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A novel building metric for PlanetScope® data optimization

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PlanetScope® data are being widely used by the scientific community in addressing important environmental issues, including cropland and tree cover loss, burned area mapping post-wildfire, imagery for river water masking, and snow-covered area mapping. However, building indices' applications on PlanetScope data for use in separating blocks and to identify the difference between altered/unaltered constructed areas are not available, primarily due to the absence of the Short-Wave Infrared (SWIR) band. In this research, three types of remote sensing data series are employed, namely, PlanetScope images, Sentinel-2A data, and Google Earth Pro data, to separate the blocks and to capture the differences between damaged and undamaged blocks in the Khan Younis town of the Gaza Strip, utilizing a novel building metric purposely developed to be used with PlanetScope data. Additionally, three change detection methodologies are utilized to assess the efficacy of the new metric, namely, image differencing, Principal Component Analysis (PCA), and metrics, including the one proposed in this paper. The proposed metric exhibited high performance with the PlanetScope data compared to Sentinel-2A data. The results of the three methodologies indicate a strong correlation, with an R-value of 0.793,263 and a P-value of 0.0002456. The average sizes of the affected areas, derived from PlanetScope data from October 2023 to April 2024, are 0, 0.05, 2.4, 2.9, 5.2, 12.8, and 13.1 km². The Sentinel data from October to January shows that the average sizes of the devastated regions are 0, 0.9, 2.1, and 7 km², while the rest of the data series was concealed and unavailable by Google Earth Engine (GEE). The accuracy assessment test conducted with the Google Earth Pro scenes to evaluate the strength of the metric showed a considerably strong percentage of compatibility with PlanetScope data. The new proposed building metric yields results that are very close to the other techniques adopted, with slight variations but clearer visual outputs.

KEYWORDS

building metric NBM, change detection, Google Earth Pro®, PlanetScope imagery, remote sensing

1 Introduction

Planet Labs PBC®, based in San Francisco, CA, USA, has developed and launched compact satellites that are more efficient in their construction and deployment compared to traditional satellites. Companies are continually enhancing these satellites' capabilities to compete in collecting high spatial-temporal resolution Earth observations and delivering accurately calibrated geometric and radiometric data (Frazier and Hemingway, 2021; Huang and Roy, 2021). The PlanetScope satellites (PS) follow low-Earth, sun-synchronous orbits at altitudes between 450 and 580 km, capturing nearly vertical images of the Earth's entire land

surface daily. The data's geographic resolution ranges from 3.123 to 4.1 m, with a 12-bit radiometric resolution. The PlanetScope constellation comprises three generations: Dove Classic, Dove-R, and Super-Doves, each consisting of multiple "flocks" of satellites launched and positioned in similar orbits simultaneously (Frazier and Hemingway, 2021). Over 200 Dove satellites can produce up to 200 million square kilometers of PlanetScope imagery daily, with the ability to revisit any location. The original Dove satellites, equipped with the PS2. SD sensor collected data in four spectral bands, while the newer Super Dove satellites, equipped with the PSB sensor, collect data in eight spectral bands. Both satellite types operate within the 430–890 nm wavelength spectrum (Huang and Roy, 2021).

PlanetScope data is widely disseminated across scientific groups, since it can be accessed through a user-friendly website that offers great precision in designating test sites and provides various measures with straightforward steps prior to downloading (Patnala et al., 2025; Wendleder et al., 2021). Consequently, the utilization of PlanetScope data has addressed numerous environmental issues in recent years. Several authors employed it to monitor vegetated regions (Andreatta et al., 2022; Lake et al., 2022); however, no index addresses building separation due to the absence of the Short-Wave Infrared (SWIR) band, as all building indices rely on this band. Consequently, the authors endeavored to create a metric that could enhance the efficacy of PlanetScope's data utilization and simplify the separation of the buildings from this source of data.

With many areas in the world in turmoil, remote sensing data plays a crucial role in retrieving information about the increase of destruction and damage in war-impacted areas, which are otherwise inaccessible (Wulder et al., 2016; Anson and Cummings, 1991; Kaplan et al., 2022; Daiyoub et al., 2023). Khan Younis in the Gaza Strip is such a severely affected town, and it has been selected to showcase the proposed remote-sensing-based methodology, as it is delineated below. Therefore, it was reasonable to apply the proposed technique on one of such severely impacted areas, as the buildings and residential blocks were exposed to several changes and gradual destruction. For the needs of this study, 14 PlanetScope scenes spanning from September 2023 to October 2024, with a 3 m resolution, were retrieved. The downloaded data showed a stable state from April 2024 to October 2024. Eight Planet Scope scenes with a 3 m resolution from September 2023 to April 2024, five Sentinel-2A images with a 10 m resolution from September 2023 to January 2024 were used, as the rest of the time series is masked by Google Earth Engine (GEE), and two scenes of historical Google Earth Pro images were utilized for the final accuracy assessment test. Three change detection techniques were employed for the calculation of the area destroyed on a monthly basis (Singh, 1989; Zhu, 2017). The results from the analysis of the two sources were subsequently used to assess how well each dataset can discriminate between damaged and undamaged blocks. Also, the effectiveness of a new proposed building metric was tested, confirming that for both datasets, this metric can be adopted for the separation of the buildings with a higher priority to PlanetScope data.

The primary aim of this study is to develop a novel building metric for application with PlanetScope data, which lacks the SWIR band, hence impeding the separation of buildings and the utilization

of existing building indices on such data. The primary aim is followed by the application of the proposed metric on the available Sentinel data to enhance comprehension of the metric's performance across both datasets. The metric was compared to several building separation strategies to enhance the understanding of its performance and reliability. The town of Khan Yunis in Gaza is used as a proof-of-concept case study.

In Section 2, an overview of the data utilized is given, and in Section 3, the methodology adopted is presented. The results are presented in Section 4, followed by a discussion in Section 5, and concluding remarks in Section 6.

2 Materials

2.1 Study area

This study focuses on the town of Khan Younis in Gaza Strip which has been severely ravaged by the war since October 2023 (Figure 1). Gaza is located in the north part of the Sinai Peninsula, is bordered to the north by the Mediterranean Sea and covers an area of 365 km². It is divided into five governorates: North Gaza, Gaza, Middle, Khan Younis, and Rafah, collectively being the home to a population of 2 million people. The town of Khan Younis, is located between 31.36233°N, 34.30973°E and 31.33038°N, 34.30786°E and is covering an area of 17.5 km². At the time of this study, the town had already suffered extensive structural devastation. The urban planning in this area is highly dense, with closely packed blocks and narrow streets compared to neighboring regions. Therefore, studying this site requires high-resolution data.

2.2 PlanetScope imagery

The PlanetScope SuperDove satellite constellation provides imagery composed of eight spectral bands. Of these, six bands are designed by Planet Labs to be broadly comparable to Sentinel-2 data, enabling multi-source analysis and integration. These bands include coastal blue, blue, green, yellow, red, and near-infrared (NIR), which correspond to commonly used Sentinel-2 bands for vegetation and urban studies. The remaining two bands, which are not directly comparable to Sentinel-2, provide additional spectral information that may enhance material discrimination. By leveraging the six Sentinel-compatible bands, the PlanetScope SuperDove imagery allows high-resolution mapping and monitoring of urban surfaces while maintaining consistency with widely used multispectral datasets (Pickering et al., 2021; Cho et al., 2022; Valman et al., 2024; John et al., 2022).

While PlanetScope SuperDove imagery differs slightly from Sentinel-2 in spectral configuration, the Red, Green, and NIR bands used in the proposed NBM index correspond closely to their Sentinel-2 equivalents, ensuring that the physical rationale of the index remains valid. To further ensure the reliability of our analysis, we specifically selected the PlanetScope bands corresponding to Sentinel-2, and comparative analysis was conducted to verify consistency between the datasets.

Fourteen Planet images at 3 m resolution from the Planet Explorer website were retrieved, using the product level-b Super Dove sensor (PSB.SD). From a preliminary examination of these

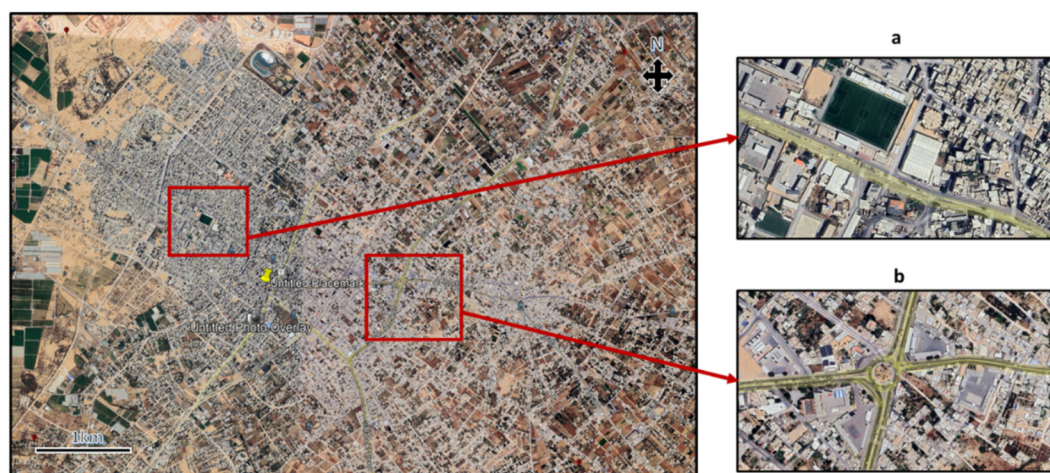


FIGURE 1
Satellite map showing Khan Younus 1 year before the war (Source: Google Earth Pro, 2022). The insets (a) and (b) on the right are enlargements of the squared parts of the image on the left demonstrating the very dense urban planning of the test site.

images, these demonstrated a stable state from April 2024 to October 2024. Therefore, in the present study only eight PlanetScope scenes with a 3 m resolution from September 2023 to April 2024 are utilized. The surface reflectance data across eight bands, includes one scene from September 2023, contemplated as a reference image (captured before the start of the war), and seven subsequent images from October 2023 to April 2024. These eight bands are: red, green, blue, near-infrared, red edge, green I, coastal blue, and yellow. The Super Dove sensor allows for mosaicking multiple images taken on the same day to cover larger areas and provides geometrically and radiometrically corrected imagery.

2.3 Sentinel-2A imagery

Using Google Earth Engine (GEE), five Sentinel images with 13 bands each at a spatial resolution of 10 m were retrieved. These scenes span the following dates: September 2023 (used as the reference scene), October 2023 November 2023, December 2023, and January 2024, each featuring a median scene. Imagery from February, March, and April were masked by the platform. More information on Sentinel data is provided by [Drusch et al. \(2012\)](#), [Gascon et al. \(2017\)](#), [Clerici et al. \(2017\)](#) and [Morsy et al., 2022](#).

2.4 Accuracy assessment data and software

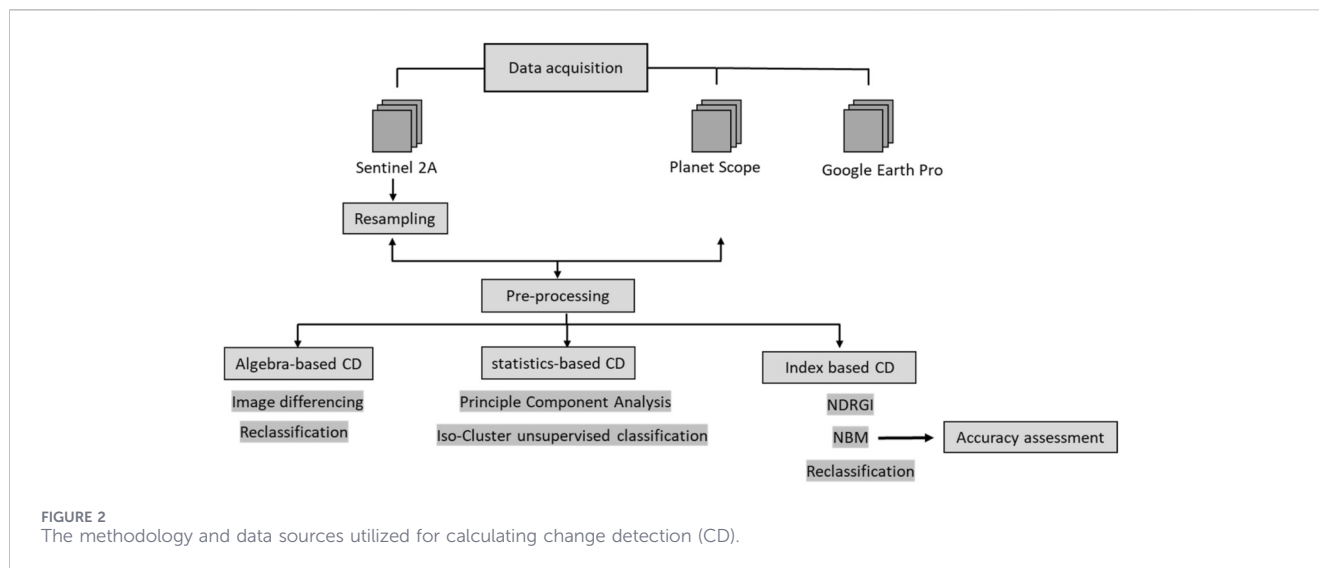
In order to accomplish the objective of the study, two historical Google Earth Pro Scenes were captured before and after the conflict for the accuracy assessment stage. Moreover, the data was acquired by utilizing Google Earth Engine (GEE), as well as PlanetScope Explorer. ArcGIS 10.8 and ArcGIS pro utilizes several work tools, including the image analysis tool, extract by mask tool, raster calculator, reclassification tool, Principal Component tool, and unsupervised iso-cluster classification tool. Subsequently, the statistics of the current work were conducted using RStudio and Excel.

3 Methodology

Data selection and acquisition were followed by a pre-processing step to prepare the dataset for the application of three different techniques. The data sources and the adopted methodology are graphically illustrated in [Figure 2](#). These three techniques were applied to detect built-up areas and the changes that occurred over a period of 7 months. Two of the techniques are widely used in the scientific community for various purposes ([Afify, 2011](#); [Kennedy et al., 2009](#); [Solomon et al., 2018](#)); therefore, we employed them to enable better understanding, comparison, and validation of the outcome of the novel index.

3.1 Data acquisition and resampling

The downloaded Sentinel-2A and PlanetScope images had been geometrically and radiometrically corrected by the platforms. The Sentinel data have been subsequently resampled to align with the 3m spatial resolution of PlanetScope data ([Figure 2](#)). The nearest adjacent resampling method has been adopted, which extracts the digital value from the original image pixel closest to the new pixel location in the corrected image. Discrete (categorical) raster data most commonly uses this fastest interpolation method, as it does not alter the pixel value. Nearest-neighbor resampling was applied solely to align pixel grids across datasets and does not modify the original Sentinel-2 radiometric values nor introduce new spatial information. Each 3 m pixel inherits the exact reflectance of its corresponding 10 m original pixel, thereby preserving the native information content of Sentinel-2. The objective of the analysis is not to extract fine-scale spatial detail from Sentinel-2, but to ensure consistent pixel-wise correspondence with the higher-resolution dataset. Downscaling all datasets to 10 m would instead introduce mixed-pixel effects and spatial averaging that could obscure sharp boundaries and reduce comparability at object edges, which are central to our analysis.



3.2 Data pre-processing

Image pre-processing is a crucial intermediate phase that is applied following the choice of the scenes with the best quality and least cloud coverage (Figure 2), and before implementing the change detection algorithm. Every pixel in the image must represent consistent measurements at the exact same location. The specified corrections encompass image registration, radiometric correction, and atmospheric correction (Khorram et al., 2013). Sentinel-2A products were used directly after downloading from Google Earth Engine (GEE). These products include atmospheric correction and quality assurance (QA) information (QA60 and Scene Classification Layer, SCL) for cloud, shadow, and snow detection. No additional masking or haze correction was applied beyond the default GEE product. The PlanetScope data (PS2.SD), however, was processed to surface reflectance using Planet's standard pipeline, and clouds, shadows, and unusable pixels were masked using the UDM2 quality flags, following recommended thresholds (clear = 1; cloud, shadow, or unusable = 0). To ensure the reliability of the data, we performed visual quality checks on all scenes to identify residual clouds, shadows, haze, or sensor artifacts, including the “white-black” artifacts known to occur in PlanetScope imagery. This workflow ensures that only high-quality pixels are included in subsequent analyses, while clearly distinguishing surface reflectance products from TOA imagery.

3.3 Image differencing

With Image Differencing, each pixel and band in two spatially registered images, recorded at different times, have their *DN* values subtracted (Misra et al., 2020), yielding a new image that reflects the temporal variations that have occurred (Figure 2) (Misra et al., 2020; Shaoqing and Lu, 2008):

$$Id(x, y) = I1(x, y) - I2(x, y) \quad (1)$$

where, *I1* and *I2* represent the values in the images taken at two different times, Equations 1, 2 respectively, and (*x, y*) are coordinates and *Id* represents difference image.

To monitor changes over the months of the war, each corrected PlanetScope image from October 2023 to April 2024 was compared with the reference image from September 2023. The comparison was made by subtracting the September image from each monthly image. Threshold values, based on standard deviations, were then calculated to separate changed pixels from unchanged ones. These pixels were counted, converted into areas, and compared across all months to track the extent of change. The same procedure was applied to Sentinel images. Finally, results from both datasets were compared to assess how closely they agree, identify differences, and evaluate the overall accuracy of the changes detected.

3.4 Principal component analysis (PCA)

PCA-based change detection has been a popular and widely utilized technique for many years. The process entails extracting the highest variations in a restricted set of perpendicular components by conducting an eigenvector analysis of the data's correlation matrix (Figure 2). This approach has become increasingly popular because of its straightforwardness and capacity to augment information regarding change (see Li and Yeh, 1998; Lu et al., 2008). The main idea behind PCA is to decrease the number of dimensions in a dataset that has many interrelated variables, while still retaining a substantial amount of the dataset's variability; this is achieved by transforming the data into a novel set of variables known as principal components (PCs). The PCs are independent and organized in a certain sequence, with the initial one's accounting for most of the observed variance in the original variables (Singh and Harrison, 1985; Fung and Ledrew, 1987; Eastman and Fulk, 1993). Consequently, the use PCA in ArcGIS turned all seven scenes acquired by the PlanetScope platform and the four scenes of Sentinel captured by GEE into new collections. Next, the iso-cluster unsupervised classification method is applied to extract the classes and identify the modified and unchanged portions of the test site.

3.5 Development of a building metric

The scientific community has employed various indices to differentiate certain information and characteristics from multispectral remote sensing data. The diverse interactions between Earth's materials and electromagnetic waves of different bands determine the fundamental concepts underpinning the indices. Every substance has a unique spectral signature, which indicates how it reflects and absorbs electromagnetic energy at different wavelengths. By analyzing these spectral features, we can differentiate between different compounds. We can examine remote sensing data to reveal hidden characteristics by employing mathematical techniques. Multiple published studies employ various indices, including vegetation index, building index, and water index, for the purpose of calculating change detection (Morsy et al., 2022; Estoque and Murayama, 2015; Polykretis et al., 2020). In the present study, in addition to the two methodologies outlined above, namely, the Image Differencing and the Principal Component Analysis, two metrics were tested for the purposes of this study. As the PlanetScope data do not include a SWIR band, all published building indices are inappropriate. An index that is compatible with PlanetScope data in distinguishing blocks from the surrounding features is the Normalized difference red green index, NDRGI (Yang et al., 2008):

$$\text{NDRGI} = \frac{\text{Red} - \text{Green}}{\text{Red} + \text{Green}} \quad (2)$$

A new metric is also proposed, by combining the red and green bands from the Normalized Difference Red-Green Index (NDRGI) and the infrared band from another index called the Urban Index (UI) (Ali et al., 2019; Kebede et al., 2022). This new metric allows for a more precise analysis of buildings and their environments using PlanetScope data (Equation 3), even in the absence of a Short-Wave Infrared (SWIR) band. The proposed metric termed the NIR-weighted Building Metric (NBM):

$$\text{NBM} = \frac{\text{Red} - \text{Green}}{\text{Red} + \text{Green}} * \text{NIR} \quad (3)$$

The proposed Normalized Building Material (NBM) index is formulated using the Red, Green, and Near-Infrared (NIR) bands based on their distinct spectral responses to urban materials and vegetation. Built-up surfaces such as concrete, asphalt, and rooftops generally exhibit higher reflectance in the Red band than in the Green band, whereas vegetation typically shows relatively higher reflectance in the Green band. Consequently, the normalized difference between the Red and Green bands enhances the spectral contrast between impervious surfaces and vegetated areas. Vegetation is also characterized by very high reflectance in the NIR region, while most urban construction materials exhibit comparatively moderate NIR reflectance. Incorporating the NIR band as a multiplicative component therefore further suppresses vegetated surfaces and enhances built-up features, improving the discrimination of buildings in heterogeneous urban environments. The NBM index is particularly well suited to the urban fabric of the Gaza Strip, where the majority of buildings are constructed from unpainted red clay bricks or gray cement-based materials. Red brick structures commonly exhibit higher reflectance in the Red band relative to the Green band, while cement-based and concrete

materials display a more neutral but still distinguishable Red-Green spectral response compared to vegetation. This material-specific spectral behavior reinforces the effectiveness of the normalized Red-Green component in highlighting built-up surfaces. Moreover, the moderate NIR reflectance of these construction materials, contrasted with the high NIR reflectance of vegetation, further supports the inclusion of the NIR multiplier for robust building detection across the diverse urban landscape of the Gaza Strip.

The workflow for processing the PlanetScope imagery and deriving the classification proceeded as follows. First, the PlanetScope data were downloaded and each spectral band was converted to surface reflectance using Planet's standard processing pipeline. Clouds, shadows, and other unusable pixels were masked using the UDM2 quality flags. Next, the relevant index was calculated for each scene, followed by the computation of the standard deviation of the index values within each scene. This information was then used to classify each scene into five classes. The standard deviation values provided thresholds that guided the visual separation of destroyed and non-destroyed pixels, ensuring consistent classification across scenes. Finally, the percentage of changed and unchanged blocks was calculated based on the number of changed and unchanged pixels, allowing for a quantitative assessment of landscape change.

Moreover, we have tested the differences between the results of the NBM in October 2023, before the start of the conflict and in April 2024, after the destruction of the selected study site to highlight the differences between the two times. It was done visually and by plotting 69 random points at the same latitude and longitude on both scenes for pixel values comparison and to reveal the areas where drastic changes took place. The final step, however, included assessing the accuracy of the NBM by comparing the before and after destruction scenes, October 2023 and April 2024, of the PlanetScope data with the recently open historical imagery of the google earth pro taken in October 2023 and June 2024. The comparison was done by adding 15 points randomly on a selected small spot of the test site in a trial of calculating the accuracy of the NBM before and after the conflict.

4 Results

In this section, we present the results of the comparison between PlanetScope and Sentinel data using all the aforementioned techniques, including the novel metric. The comparison highlights the degree of compatibility between the two datasets in delineating built-up areas. The procedure started with the resampling of the Sentinel imagery, although it has a coarser spatial resolution than PlanetScope data, our comparative analysis demonstrates strong agreement between the two datasets after resampling. This indicates that mixed-pixel effects do not significantly impact the results at the spatial scale of this study, supporting the use of Sentinel data as a reliable reference.

4.1 Image differencing

A longer time series of PlanetScope imagery is available compared to the Sentinel imagery. The PlanetScope scenes

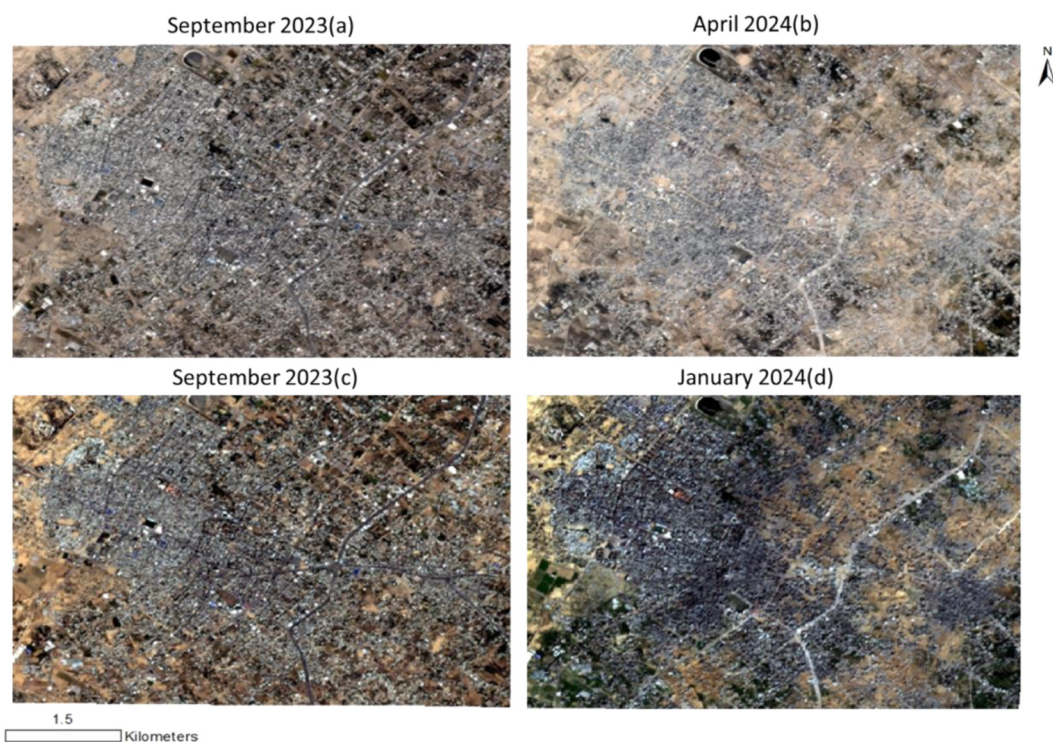


FIGURE 3
(a,b) display the differences between the reference scene captured in September 2023 and the scene captured in April 2024 in the PlanetScope dataset. (c,d) display the differences between the reference scene captured in September 2023 and the last scene provided by the GEE in January 2024 of Sentinel data.

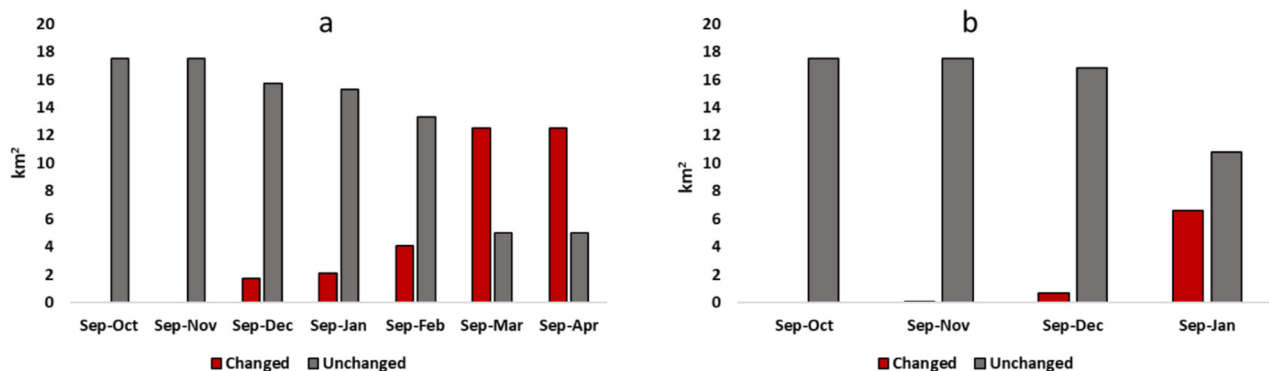
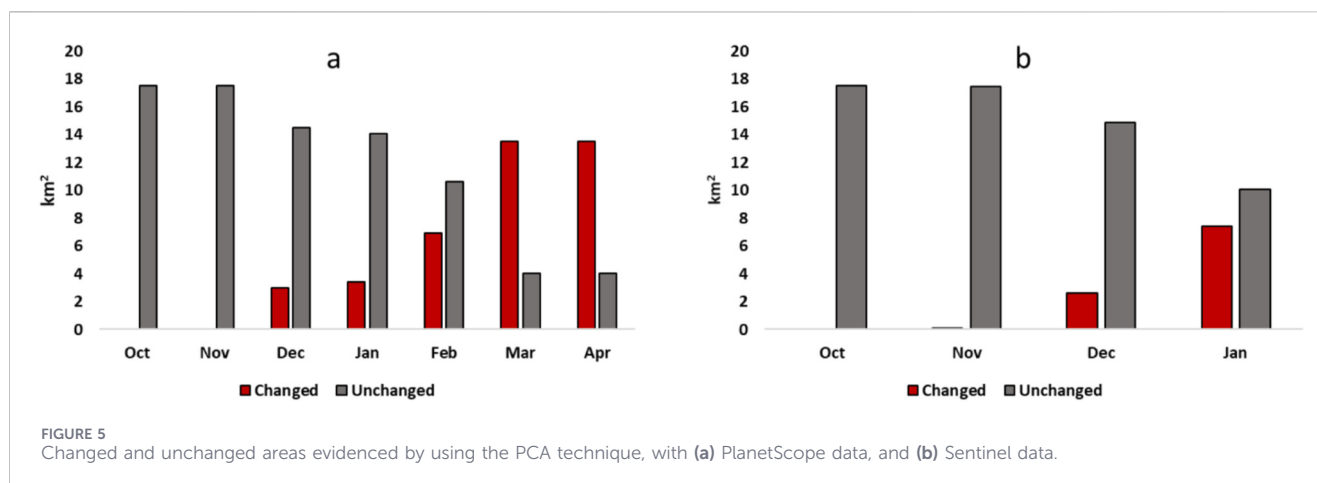


FIGURE 4
Changed and unchanged areas evidenced by using the image differencing technique, with (a) PlanetScope data, and (b) Sentinel data.

exhibited significant visual changes between the reference scene in September 2023 and the final scene in April 2024 (Figures 3a,b). The reference scene is used to separate the blocks and calculate the changes or damage at the research location along the conflict that started in October 2023. The subtraction of the respective scenes showed that the difference in built-up areas between September and November was 0 km² for the changed area, while the unchanged area remained at 17.5 km². Between September and December, there was a recognized change over an area of 1.7 km², while an area of 15.7 km² remained unaltered. The area that underwent changes

was subject to a minor increase from September 2023 to January 2024, reaching a total of 2.1 km²; in contrast, the area that remained unchanged declined to 15.3 km². In the September-February period, the area that underwent changes increased by 4.1 km², while in the September-March period, it increased by 12.5 km²; the areas that remained unchanged decreased by 13.3 km² and 5 km² over the same respective months. From September till April, the measurements were consistent with those obtained from September to March (Figure 4).



As previously stated, Google Earth Engine (GEE) supplied Sentinel scenes of the study site until January. However, all of the scenes were veiled. The selected September scene serves as a reference. Comparing visually the reference scene with the most recent scene from January (Figures 3c,d) reveals notable changes. The change detection analysis between September and November, using image differencing, revealed a modified region of 0.03 km^2 and an unaltered area of 17.5 km^2 . In the months of September to December, the area that underwent changes expanded to 0.7 km^2 , while the area that remained the same declined to 16.8 km^2 . In September and January, the situation deteriorated, resulting in an expanded damaged area of 6.6 km^2 , while the unaffected area remained at 10.8 km^2 (Figure 4).

4.2 Principal component analysis (PCA)

Principal Component Analysis and iso-cluster unsupervised classification on PlanetScope data revealed no changes at the site from October to November. Starting in December, the research location began documenting an increase in destruction from 3 km^2 to 3.4 km^2 in January. The extent of destruction exhibited a substantial increase in February, reaching 6.9 km^2 , and subsequently expanded to 13.5 km^2 in both March and April. The unaltered region exhibited a decrease in size from 17.5 km^2 in October and November to 14.5 km^2 in December, then further decreased to 14.1 km^2 , 10.6 km^2 , 4 km^2 , and 4 km^2 in each month from January to April, respectively (Figure 5). However, the application of PCA on sensor data revealed a distinct pattern of damage. The changes started in November, covering an area of 0.06 km^2 , and continued to grow in December and January, expanding to 2.6 km^2 and 7.4 km^2 , respectively. The unaltered region declined from 17.5 km^2 in October to 17.44 km^2 in November. This downward trend persisted in December and January, resulting in an area of 14.9 and 10.1 km^2 , respectively (Figure 5).

4.3 Development of building index

Using the Normalized Difference Red-Green Index, NDRGI, on PlanetScope data, no changes were observed in October, but a variation of 0.2 km^2 was noted between September and

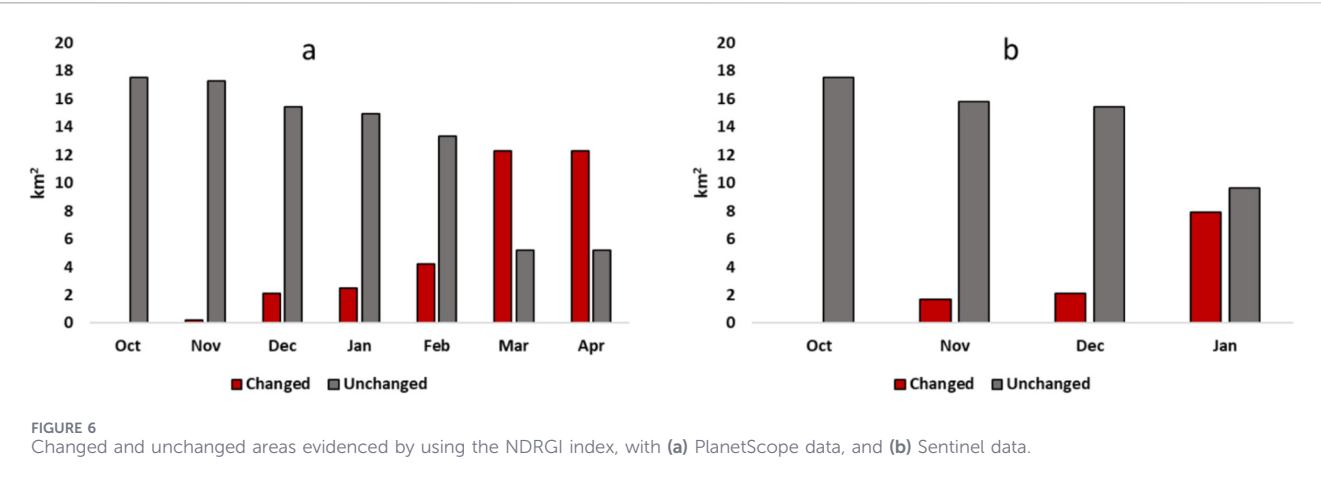
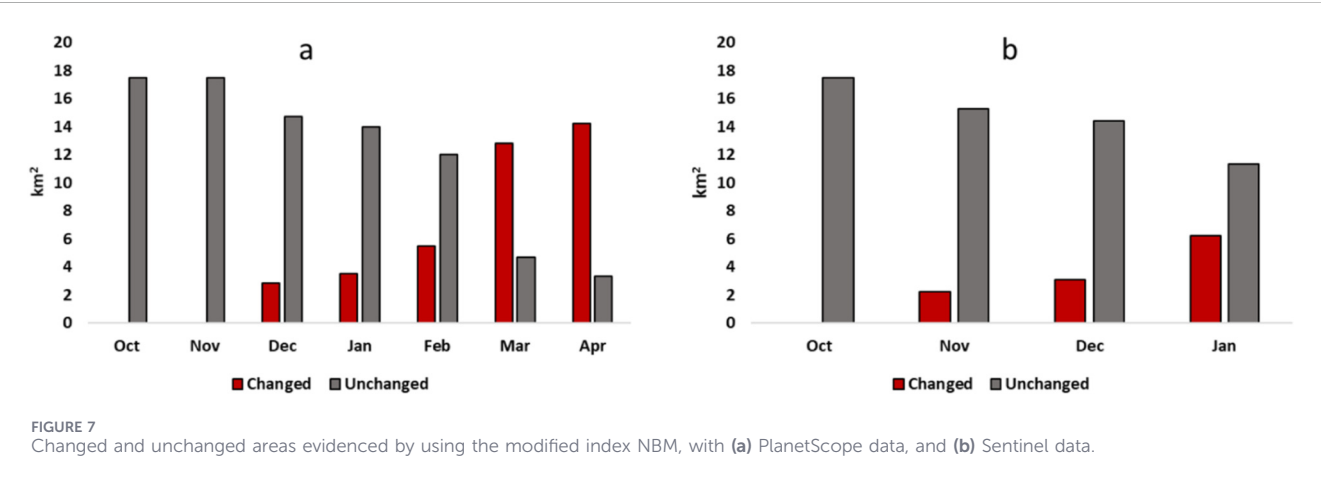
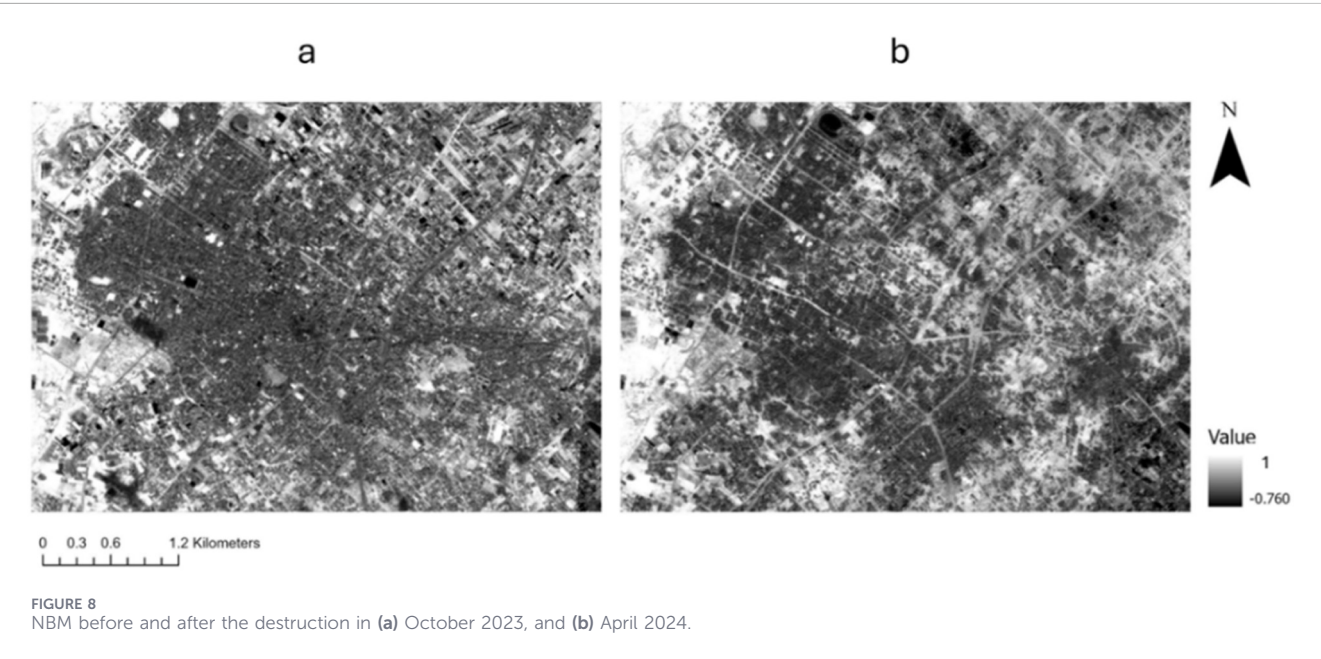
November. The rate of damage exhibited a progressive increase from December 2023 to March 2024, with values of 2.1 , 2.5 , 4.2 , 12.3 , and 12.3 km^2 , in each of the months, respectively. The unaltered areas exhibited a consistent decline from 17.5 km^2 to 5.5 km^2 during the months of October and April (Figure 6). When we used the same index on Sentinel data, we obtained slightly varied outcomes. The modified regions varied in size, ranging from 0 , 1.7 , 2.1 , and 7.9 km^2 in October, November, December, and January, respectively. The unaltered region decreased from 17.7 km^2 to 9.6 km^2 between October and January (Figure 6).

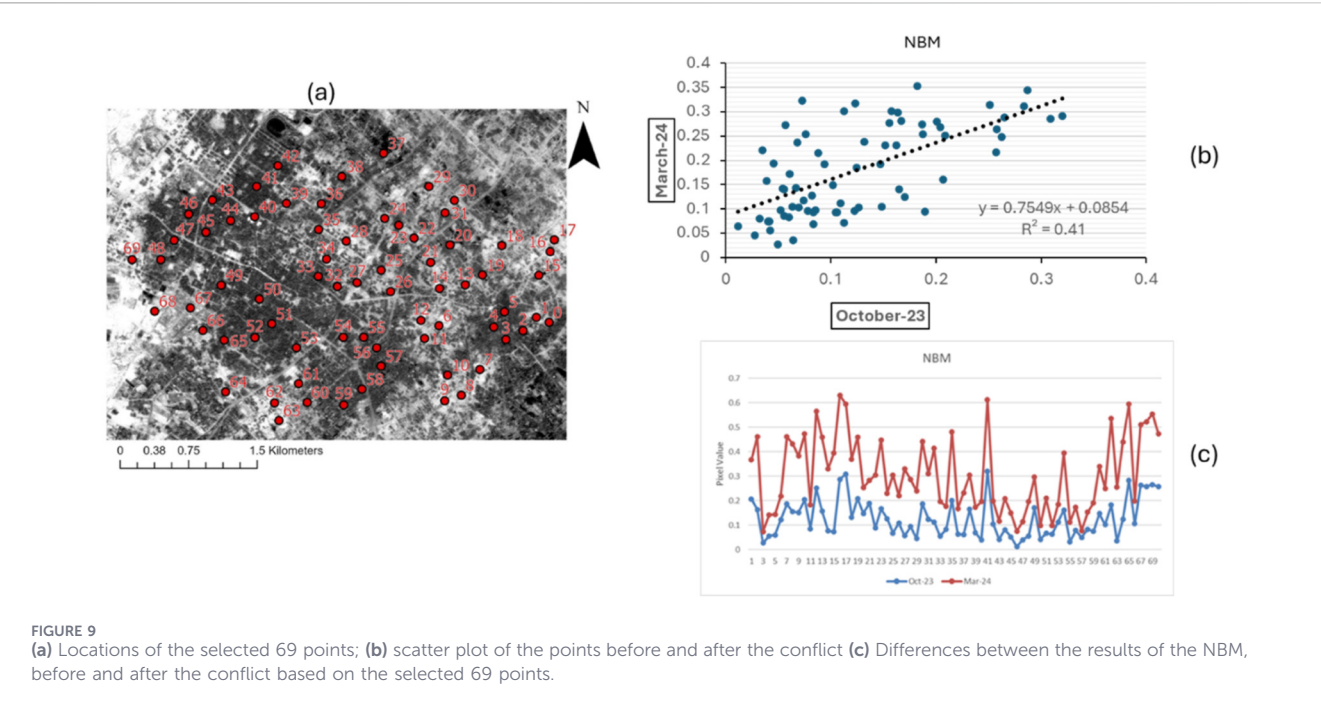
Subsequently, we tested the presented metric NBM to differentiate between the destroyed and unchanged areas. Planet Scope data showed comparable results with the Sentinel data as it recorded no devastated area in October and November; also, it recorded 2.8 , 3.5 , 5.5 , 12.8 . And 14.2 km^2 in each of the months from December to April, respectively. However, the unchanged areas decreased from 17.5 km^2 in October to 3.3 km^2 in April (Figure 7). Sentinel data, however, showed a gradual increase in the destroyed areas from 0 km^2 in October to 6.2 km^2 in January. November and December estimations reached 2.2 km^2 and 3.1 km^2 ; also, the unchanged area decreased from 17.5 km^2 in October to 11.3 km^2 in January (Figure 7).

The comparison of the NBM results before and after the conflict reveals pronounced spatial variability in building damage across the study area. Both visual inspection of the NBM maps and the quantitative analysis of 69 randomly selected sample points show substantial differences between the two time periods, indicating varying levels of destruction (Figures 8, 9).

The profile of NBM values derived from the sampled points exhibits distinct segments corresponding to different damage intensities. From points 3 to 7, only minor or negligible changes are observed, suggesting areas where buildings remained largely intact. In contrast, the interval from points 8 to 40 displays considerable differences in NBM values, reflecting zones that experienced extensive structural damage. These changes are consistent with the visual patterns observed in the post-conflict NBM map, where built-up areas appear significantly altered.

Between points 40 and 57, the differences in NBM values are again relatively small, indicating regions of partial or limited damage. However, a sharp increase in the magnitude of change is evident from points 58 to 69, where drastic differences are





recorded. These locations correspond to areas of intensive destruction, where the built-up fabric was severely disrupted or completely removed. Overall, the combined visual and point-based analyses confirm the capability of the NBM index to capture varying degrees of building damage, ranging from minimal impact to severe destruction, across the study area.

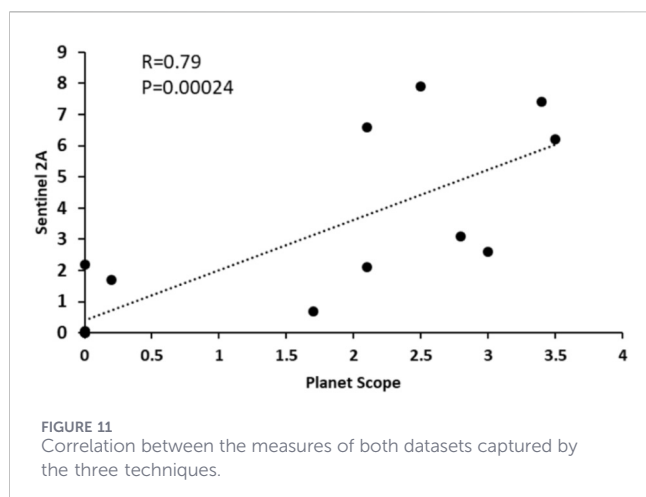
The accuracy assessment of the NBM based on random 15 points on geographically limited spot of the test site before and after the conflict by the use of historically imagery of the google earth pro showed the following results [Figure 10](#); [Table 1](#). The accuracy assessment test showed 100% compatible 15 points of non-destructed blocks by the PlanetScope NBM scene and google earth pro, while it shows 86% compatible results after the complete destruction.

TABLE 1 Accuracy assessment of the results of the NBM applied on the PlanetScope data, before and after the conflict.

Accuracy assessment of	Before conflict	After conflict
PlanetScope data (NBM)	100%	86%

5 Discussion

The present study aims at evaluating three methodologies for identifying the damaged and undamaged regions in Khan Younis in Gaza Strip, and to demonstrate an innovative utilization of PlanetScope data. The methodologies were applied to two



distinct satellite-based datasets, namely, PlanetScope and Sentinel data. The most challenging aspect was retrieving the data, as the GEE masked the Sentinel data starting from February 2024. Additionally, hazy conditions obscure a significant part of the PlanetScope data, introducing white and black artifacts. Hence, a total of eight PlanetScope scenes spanning from September to April, as well as five Sentinel scenes from September 2023 to January 2024, were used. By implementing the methodologies explained above, the damaged regions were distinguished from the unaffected regions, accurately identifying on a monthly basis the respective areas with each methodology.

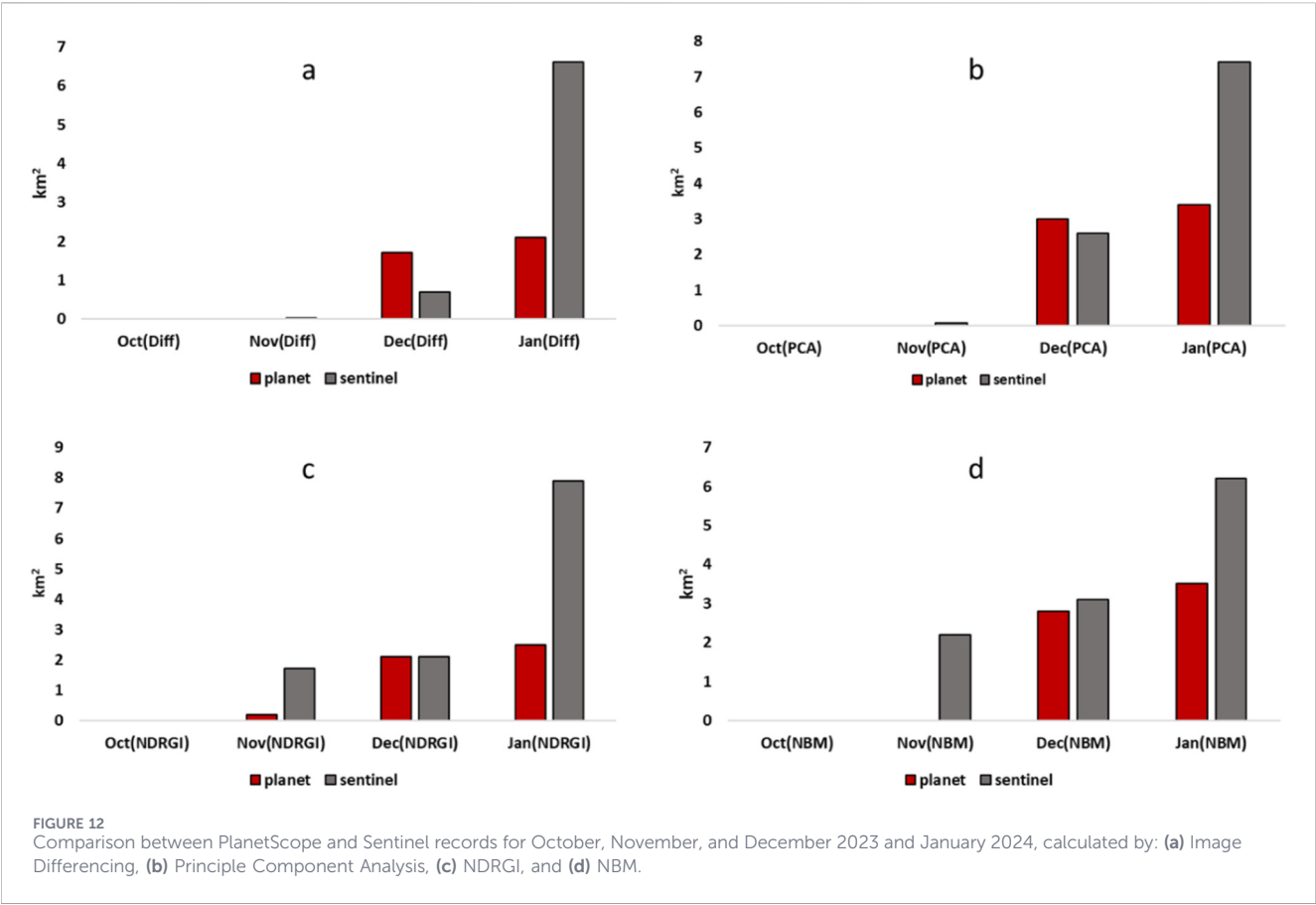
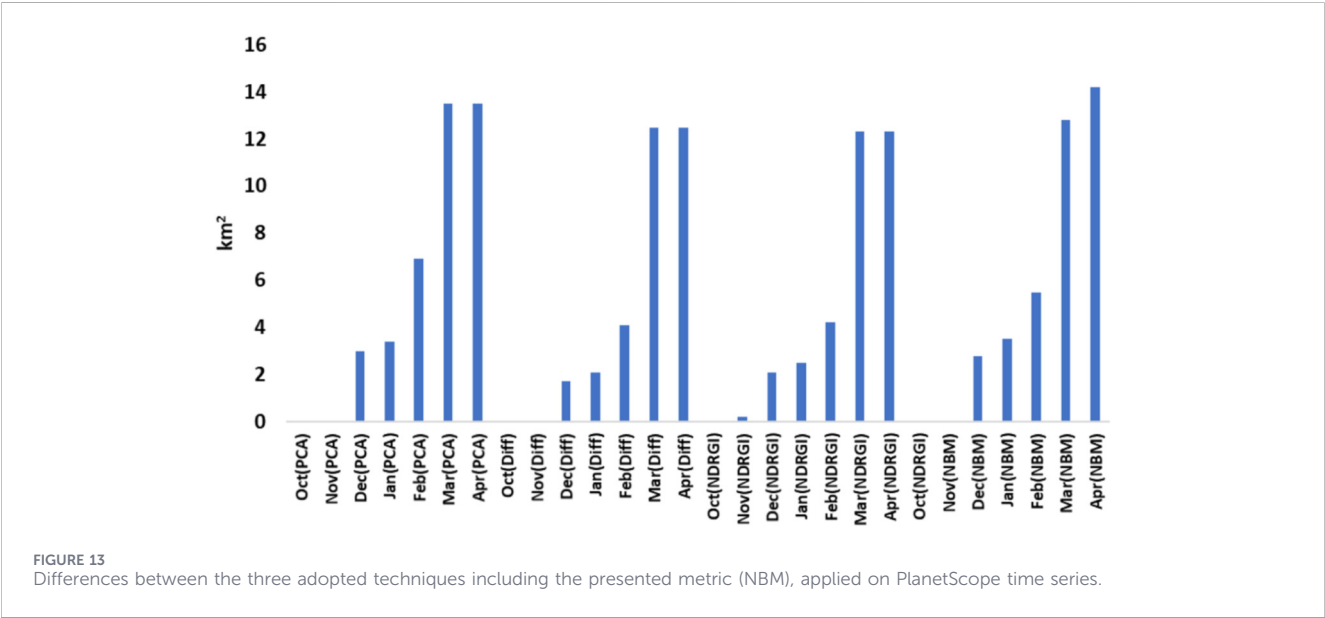
The correlation between the PlanetScope data and Sentinel data was subsequently computed (in this task, the months for which the Sentinel data were not available were excluded). We then combined the resulting datasets from the three techniques (image differencing, principal component analysis, and indices) into one column for each dataset. Using the RStudio software, the correlation between the two data sets obtained from the three-procedure model appeared to be robust, with a correlation coefficient (R) of 0.79, and a P -value of 0.00024 (Figure 11). The P -value indicates a highly statistically significant correlation implying a very low possibility that the observed linkage is a result of chance. All the methodologies used observe a significant connection despite the variations between the two datasets, all methodologies yield a significant correlation. Nevertheless, it was crucial to emphasize the strategies that yielded the most accurate alignment between the two datasets. Thus, we conducted a comparison of the outcomes of each methodology, while systematically removing the additional data from the PlanetScope imagery captured in February, March, and April. The PCA analysis revealed that the records of the PlanetScope and Sentinel datasets had similar measurements in October, November, and December 2023 (Figure 12). However, there was a notable disparity between the two datasets in January 2024. The second technique of image differencing revealed that the records for October and November were fairly similar, but there were modest variances between the data sets for December 2023. In contrast, January 2024 exhibited a large departure. After NDRGI was put into place, the third technique used with the image indices showed similar results in October and December. However, there was a noticeable difference in November 2023 and a significant difference in January 2024. The most recent applied metric, namely, NBM, displayed consistent measurements in

October and modest variations in December. However, in January, the differences were substantially lower compared to the other methods. This step led to the comparison of the performance of the adopted techniques on one dataset and PlanetScope data was selected as its missing the SWIR band and for the case study it provided longer time series data. The records showed symmetry with limited differences (Figure 13), moreover the NDRGI and NBM showed significantly close output when applied on Planet Scope data (Figure 14). Overall, as the affected area expanded over time, the disparity between the two datasets also increased. In January 2024, the NBM had the smallest disparity between the two datasets. Furthermore, it enhanced the visual clarity of the PlanetScope images and facilitated the separation of the blocks and the differentiation between the devastated area and the unaffected one. Due to inter-scene radiometric variability in PlanetScope imagery, a global fixed threshold was not applied. Instead, a scene-adaptive thresholding scheme was used, where change is defined relative to each scene's statistical distribution.

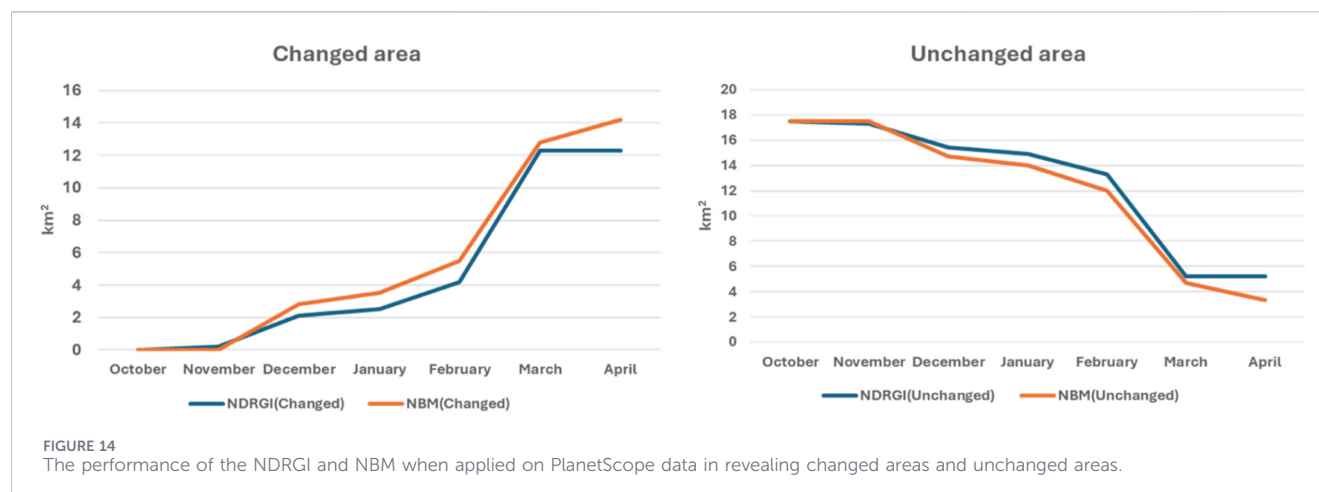
In the proposed workflow, the scene-adaptive, standard deviation-based thresholds inherently account for inter-scene variability. As a result, normalization of the index is not strictly required, because the classification relies on relative differences within each scene rather than absolute values. Nevertheless, it is important to note the potential effects of not normalizing the index: differences in overall scene brightness or sensor-specific offsets could slightly influence the absolute index values, but the adaptive thresholding ensures that these variations do not bias the classification outcomes. This approach maintains the robustness of the index while preserving its sensitivity to meaningful changes within each scene.

6 Concluding remarks

The current research aims to advance the use of PlanetScope data by introducing an index that is capable to extract blocks and buildings; moreover, it can be used to record any alterations that happen to the buildings by applying it to the PlanetScope data series. The SWIR band, which almost all building indices make use of, is absent from this type of data. This is why the introduced index relies on three different bands: red, green, and NIR (near infrared). That would provide better results when applied to dense areas packed with buildings, like in Khan Younis in the Gaza Strip. In general, PlanetScope imagery, which, despite its high spatial and temporal resolution, is subject to known limitations related to atmospheric haze and sensor artifacts. Residual haze effects, particularly in humid or aerosol-rich conditions, can alter surface reflectance values and reduce spectral contrast, potentially influencing the accuracy of derived indices and classifications. Although we applied standard preprocessing and quality control procedures and selected an arid location for the study to minimize these effects, complete removal of haze-related distortions is not always achievable. Moreover, it showed less clarity compared to Sentinel data despite its higher resolution. As the PlanetScope data shows from-scene-to-scene variation in reflectance, it contains more noise, especially in urban environments, and lacks consistent atmospheric correction if not preprocessed. However, the application of the presented index is more efficient and provides brighter and clearer results when applied to PlanetScope data compared to Sentinel data.



The proposed metric can help as a rapid scan indicator in cases of long conflicts, intense fire, and natural disasters, as an indicator of the intensity of the disaster and how governments and stakeholders should deal with it to limit the destruction and the negative impact on societies and vulnerable areas. To reach this step, more validation of the proposed index is required. It should be applied to less crowded areas, humid regions, and with more remote sensing datasets to highlight its effectiveness as a building index in all cases. Future work will involve analyzing additional PlanetScope data for carefully selected locations where Google Earth Pro provides active coverage. This will facilitate easier comparison and enable a more robust evaluation of the effectiveness of the novel index.



Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: <https://www.planet.com/nextgenplanetscope/>.

Author contributions

MM: Conceptualization, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Writing – original draft. SM: Supervision, Writing – review and editing, Validation. PD: Supervision, Writing – review and editing, Funding acquisition.

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Conflict of interest

Authors MM and PD were employed by Helmholtz Centre for Environmental Research GmbH-UFZ.

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