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THE USE OF REMOTE SENSING TECHNIQUES FOR MODELING AND ANALYSIS OF THE URBAN EXPANSION OF AIN SALAH CITY IN THE ALGERIAN SAHARA BETWEEN 2000- 2023

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Abstract: This study examines the urban expansion of Ain Salah City in Algeria between 2000 and 2023 using remote sensing techniques and data. The analysis reveals significant changes in land use patterns, with rapid urbanization and infrastructure development driven by population growth, economic development, and infrastructure improvements. The study employed satellite imagery and geographic information systems (GIS) to detect urban sprawl and analyze the environmental impacts of urbanization. The results show that the city center has undergone significant changes, with more built-up areas and infrastructure emerging. The study's findings have implications for urban planning and management, highlighting the need for sustainable urban development strategies to address concerns about traffic congestion, waste management, and public health issues. The study's use of machine learning algorithms and high-resolution satellite imagery provides valuable insights into the dynamics of urbanization in arid environments and can inform future urban planning and sustainable development strategies in similar regions.

Keywords: remote sensing techniques, modeling, urban expansion, Ain Salah city

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INTRODUCTION

The world has witnessed rapid urban expansion in recent decades, driven primarily by a large influx of people migrating to cities in search of better economic opportunities, improved living conditions, and access to services.

Zhong (2023) highlights that this trend is not limited to Ain Salah but is a global phenomenon affecting cities across various continents. As populations continue to grow, urban centers like Ain Salah must adapt to the challenges posed by climate change, resource management, and sustainable development. Ain Salah is a city that embodies the complex relationship between geology, climate and urbanization. Its unique characteristics are shaped by the interplay of natural processes and human activity, making it a fascinating subject for scientific exploration and study. Understanding these dynamics is essential for developing effective strategies to address the challenges faced by urban areas in arid environments. The results of the study show the performance of the GEE platform in detecting urban sprawl in the city of Ain Salah.

The GEE platform can serve as a facilitative tool for deriving lessons from urbanization experiences to inform policymaking (Okan Yılmaz, 2024). The GEE platform enables the management and analysis of Earth observation big data, providing free access to numerous satellite images in the cloud. It also allows these images to be exported and used via APIs for various programming languages (Tamiminia et al., 2020). The capability of remote sensing technology to gather extensive data quickly presents significant opportunities for delivering precise and detailed energy demand evaluations in urban regions (Arunim et al., 2024). Unsupervised change detection methods in remote sensing have attracted considerable interest because they can identify changes on the Earth's surface without the need for ground truth data (Bipin et al., 2024).

Our planet is experiencing an extraordinary pace of urbanization, with over half of the global population currently living in urban areas. This figure is expected to rise to 68% by 2050 (Anand et al., 2024; United Nations, 2018). Ain Salah City, a vibrant urban center located in the heart of the desert, exemplifies this trend. Developed surfaces such as roads, buildings, and parking lots are prominent characteristics of urban areas (Tian et al., 2018; Rajveer et al., 2022; Weng, 2008). The world has witnessed rapid urban expansion, largely driven by a significant influx of people migrating to cities in search of better economic opportunities and improved living conditions (Zhong et al., 2023). In recent years, Ain Salah has experienced notable urban development. The construction of rads, buildings, and parking lots has become a defining feature of its urban landscape. These developments are crucial for facilitating transportation, commerce, and daily activities within the city. Research by Tian et al. (2018), Rajveer et al. (2022), and Weng (2008) underscores that such expansion is often accompanied by significant changes in land use and environmental impacts.

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The transformation of natural landscapes into urbanized areas can alter local climate patterns, contributing to phenomena such as the urban heat island effect, where built-up areas become significantly warmer than their rural surroundings (Ahmed Amine et al., 2023; Bouhennache et al., 2019; Bouzekri et al., 2015). This trend of rapid urban expansion is not confined to Ain Salah but reflects a global phenomenon affecting cities across various continents (Zhong, 2023; Zha et al., 2003; Zhong et al., 2023; Zha et al., 2003). As populations continue to grow, urban centers like Ain Salah face the dual challenges of adapting to climate change and managing resources sustainably. The city's unique characteristics, shaped by the interplay of natural processes and human activities, make it a compelling subject for scientific study. Understanding these dynamics is crucial for developing effective strategies to address the challenges posed by urbanization in arid environments (Hachemi and Benkouider, 2023; Dib et al., 2020).

The application of remote sensing in urban studies not only enhances our understanding of spatial dynamics but also aids in the formulation of effective urban policies" (Johnson et al 2023). The integration of remote sensing data with machine learning algorithms has revolutionized our understanding of urban expansion patterns, allowing for more accurate predictive modeling (Smith et al., 2024). Remote sensing techniques provide a unique vantage point for analyzing urban growth, enabling researchers to monitor changes over time with unprecedented details (Lee et al., 2024). The application of satellite imagery in urban studies not only enhances our analytical capabilities but also supports sustainable urban planning initiatives (Garcia and Patel, 2024). Remote sensing has revolutionized our capacity to monitor urban growth through the provision of high-resolution, multi-temporal imagery. Techniques such as sparse-constrained adaptive structure consistency have been successfully employed to facilitate change detection in remote sensing images, enabling precise identification of spatial changes over time (Sun et al., 2011).

This technique not only enhances change detection accuracy but also allows for the detection of gradual transformations within heterogeneous landscapes. One of the critical advancements in remote sensing is the development of soft change detection techniques, which enable the extraction of meaningful changes in optical satellite images with improved accuracy (Luo and Li, 2011). These techniques allow for more nuanced analyses by addressing uncertainties in change identification, making them particularly valuable for urban studies in heterogeneous environments. Applying such methodologies to Ain Salah City will enhance our understanding of the patterns and drivers of urban expansion in this unique desert context.

Recent studies have advanced our methodologies for continuous change detection, utilizing multi-source heterogeneous satellite image time series to track various alterations, including urban sprawl (Wang et al., 2023). Such approaches are crucial for cities like Ain Salah, where understanding the nuances of land coverage and urban morphology is essential for effective management and urban planning. Additionally, unsupervised change detection methods, such as those employing local gradual descent algorithms, have been introduced to address the challenges of extracting valuable insights from satellite imagery (Yandgin, 2012). These innovative strategies enable researchers to operate without the need for extensive training data, thus making them adaptable for diverse urban contexts.

The integration of these techniques culminates in the development of robust processes for change detection, including sparse-constrained adaptive structure consistency-based unsupervised image regression (Sun et al., 2022). This approach not only refines the detection of changes but also enhances the interpretability of results, allowing for a clearer understanding of urbanization patterns. The performance of the Google Earth Engine (GEE) platform in detecting urban sprawl in Ain Salah highlights its potential as a valuable tool for deriving insights from urbanization experiences and informing policymaking (Okan, 2024). The GEE platform facilitates the management and analysis of Earth observation big data, providing free access to numerous satellite images and allowing for their export and use via APIs for various programming languages (Tamiminia et al., 2020). The capability of remote sensing technology to rapidly gather and analyze extensive data presents significant opportunities for precise evaluations of energy demand and environmental impacts in urban regions (Anand et al., 2024; Lu et al., 2014; Ramadhan et al., 2022). Unsupervised change detection methods in remote sensing have garnered considerable interest due to their ability to identify changes on the Earth's surface without requiring ground truth data (Shah, 2024; Waqar et al., 2012; Benkouider et al., 2019). In summary, Ain Salah embodies the complex relationship between urbanization and environmental change, emphasizing the need for advanced remote sensing technologies to navigate the challenges posed by rapid urban expansion.

MATERIALS AND METHODS

1. Study Area

Ain Salah, a newly established province in Algeria, has been chosen as a model for studying urban expansion due to several compelling reasons. Firstly, as a new province, it is expected to undergo significant developmental projects and the construction of new buildings, providing a unique opportunity to observe and analyze urban growth from its inception. Additionally, Ain Salah has a strategic geographical location (Figure 1), connecting four major provinces in Algeria (Tamanrassand, Ouargla, Timimoun, El Menia), making it a critical hub for regional connectivity and development. This positioning not only enhances its importance but also offers a diverse range of urban planning challenges and opportunities, making it an ideal case study for urban expansion.

2. Data acquisition

Satellite images of Landsat 7, and Landsat 8 (OLI) with surface reflectance was the primary data source for this study. The Landsat data circa 1999 was sourced from the Landsat 7 Enhanced Thematic Mapper Plus (ANDM+) satellite, while data for 2023 were obtained from the Landsat 8 Operational Land Imager (OLI) satellite. In addition, reference data used in this study were in very high spatial resolution (15–30 cm) satellite imagery for 2023 was available from Google Earth Pro software. From this reference data, some data were used as training samples in the Landsat image classification process, while the rest were used for validation. A total of 2278 training features were processed for this study. As ancillary data, this study used administrative boundaries vector maps from The GADM database (https://gadm.org/).

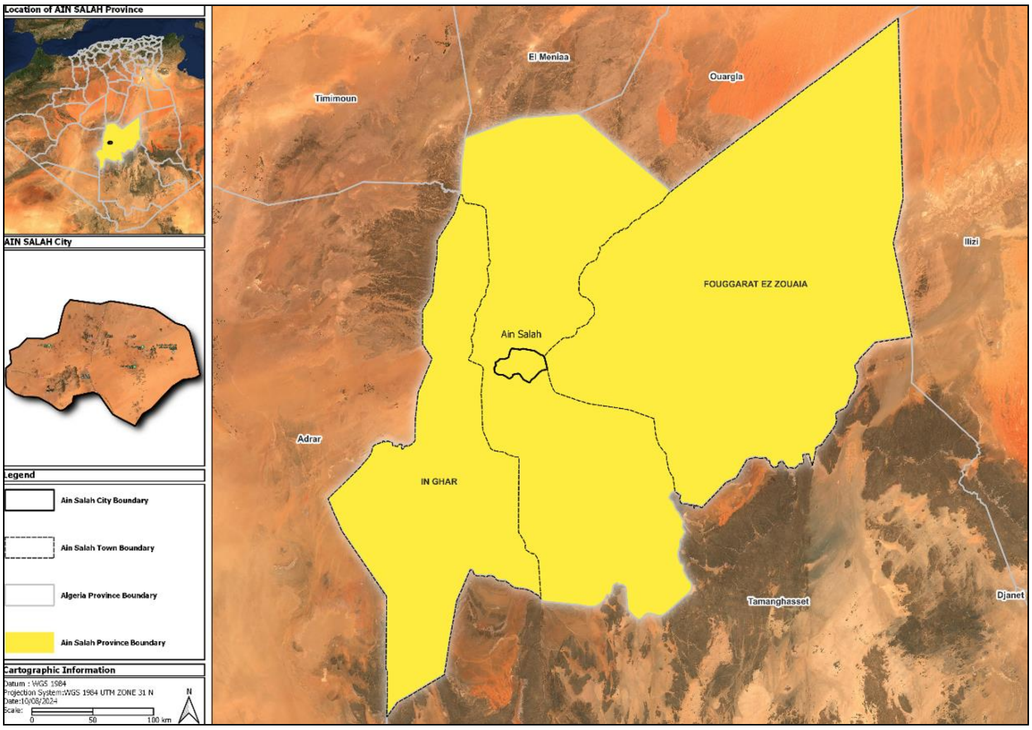

Figure 2. Study area (Source: GADM database, realized by authors)

3. Method

The workflow used in this study is depicted in Figure 2.

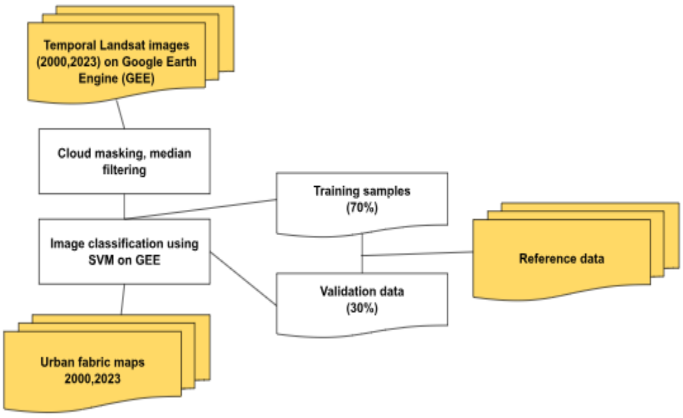

Figure 2. Methods used

3.1. Image Classification on Google Earth Engine (GEE)

The study utilized Landsat images from the google earth engine (GEE) database (Figure 3), specifically surface reflectance (SR) products. The data was selected from Landsat 7 ANDM+ for circa 2000, and from Landsat 8 OLI for 2013 and 2020. To ensure accuracy, cloud-free pixels were identified using the cloud masking function. The study focused on visible (VIS), near-infrared (NIR), and short-wave infrared (SWIR) bands, all with a spatial resolution of 30 meanders. A median filter was applied to obtain representative pixels for each location and spectral band from each year. To enhance the accuracy of image classification results, the 2000 and 2023 Landsat data bundles were combined with high-resolution satellite imagery data from the corresponding years and then clipped to the study area (city of Ain Salah).

The reference data were then prepared, with 70% being used as training samples to classify the Landsat images for 2000 and 2023 and the remainder being used to validate the image classification results. The reference data were distributed at random points generated from the high-resolution satellite imagery. These points represented the five land use/land cover categories addressed in our study area: (1) agriculture (farms, palm, fields), (2) built-up (settlements, industrial areas), (3) strand (4) water bodies (rivers, lakes, canals, and others) and (5) others (bare ground, others). Points were distributed across the study area, with a total number of 2278 points taken from each data year (Figure 4)

Before use, the data were visually checked using historical high-resolution images from Google Earth Pro. The training samples were used to classify the Landsat images using the support vector machine (SVM) algorithm, resulting in land use/land cover (LULC) maps for 2000 and 2023. The SVM classification results were then refined through post-processing techniques, which included a weighted smoothing process using a 3x3 moving window to remove noise and manually editing misclassified areas to produce final, accurate LULC maps. Accuracy assessment was performed for each of the LULC maps individually. To validate the accuracy, a random sample of 30% of the reference data was used. An error matrix was utilized to calculate the overall accuracy values for each LULC map, specifically for the years 2000 and 2023.

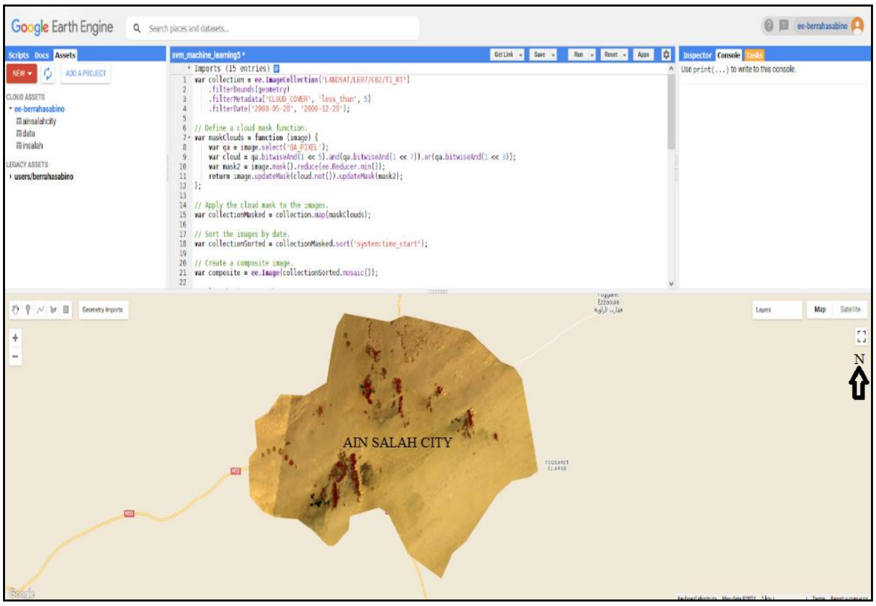

Figure 3. Satellite imagery data (Source: GEE database, realized by authors)

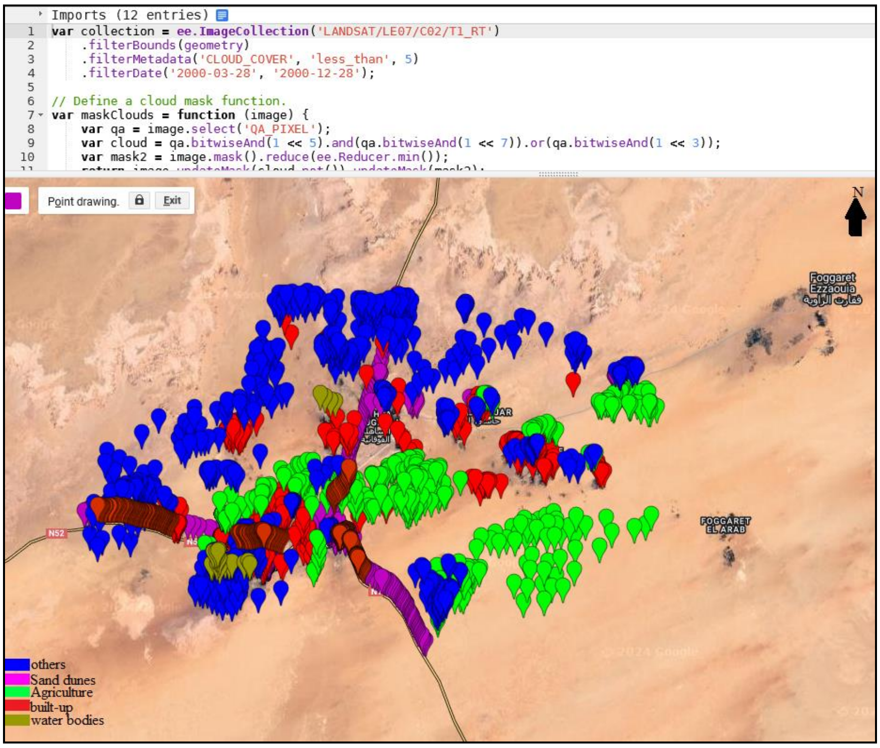

Figure 4. Training samples

3.2. Urban fabric Analysis

The machine learning approach aims to extract the urban fabric patterns of the city using Support Vector Machine (SVM) classification. This method involves collecting high-resolution satellite imagery, preprocessing the data, and extracting relevant features such as spectral features.

The extracted features are then used to train an SVM classifier on labeled data and urban fabric classes, including residential, commercial, and industrial spaces. The trained classifier is then applied to the preprocessed image data to classify each pixel into one of the urban fabric classes using the following equation (Cortes et al., 1995).

$$\mathbf{f(x) = sign(\sum \alpha i * K(x, xi) + b)}$$

where f(x) is the predicted class label, αi are the Lagrange multipliers, K(x, xi) is the kernel function, and b is the bias term (Cortes et al., 1995).

The kernel function is commonly associated with the Radial Basis Function (RBF) kernel, which is widely used in SVM literature but does not have a single author. It is a standard formulation in the context of SVMs used is defined as:

$$\mathbf{K(x, x\_i) = exp(-\gamma \|x - x\_i\|\text{^}2)}$$

where: γ is a hyperparameter that controls the width of the RBF; ||x - x_i||^2 is the squared Euclidean distance between the input vector x and the training vector xi

RESULTS

1.Urban fabric Maps and Patterns

Feature maps of the study area showing distribution of urban fabric in each urban cluster for the years 2000 and 2023. The maps were created from the Landsat image classifications using the SVM algorithm provided on GEE. The accuracy assessment results for these three maps show an overall accuracy of 87% and 88% for 2000 and 2023, respectively. The urban expansion of Ain Salah City center has markedly extended north and south, while growth towards the west and east has been limited (Figure 5). This is due to the presence of old private oasis lands to the west, which restrict urban development, and dense sand dunes to the east, which are challenging to remove. As a result, the city has developed predominantly in a linear pattern along the north-south axis, closely following National Road N°01. According to the study results, the built-up area in the city center was estimated to be 138.19 hectares in the year 2000, and it increased to 334.18 hectares by the year 2023, showing a difference of 196 hectares (Figure 11). This significant expansion indicates a substantial growth in urban development over the 23-year period, reflecting increased urbanization and potentially higher demand for infrastructure and services within the city center. The expansion could be attributed to factors such as population growth, economic development, or changes in land use policies, highlighting the dynamic nature of urban planning and the need for strategic management to accommodate this growth.

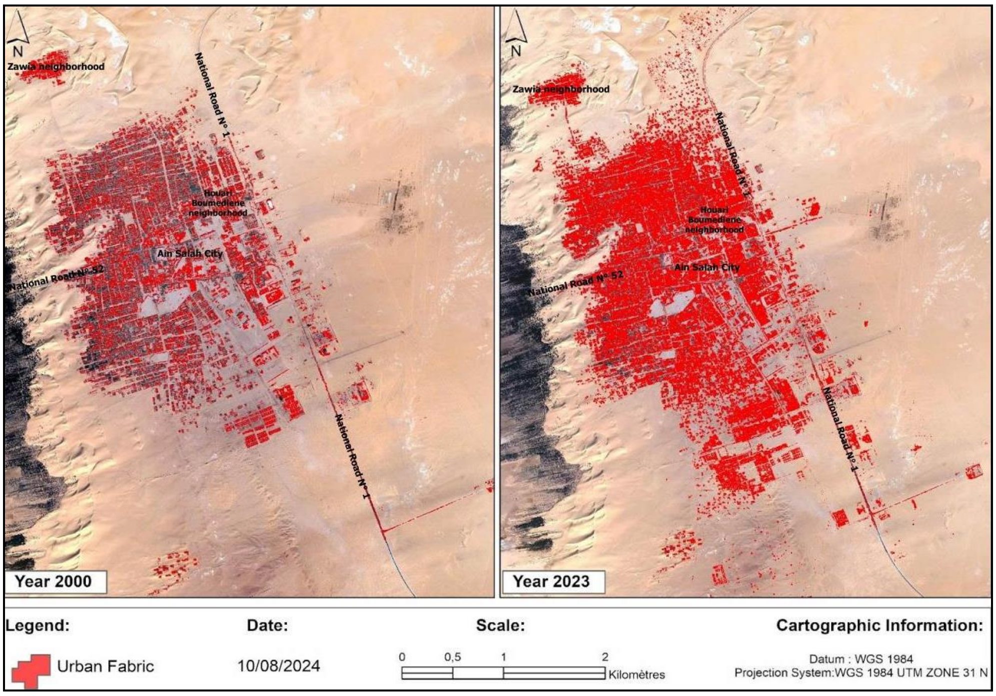

Figure 5. Urban expansion result 2000-2023, City center - AIN SALAH (Source: Output Raster from GEE, realized by authors)

The results from the Hassi El-Hjar settlement (Figure 6) show that the expansion pattern is divided into two parts: east and west. This division is due to the presence of oases in the central area of the settlement, which has posed a barrier to expansion. In the eastern part, urban expansion initially occurred, but due to the surrounding palm oases, more buildings began to emerge in the western part of the settlement. Consequently, urban growth has shifted towards the west.

According to the study results, the built-up area in the Hassi El-Hjar urban cluster was estimated to be 5.96 hectares in the year 2000, and it increased to 10.48 hectares by the year 2023, showing a difference of 4.52 hectares (Figure 11). This growth highlights a moderate expansion in urban development over the 23-year period. The increase of approximately 4.52 hectares reflects gradual but steady urbanization, suggesting a growing demand for residential or commercial space. The moderate expansion could be indicative of controlled development, which was influenced by geographic constraints such as the central oases that limit growth in certain directions. This pattern of development points to a strategic expansion towards areas with fewer obstacles, revealing a tendency for urban sprawl to adapt to environmental and spatial constraints.

The results from the El-Baraka settlements indicate that the expansion pattern is directed towards the north, south and east, but not west (Figure 7). This is due to the presence of oases to the west of the settlement, which hinders expansion in that direction. Additionally, the proximity to the city center in the east makes it an attractive area for growth. As a result, the city center is likely to be a key factor driving the settlement's expansion towards the east. According to the study results, the built-up area in the El-Baraka urban cluster was estimated to be 21.95 hectares in the year 2000, and it increased to 25.88 hectares by the year 2023, showing a difference of 3.93 hectares (Figure 11). This relatively moderate growth suggests a steady but controlled expansion over the 23-year period. The increase of approximately 3.93 hectares reflects ongoing urban development, potentially influenced by geographic and infrastructural constraints, such as the presence of oases to the west and proximity to the city center. These factors have directed the expansion towards the north, south and east, with the city center acting as a significant attraction for further growth.

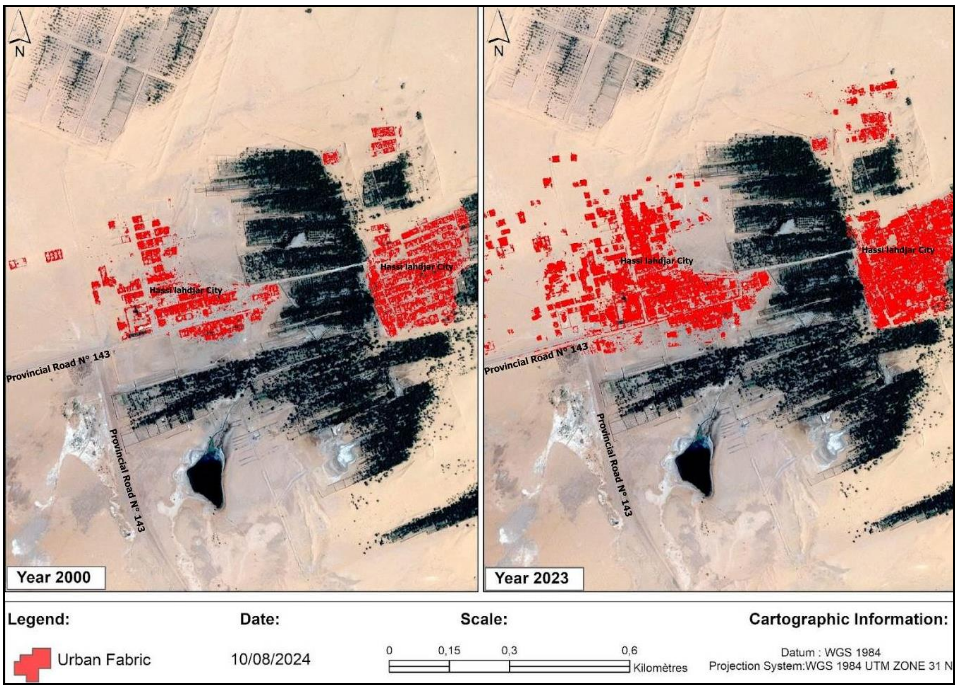

Figure 6. Urban expansion result 2000-2023, Hassi Lahdjar-AIN SALAH (Source: Output Raster from GEE, realized by authors)

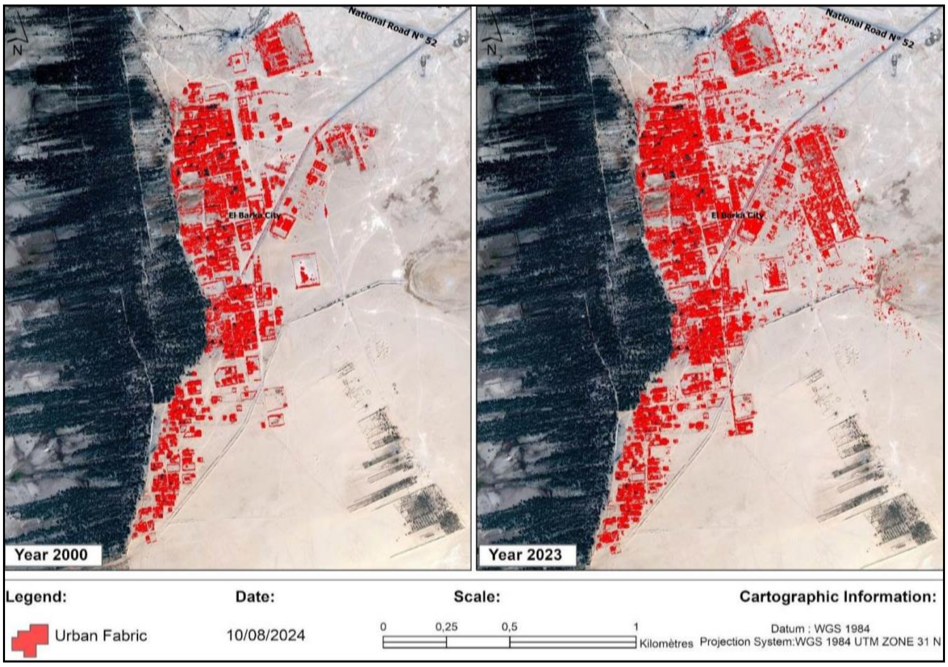

Figure 7. Urban expansion result 2000-2023, El Barka-AIN SALAH (Source: Output Raster from GEE, realized by authors)

The results indicate that the expansion of the Sahela Tahtania Est settlement has been directed towards the northeast and west, while avoiding the center and south (Figure 8). This is due to the presence of oases in the central and southern areas of the settlement, which have influenced the nature of the expansion by limiting growth in those directions. According to the study results, the built-up area in the Sahela Tahtania EST urban cluster was estimated to be 42.83 hectares in the year 2000, and it increased to 140.37 hectares by the year 2023, showing a difference of 97.54 hectares (Figure 11). This substantial increase in built-up area indicates a significant expansion of the urban cluster over the 23-year period. The growth of approximately 97.54 hectares reflects a high rate of urban development and urban sprawl, suggesting robust economic growth, rising population, or changes in land use policies. The dramatic increase also highlights the urban cluster's ability to accommodate growing demands for residential, commercial, or industrial spaces. This rapid expansion may necessitate enhanced infrastructure and urban planning to manage the growth effectively and ensure sustainable development in the future.

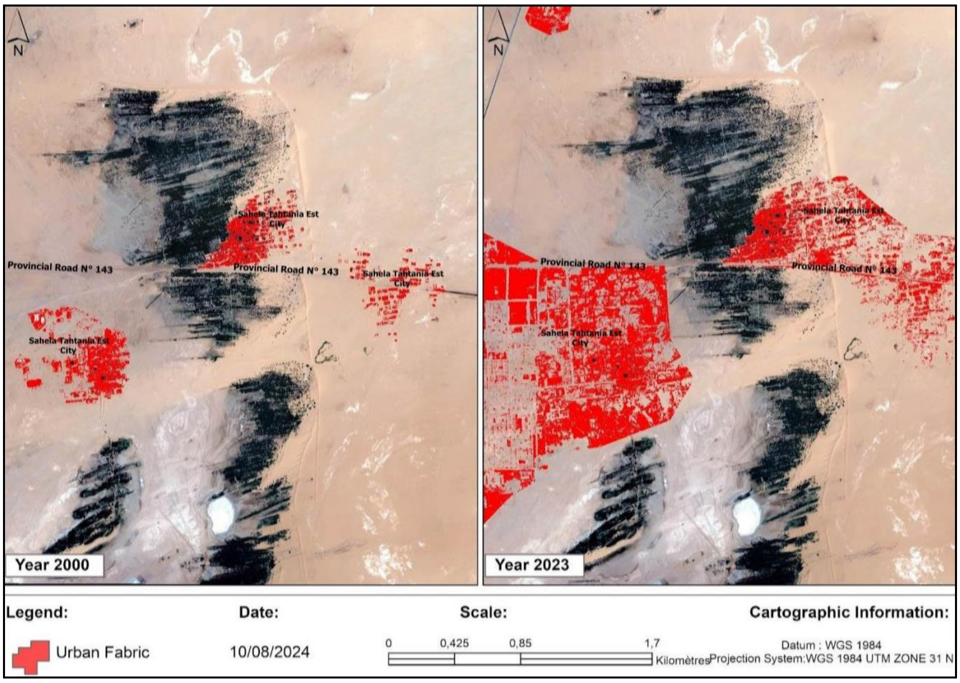

Figure 8. Urban expansion result 2000-2023, Sahela Tahtania Est-AIN SALAH (Source: Output Raster from GEE, realized by authors)

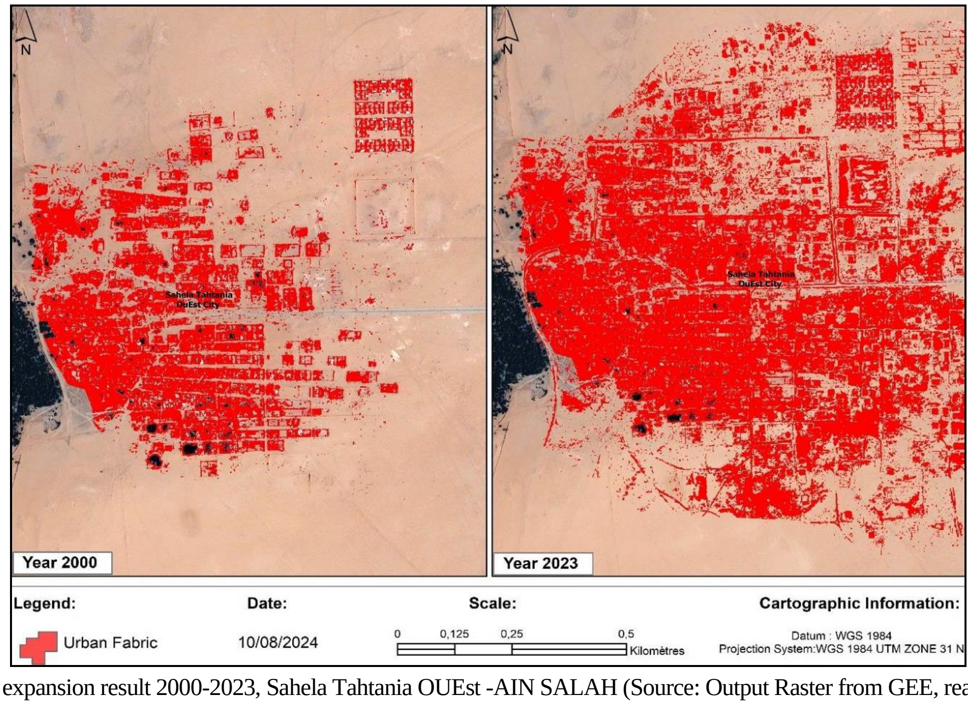

Figure 9. Urban expansion result 2000-2023, Sahela Tahtania OUEst -AIN SALAH (Source: Output Raster from GEE, realized by authors)

The results indicate that the expansion of the Sahela Tahtania ouEst settlement has been directed towards the northeast and south, while avoiding the west (Figure 9). This pattern is due to the presence of oases to the west of the settlemet, which has influenced the nature of the expansion. As a result, growth has primarily occurred towards the east, following the main road and extending to the settlement's periphery. According to the study results, the built-up area in the Sahela Tahtania ouEst urban cluster was estimated to be 22.76 hectares in the year 2000, and it increased to 48.85 hectares by the year 2023, showing a difference of 26.09 hectares (Figure 11). This increase indicates a substantial growth in the urban area over the 23-year period. The expansion of approximately 26.09 hectares reflects a notable rise in urban development, suggesting a significant demand for space and potentially driven by population growth or economic factors. The expansion trend, directed towards the northeast and south while avoiding the west due to the presence of oases, underscores the impact of geographic constraints on urban growth patterns. This considerable growth may necessitate further investment in infrastructure and urban planning to accommodate the increasing population and ensure sustainable development in the future.

The urban expansion of Igostene has markedly extended north and south, while growth towards the west and east has been limited (Figure 10). This is due to the presence of old private oasis lands in those parts which restrict urban development. According to the study results, the built-up area in the Igostene urban cluster was estimated to be 17.50 hectares in the year 2000, and it increased to 27.57 hectars by the year 2023, showing a difference of 10.07 hectares (Figure 11). This growth highlights a moderate expansion in urban development over the 23-year period. The increase of approximately 4.52 hectares reflects gradual but steady urbanization, suggesting a growing demand for residential or commercial space. towards areas with fewer obstacles, revealing a tendency for urban sprawl to adapt to environmental and spatial constraints.

The study's findings highlight the rapid expansion of built-up areas in the Ain Salah urban cluster, which is consistent with the rapid urbanization trend in many parts of Africa. The increasing urbanization has led to changes in land use patterns, with more commercial and industrial areas emerging, and a decrease in agricultural and open spaces.

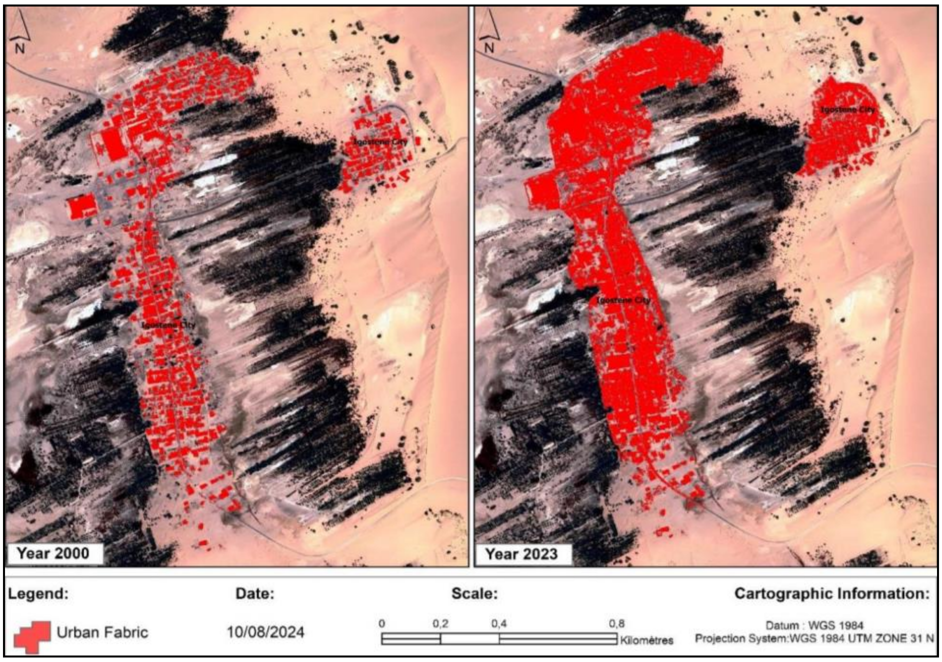

Figure 10. Urban expansion result 2000-2023, Igostene - AIN SALAH Source: output Raster from GEE, realized by Ali SAIDOU

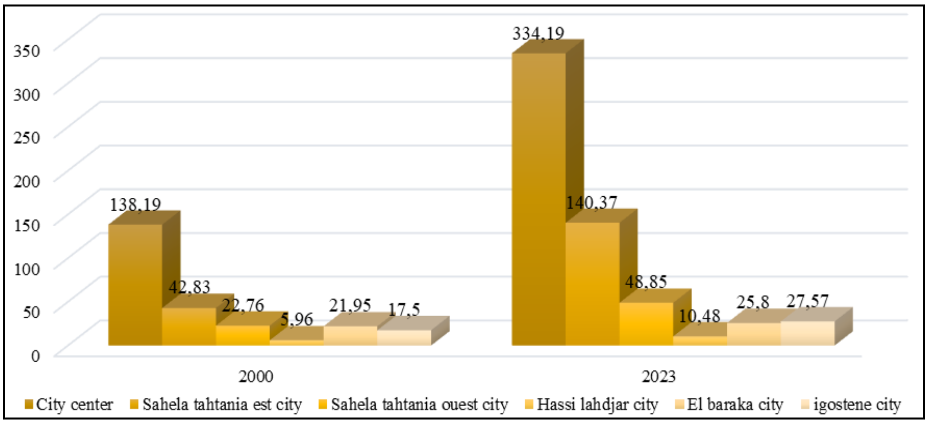

Figure 11. Evolution of built-up area from 2000-2023

CONCLUSION

In conclusion, this study demonstrates the effectiveness of remote sensing techniques and data in modeling and analyzing the urban expansion of Ain Salah City in the Algerian Sahara between 2000 and 2023. The findings highlight the significant changes in land use patterns, with a rapid increase in built-up areas and infrastructure development, driven by population growth, economic development, and infrastructure improvements. The results of this study provide valuable insights into the dynamics of urbanization in arid environments and contribute to a better understanding of urban development in similar regions. The study's use of machine learning algorithms and high-resolution satellite imagery enabled the classification of land use/land cover categories, including urban fabric patterns, with an overall accuracy of 87% and 88% for 2000 and 2023, respectively. The results show that the city center has undergone significant changes, with more built-up areas and infrastructure emerging, and the existing urban areas have become more densely populated.

The study's findings have implications for urban planning and management in Ain Salah City, highlighting the need for sustainable urban development strategies to address concerns about traffic congestion, waste management, and public health issues. The limitations of the study, including the use of satellite imagery and Landsat data, are acknowledged, but the study's results demonstrate the potential of remote sensing techniques for analyzing urban expansion and development.

Overall, this study provides valuable insights into the changes in urban fabric patterns over time and highlights the importance of using machine learning algorithms and high-resolution satellite imagery to analyze urban development. The study's findings can inform future urban planning and sustainable development strategies in Ain Salah City and similar regions, promoting sustainable urban development and ensuring the well-being of urban residents.

Author Contributions: Conceptualization, A.S. and S.M.; methodology, A.S. and S.M; software, S.A.; validation, S.A. and S,M; formal analysis, A.S. and S.M; investigation, A.S. and S.M; data curation, A.S. and S.M and S.B.; writing - original draft preparation, A.S.; writing - review and editing, A.S.; visualization, A.S.; supervision, A.S. and S.M.; project administration, A.S. All authors have read and agreed to the published version of the manuscript.

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