study (Figure 1). These urban centres, nestled in highland areas, are renowned for their rich biodiversity, representing the Asir region and the Kingdom of Saudi Arabia's most varied ecological zones, making them prominent tourist attractions. The predominant vegetation in the locale includes *A. gerrardii*, Acacia origena, and *J. procera* trees, covering an expanse of 1,291 square kilometres (as shown in Figure 1). Geographically, these cities are positioned between 18°9′33.126″N to 18°30′56.566″N latitudes and 42°23′52.477″E to 42°51′42.832″E longitudes, with the elevation varying from 1,564 to 2,736 metres and an average elevation of 2,102 metres above sea level. The region's geology is characterized by sedimentary soils, encompassing soft clay and compact silt, and presents a geographically diverse terrain, as noted by the Saudi Geological Society. This area is part of the Afromontane zone, known for its cool, semi-arid climate. Historical weather data from the past 55 years (1965–2019) indicates an average annual rainfall of 245 mm, primarily occurring from February to June. Temperature records show average lows and highs of 9.4 °C and 30.8 °C, respectively. Additionally, the region is prone to intense rainfall, leading to flash floods in several rural areas during the winter season.

2.2 Materials

Landsat 4–5 Thematic Mapper and Landsat 8 Operational Land Image (with a spatial resolution of 30 metres and coverage of path/row 167/047) for the years 1990, 2000 and 2020 were obtained from the USGS Earth Explorer Portal (https://earthexplorer.usgs.gov). This information was used to create a geographically corrected composite image of the Earth's terrain.

2.3 Land use land cover mapping using support vector machine in Google Earth Engine and Google Colab

Land Use and Land Cover (LULC) modelling in Google Earth Engine (GEE) uses the robust cloud computing platform to process and analyse large data sets for environmental

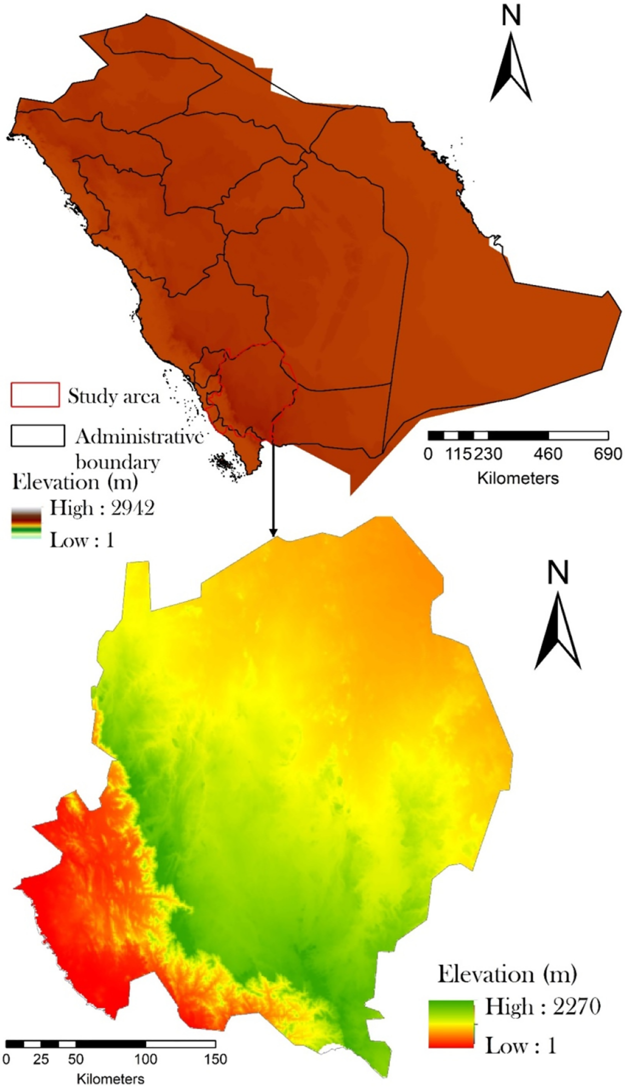

Figure 1.
Location of the study area

Source(s): Figure by authors

monitoring. For LULC classification, the Support Vector Machine (SVM) algorithm is commonly used because it can effectively process high-dimensional data and is capable of modelling complex non-linear boundaries between classes (Talukdar *et al.*, 2020). In this context, the SVM works by finding the hyperplane that best separates the different land cover classes in the feature space, thus maximising the distance between classes (Mallick *et al.*, 2021). The input data for the SVM usually includes multispectral image data, such as that from Landsat, which provides detailed spectral information for different land cover types. This data is pre-processed to correct for atmospheric and sensor distortions, followed by segmentation and feature extraction processes that facilitate classification.

In the practical application of LULC mapping with SVM in GEE and visualisation of the results in Google Colab, the workflow starts with the import of satellite imagery and the selection of relevant bands corresponding to different land cover signatures. The classes for LULC mapping are predefined, e.g. built-up, water bodies, dense vegetation, sparse vegetation, farmland, scrubland, bare soil and exposed rock. For each pixel in the image, the SVM algorithm assigns a class based on the spectral signature. Training the SVM model requires a set of labelled data (training samples) representing each land cover class. Once the model is trained and validated, it is applied to the entire dataset to create the LULC map. In Google Colab, the mapping results are enriched with visual elements such as north arrows and scale bars using matplotlib, as shown in the code snippet provided. This approach not only facilitates the understanding and interpretation of the spatial distribution of the different land cover types, but also improves the accuracy of the spatial analysis by including additional geographic reference information.

2.4 Accuracy assessment of LULC maps

The accuracy assessment of LULC maps is a critical step to validate the reliability and precision of classified satellite imagery, and the kappa coefficient is widely used for this purpose (Talukdar *et al.*, 2020). This statistical measure compares the observed accuracy (the proportion of correctly classified pixels) against the expected accuracy (the probability of random agreement) to provide a robust assessment of classification performance. To implement this, a confusion matrix is first constructed, detailing the actual versus predicted classifications of a sample of pixels. Each element in the matrix represents the count of pixels for each actual-predicted class pair, allowing for the calculation of overall accuracy and class-specific metrics. The kappa coefficient is then calculated from this matrix to quantify the agreement level, adjusting for the chance agreement. A value of 1 indicates perfect agreement, while a value of 0 or less suggests no agreement better than random chance. This method not only assesses the overall accuracy but also helps in identifying specific classes that may be consistently misclassified or confused, guiding further refinement of the classification process (Talukdar *et al.*, 2021).

2.5 Quantification of urban growth using MSPA in Google Colab

Quantifying urban growth using Morphological Spatial Pattern Analysis (MSPA) in Google Colab involves a systematic approach to differentiating and categorising spatial patterns in urban environments (Liu *et al.*, 2024a, b). MSPA is a method by which a binary landscape can be broken down into several spatial core components such as cores, edges, bridges, loops, perforations, islands and bifurcations (Jiang *et al.*, 2024). This is particularly useful in urban studies to quantify and understand the growth and structural complexity of urban areas over time. The process begins with the reclassification of Land Use and Land Cover (LULC) maps into binary images where built-up areas are labelled with one value (often 1) and all other land uses with another value (usually 0). This binary conversion is crucial for MSPA as it simplifies the landscape into urban and non-urban areas and allows for detailed analysis of urban structure and patterns (Ding *et al.*, 2024).

The implementation of MSPA in Google Colab involves several steps of image processing and analysis using tools from libraries such as NumPy, Matplotlib and skimage for morphological operations. First, binary images representing built-up areas for different years are generated to perform morphological operations. The function identify_core_areas removes small objects and thus isolates significant urban cores. The identify_complex_structures function further analyses the binary image to identify specific morphological elements such as bridges (narrow connections between larger urban areas), islets (small isolated urban patches) and branches (linear extensions of urban areas). These elements are crucial for understanding urban connectivity and fragmentation. MSPA operations such as binary_opening and skeletonise are used to distinguish between urban core areas, edges and other structural components. The MSPA analysis results in a segmentation of the urban landscape into different elements, each representing a unique aspect of the urban form, such as core areas, edges and connections. In the final step, each MSPA element in the landscape is assigned a unique index that facilitates the visualisation and comparison of urban growth patterns over time. These elements are quantified and mapped to visualise the spatial configuration and evolution of urban areas. The resulting MSPA classes are then mapped onto the original spatial grid, creating a composite image that vividly depicts urban growth and morphological changes over the selected time periods.

2.6 Trend analysis using bootstrapping in Google Colab

Trend analysis using bootstrapping is a robust statistical method to understand the temporal dynamics of LULC changes and MSPA categories. This technique is critical for quantifying the rate of change and determining the significance and reliability of observed trends over time. The process begins by compiling temporal data into a structured dataset, with each dataset representing a snapshot in time and containing measurements for different LULC and MSPA categories. In the context of LULC and MSPA, these data could represent the extent of built-up areas, water bodies, vegetation types and MSPA-defined structures such as core, bridge, loop, island and bifurcation areas.

When performing trend analysis with bootstrapping, numerous samples of the original dataset are generated with replacement to create a distribution of trend estimates. This method enables the calculation of a more accurate trend estimate and the creation of confidence intervals around the trend, which provide a measure of the variability and reliability of the estimate. The statistical significance of the trend is determined by hypothesis testing, usually using a p-value from a linear regression model of the original data. By repeatedly sampling the data and recalculating the slope (of the trend) for each sample, the analysis takes into account the uncertainty and variability of the data, resulting in more robust and reliable trend estimates. The bootstrapping approach is particularly useful for ecological and environmental studies where the data may be noisy or have a non-normal distribution, making traditional parametric trend tests less reliable. The final result of this analysis includes the estimated trend, the confidence interval around this trend and the p-value, which indicates the significance of the observed trend and provides a comprehensive overview of the temporal dynamics of the phenomena under investigation.

The methods used for this study is presented in Figure 2.

3. Results

3.1 Dynamics and quantification of LULC

The kappa coefficient values, which reflect the accuracy of LULC classification over three decades, show a high degree of consistency, with values of 81.43 in 1990, 80.60 in 2000 and 85.40 in 2020. These coefficients indicate reliable classification performance over time, with a slight improvement in 2020. The kappa values, which are above 80, indicate a very good agreement between the classified images and the reference data, thus confirming the reliability of the LULC maps produced. The area covered by each LULC class has changed considerably between 1990 and 2020 (Figure 3). Built-up areas increased dramatically from 62.46 km^2 in 1990 to 271.45 km^2 in 2020, indicating strong urban growth. In contrast, the area of water bodies decreased from 1.36 km^2 to 0.52 km^2, indicating a decline in aquatic habitats. Dense vegetation showed a notable increase from 1.28 km^2 to 9.44 km^2, which could indicate effective protection measures or a recovery of natural vegetation. Areas of sparse vegetation

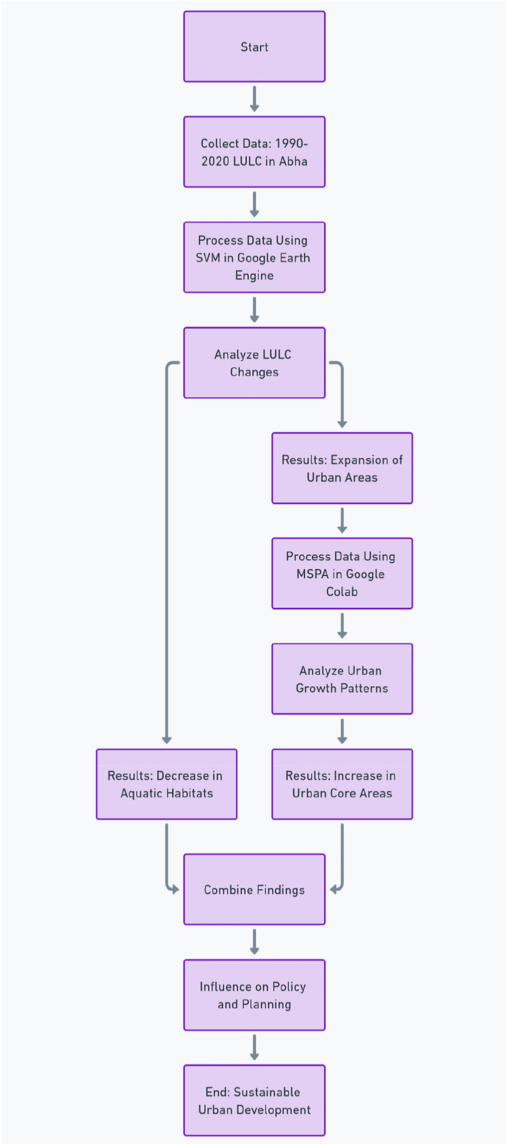

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Figure 2.
Hierarchical structure of the methods employed in this study

and cropland fluctuated, with sparse vegetation first decreasing and then increasing and cropland steadily decreasing over the 30-year period.

The bootstrapping trend analysis provided detailed insights into the temporal changes of the LULC categories and quantified the annual rate of change with a high degree of precision (Table 1). For built-up areas, the trend analysis revealed a remarkable expansion rate of 7.16 km^2 per year. Although the p-value of the trend was 0.09, which means that it is not statistically significant at the usual threshold of 0.05, the magnitude of change indicates a

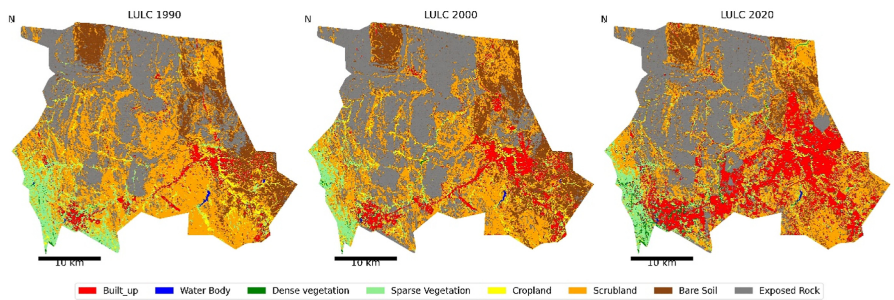


Figure 3.
LULC dynamics in Abha, Saudi Arabia from 1990 to 2020

Note(s): The panels display the classified satellite imagery of Abha city over a 30-year period, illustrating the changes in various LULC categories
Source(s): Figure by authors

Table 1.
Trends in LULC Classes in Abha, Saudi Arabia, with Corresponding Statistical Significance

LULC classes	Estimated trend	95% confidence interval	*p*-value
Built_up	7.1586	[7.15861929, 7.15861929]	0.0883
Water_Body	−0.0283	[−0.02832429, −0.02832429]	0.0390
Dense_vegetation	0.2815	[0.28153286, 0.28153286]	0.1108
Sparse_Vegetation	−0.1213	[−0.12133286, −0.12133286]	0.9283
Cropland	−0.3324	[−0.33237643, −0.33237643]	0.1581
Scrubland	−4.3598	[−4.35983143, −4.35983143]	0.3321
Bare_Soil	−2.2999	[−2.29987929, −2.29987929]	0.4339
Exposed_Rock	−0.2983	[−0.29831143, −0.29831143]	0.9335

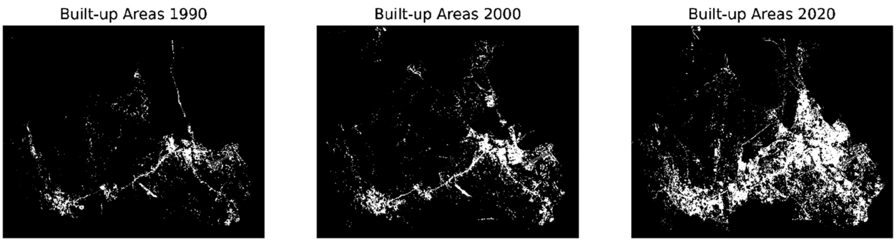
Note(s): The table quantifies the estimated annual trend for each LULC category, with the 95% confidence interval and *p*-values indicating the precision and statistical significance of the trend estimates. A positive trend value indicates an increase, while a negative value denotes a decrease in the area of the respective LULC class
Source(s): Table by authors

substantial urbanisation process. For water bodies, a negative trend of −0.03 km^2 per year was observed, which despite its small magnitude was statistically significant with a *p*-value of 0.04, indicating a steady reduction in water areas during the study period. For dense vegetation, an increasing trend of 0.28 km^2 per year was observed, indicating a gradual expansion of vegetated areas. Although this trend did not reach statistical significance ($p = 0.11$), it reflects a positive ecological change. Sparse vegetation showed a slightly negative trend of −0.12 km^2 per year, with a high *p*-value of 0.93, suggesting that the changes in sparse vegetation areas are due to natural fluctuations rather than a definite declining trend. Cropland decreased by an estimated −0.33 km^2 per year, with a *p*-value of 0.16, indicating a trend towards decreasing agricultural use, but this trend was not statistically robust. For scrubland, the decline was more pronounced at −4.36 km^2 per year, but with a *p*-value of 0.33, indicating that although there is a downward trend, it is not statistically significant. Bare ground areas showed a decrease of −2.30 km^2 per year (*p*-value = 0.43), and exposed rock areas showed a slightly negative trend of −0.30 km^2 per year with a *p*-value of 0.93, both indicating small decreases that could be influenced by methodological uncertainties or the natural variability of land cover. These trends with associated confidence intervals and *p*-values provide a nuanced view of the dynamics of the landscape. They show that while some LULC categories experience notable changes, others remain relatively stable or are subject to subtle shifts.

The dynamics of LULC changes and their statistical significance have wider environmental and socio-economic implications. The substantial growth of built-up areas can lead to habitat loss, increased runoff and heat island effects in cities. The decline of water bodies could have an impact on local hydrology and biodiversity. However, the increase in dense vegetation areas could offset some negative environmental impacts, indicating a possible trend towards greening the region. These changes emphasise the need for integrated urban planning and environmental protection strategies to create a balance between development and environmental sustainability. This is supported by continuous monitoring and analysis using platforms such as Google Earth Engine and Google Colab for accurate and timely data processing.

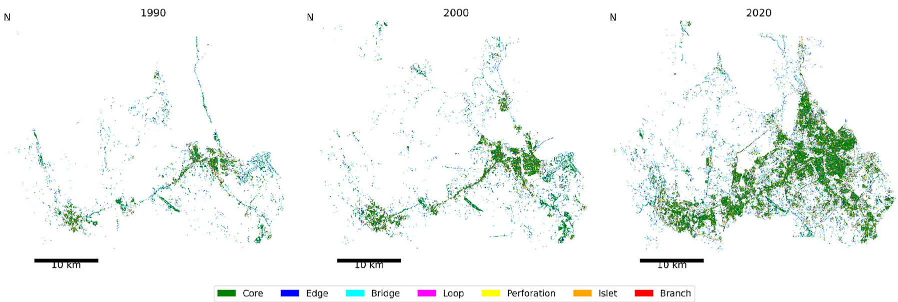
3.2 Application of MSPA for urban growth quantification in Google Colab

The application of MSPA in Google Colab to quantify urban growth provided insightful results about the structural changes in urban areas (Figure 4). MSPA categories such as core, bridge, loop, and branch were analysed over the years 2001, 2011 and 2021, revealing the evolving urban landscape (Figure 5). Core areas, which represent the most consolidated



Note(s): The sequence of images represents an overlay analysis of built-up areas over three decades, with white representing built-up structures and black denoting non-built-up land cover
Source(s): Figure by authors

Figure 4. Temporal analysis of Built-up Areas in Abha, Saudi Arabia



Note(s): This figure presents the results of Morphological Spatial Pattern Analysis (MSPA) to identify various urban form elements over a 30-year period. Key MSPA elements are color-coded: core urban areas (green), edges (blue), bridges (cyan), loops (magenta), perforations (yellow), islets (orange), and branches (red). The temporal progression from left (1990) to right (2020) demonstrates the expansion and densification of core urban areas alongside the development of urban form elements such as edges and bridges, indicating an intricate evolution of the city's spatial structure
Source(s): Figure by authors

Figure 5. Evolution of Urban Morphological Patterns in Abha, Saudi Arabia (1990–2020)

urban zones, have increased significantly from 41.66 km^2 in 2001 to 194.97 km^2 in 2021. This increase reflects the intensification and expansion of urban development and indicates a shift towards a more densely built-up environment. The areas for bridges and loops, which represent connectivity and circular urban structures respectively, have also grown, albeit at a slower rate. Over the two decades, the bridge areas increased from 4.11 km^2 to 13.74 km^2 and the loop areas from 9.40 km^2 to 14.76 km^2. These changes indicate an improvement in urban connectivity and the complexity of urban layouts, possibly reflecting improved infrastructure development and urban planning strategies. Islet and 'branch' categories, representing isolated urban elements and linear extensions of urban areas respectively, experienced growth, with island areas increasing from 1.64 km^2 to 4.83 km^2 and branch areas increasing from 5.65 km^2 to 43.14 km^2. The increase in branch areas is particularly notable as it indicates the expansion of urban growth into the surrounding non-urban areas.

The bootstrapping trend analysis provides a comprehensive assessment of the dynamics within each MSPA category during the study period (Table 2). In particular, the Core category, which represents the heart of the urbanised areas, showed a pronounced growth trend, increasing on average by 5.24 km^2 per year. This figure, together with a *p*-value of 0.08, indicates a strong tendency towards urban consolidation, although it is slightly below the conventional statistical significance threshold of 0.05, suggesting a trend that, while indicative of substantial urban growth, must be interpreted cautiously due to the potential variability of the data. When examining the other MSPA categories, we find different rates of change, each reflecting different aspects of urban development. The bridge category, which denotes areas connecting different urban segments, grew by 0.33 km^2 per year, indicating improved urban connectivity. The loop category, which represents enclosed urban spaces, increased by 0.17 km^2 per year, indicating the development of circular or enclosed urban forms. The island category, which covers small, isolated urban areas, increased by 0.11 km^2 per year, indicating the emergence of new, discrete urban developments. Finally, the Branch category, which captures the linear expansion of urban areas, showed a significant growth rate of 1.30 km^2 per year, illustrating the expansion of urban areas into neighbouring non-urban areas. Although these trends provide valuable insights into the evolving urban landscape, their p-values — which range from 0.08 to 0.13 — indicate that the observed trends are not statistically significant at the strict 0.05 level. The quantitative trends combined with the *p*-value considerations provide a nuanced perspective on urban expansion and morphological change. They form the basis for informed urban planning and policy design that recognises the multi-faceted nature of urban growth and its environmental and social impacts.

The results of the MSPA emphasise the dynamic nature of urban growth and highlight both the densification of urban core areas and the expansion of urban characteristics into the periphery. In particular, the increasing trend in core and peripheral areas shows a pattern of urban sprawl and densification that has implications for land use planning, infrastructure development and environmental sustainability. These trends, quantified through MSPA and

MSPA categories	Estimated trend	95% confidence interval	*p*-value
Core	5.242	[5.24160643, 5.24160643]	0.0824
Bridge	0.333	[0.33338571, 0.33338571]	0.1217
Loop	0.173	[0.17278071, 0.17278071]	0.1096
Islet	0.110	[0.10995429, 0.10995429]	0.0995
Branch	1.301	[1.30089214, 1.30089214]	0.1280

Source(s): Table by authors

Table 2. Trends in LULC Classes in Abha, Saudi Arabia, with Corresponding Statistical Significance

trend analysis, provide a valuable basis for understanding the spatial dynamics of urban growth and inform policy and planning to address the environmental and social impacts of urbanisation.

3.3 Management strategies

Based on the detailed MSPA analysis of the City of Abha, specific urban planning strategies can be tailored to each MSPA category to address the unique challenges and opportunities presented by urban growth patterns. For the Core category, which saw an increase of 5.24 km^2/year, the strategy should focus on sustainable densification. This includes promoting vertical development to accommodate the growing population while minimising the footprint of new construction. The introduction of green building standards, the improvement of public transport networks and the preservation of green spaces within these core areas are crucial to maintaining quality of life and environmental quality. For the expanding Bridge and Branch categories, with growth rates of 0.33 km^2/year and 1.30 km^2/year, respectively, strategic planning should aim to seamlessly integrate these areas into the existing urban fabric to facilitate connectivity and accessibility. For bridge areas, improving infrastructure that promotes safe and efficient movement between different urban zones, such as pedestrian bridges, cycle paths and public transport corridors, can improve connectivity. In branch areas where sprawl is evident, land use planning should focus on controlled expansion to prevent uncontrolled growth. This could include land use regulations that encourage mixed use, preserve natural habitats and agricultural land to prevent uncontrolled sprawl, and establish green buffer zones to maintain ecological balance. In the case of the Loop and Islet categories, with modest increases of 0.17 km^2/year and 0.11 km^2/year, respectively, the focus should be on integrating these features into the urban landscape as unique elements that enhance the character of the city and biodiversity. For loops, the creation of recreational and green spaces that encourage community interaction and biodiversity conservation within these enclosed areas can improve urban quality of life. Islands, as emerging urban fragments, should be developed with a focus on sustainability and innovation, potentially serving as hubs for smart city initiatives, community gardens or renewable energy projects. These strategies should be underpinned by comprehensive planning, stakeholder engagement and environmental assessment to ensure they make a positive contribution to Abha's urban ecosystem and the wellbeing of its residents.

4. Discussion

In this study, we conducted a comprehensive analysis of LULC dynamics and quantified urban growth using MSPA in a cloud computing platform, spanning from 1990 to 2020. Our research applied advanced cloud computing technologies to assess changes in land cover and urban expansion. The reliability of our LULC classification, affirmed by robust kappa coefficient values, shows high consistency over the years. We observed significant increases in built-up areas and declines in water bodies, indicating a notable shift in vegetation patterns during the study period.

Similar to the findings by Zhang *et al.* (2024), who optimized ecological networks in arid regions using MSPA-MCR, our study enhances understanding of urban ecological frameworks by integrating MSPA to assess urban growth patterns. Our approach aligns with Liu *et al.* (2024a, b), who enhanced the MSPA method to include ecological sensitivity, by using cloud computing to improve MSPA's capability in identifying critical ecological and urban areas. Li *et al.* (2024) and Jiang *et al.* (2024) discuss the synergy in ecological networks and heat exposure mitigation in urbanized areas, respectively. These studies, together with our findings, highlight the urgent need for methodologies that integrate environmental and urban planning to sustainably manage urban sprawl and its ecological impacts. Our work adds to this discussion by providing quantitative measures of LULC changes, leveraging cloud computing for improved data processing and analysis efficiency. Additionally, the novel use of Google Earth Engine and Google Colab in our study has revolutionized the process of LULC classification and trend analysis. As highlighted by Talukdar *et al.* (2020) and Mallick *et al.* (2021) in their reviews and novel classifier improvements for satellite observations, our application of these platforms facilitated detailed classification and real-time analysis, offering a robust framework for evaluating urban and environmental changes. Our methodology uniquely integrates Google Earth Engine for detailed land cover classification and Google Colab for conducting complex calculations necessary for trend analysis and MSPA. This methodological innovation is crucial for understanding urban forms and structures, similar to Ding *et al.* (2024), who analysed habitat isolation using an ecological network approach. Our findings contribute to both the academic understanding of LULC dynamics and the strategic goals of Saudi Vision 2030, promoting sustainable development strategies that balance economic growth with environmental protection.

By leveraging advanced technologies and analytical methods, our study supports the vision for a more sustainable and resilient urban future, aligning with the digital transformation objectives of Saudi Arabia. This integration not only highlights the novelty of our research but also positions it as a significant contributor to the field of urban LULC analysis, offering actionable insights for other regions experiencing similar rapid urban transformations.

5. Conclusion

This study conducted a detailed analysis of Land Use and Land Cover (LULC) changes in Abha City, Saudi Arabia, from 1990 to 2020 using Support Vector Machine (SVM) classification within the Google Earth Engine and Morphological Spatial Pattern Analysis (MSPA) in Google Colab. Quantitatively, the study documented a significant urban expansion with built-up areas growing from 62.46 km^2 in 1990 to 271.45 km^2 in 2020, representing a more than fourfold increase. Concurrently, water bodies witnessed a notable reduction, shrinking from 1.36 km^2 to 0.52 km^2 during the same period. MSPA further revealed a substantial transformation in urban structure, with urban core areas increasing from 41.66 km^2 in 2001 to 194.97 km^2 in 2021. This quantification of urban densification underscores the ecological and urban pressures from expanding city boundaries. These findings are crucial for sustainable urban planning and environmental management and are in line with the goals of the Saudi Vision 2030 for sustainable development and urbanisation. The significance of this work lies in the innovative integration of cloud computing and machine learning for detailed temporal and spatial environmental analysis. It offers valuable insights into the impact of urbanisation on the natural landscape and provides a methodological framework for similar studies in other regions. However, the study encountered limitations, such as the potential for misclassification in the SVM and dependence on available satellite imagery, which could affect the accuracy of historical LULC assessments. Future research should focus on incorporating more diverse data sources, such as drone imagery and ground data, to improve classification accuracy and depth. Longitudinal studies could extend the analysis to predict future changes in LULC under different scenarios of urban planning and climate change. Encouragingly, the methodology and results of this study provide a solid foundation for other researchers advocating the use of advanced technologies in environmental monitoring and urban planning. The research highlights the need for continuous and detailed LULC analysis to support sustainable development initiatives, especially in rapidly urbanising regions such as Abha City.

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Supplementary file

The supplementary material for this article can be found online.

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