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ARTICLE
RESEARCH ARTICLE

Temporal analysis of canopy gap distribution in natural forests: comparing managed and unmanaged stands using Quickbird and UltraCam-D imagery

Análisis temporal de la distribución de claros del dosel en bosques naturales: comparación de rodales manejados y no manejados mediante imágenes QuickBird y UltraCam-D

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Abstract: *Aim of study:* To investigate and analyze the temporal and spatial distribution patterns of canopy gaps in managed and unmanaged forest stands using remote sensing images from different sources, emphasizing the relevance of these patterns in the context of natural processes and human interventions. *Area of study:* Managed and unmanaged stands of Dr. Bahramnia Forestry Plan, Hyrcanian forest, Golestan Province, Iran. *Material and methods:* High-resolution satellite imagery, including QuickBird (2007) and UltraCam-D (2011) digital aerial images, were utilized to detect canopy gaps. This study employed pixel-based classification methods, such as Support Vector Machine (SVM) and Maximum Likelihood (ML) algorithms, along with object-based methods, including Nearest Neighbor (NN), Random Forest (RF), Decision Tree (DT), and Bayes, for classification and to extract canopy gaps. Spatial distribution patterns were analyzed using the Nearest Neighbor Index, spatial autocorrelation, and clustering based on gap size, employing global Getis-Ord and local Moran's I statistics. *Main results:* The results indicated that pixel-based classification methods achieved higher accuracy in mapping gap and non-gap areas, with the ML algorithm attaining 98.763% accuracy and a Kappa coefficient of 0.974 in 2007, and the SVM algorithm achieving 98.899% accuracy and a Kappa coefficient of 0.976 in 2011. The Nearest Neighbor Index revealed a regular spatial distribution of gaps in both managed and unmanaged stands. Clustering analysis showed distinct patterns for small, medium, and large gaps, with managed stands exhibiting clustering and unmanaged stands displaying random and regular patterns. *Research highlights:* This study underscores the importance of high-resolution remote sensing data and advanced classification algorithms for accurately mapping canopy gap dynamics, providing valuable insights for sustainable forest management.

Keywords: classification; getis-ord; high-resolution images; remote sensing.

Resumen: *Objetivo del estudio:* Tiene como objetivo investigar y analizar los patrones de distribución temporal y espacial de los claros del dosel en masas forestales manejadas y no manejadas utilizando imágenes de teledetección de diferentes fuentes, enfatizando la relevancia de estos patrones en el contexto de los procesos naturales y las intervenciones humanas. *Área de estudio:* Rodales gestionados y no gestionados del Plan Forestal Dr. Bahramnia, bosque de Hircanian, provincia de Golestán, Irán. *Material y métodos:* Se utilizaron imágenes satelitales de alta resolución, incluidas imágenes aéreas digitales QuickBird (2007) y UltraCam-D (2011), para detectar espacios en el dosel. Este estudio empleó métodos de clasificación basados en píxeles, como los algoritmos Support Vector Machine (SVM) y Maximum Likelihood (ML), junto con métodos basados en objetos, incluidos el vecino más cercano (NN), el bosque aleatorio (RF), el árbol de decisión (DT) y Bayes, para clasificar y extraer espacios en el dosel. Los patrones de distribución espacial se analizaron utilizando el índice del vecino más cercano, la autocorrelación espacial y la agrupación basada en el tamaño de la brecha, empleando estadísticas globales de Getis-Ord y locales de Moran. *Resultados principales*: Los resultados indicaron que los métodos de clasificación basados en píxeles lograron una mayor precisión en el mapeo de áreas con y sin brechas, con el algoritmo ML alcanzando una precisión del 98,763% y un coeficiente Kappa de 0,974 en 2007, y el algoritmo SVM logrando una precisión del 98,899% y un coeficiente Kappa de 0,976 en 2011. El índice de vecino más cercano reveló una distribución espacial regular de las brechas tanto en áreas administradas como no administradas. se encuentra. El análisis de agrupamiento mostró patrones distintos para espacios pequeños, medianos y grandes, con rodales gestionados que exhiben agrupamiento y rodales no gestionados que muestran patrones aleatorios y regulares. *Aspectos destacados de la investigación:* Este estudio subraya la importancia de los datos de teledetección de alta resolución y los algoritmos de clasificación avanzados para mapear con precisión la dinámica de los claros del dosel, proporcionando información valiosa para el manejo forestal sostenible.

Palabras clave: clasificación; getis-ord; imágenes de alta resolución; teledetección.

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Supplementary information ↓

1. INTRODUCTION

Forest structure is shaped by past natural and human disturbances, as well as tree regeneration, composition, dynamics, and mortality, all of which contribute to canopy gap formation (Watt, 1947; Runkel, 1981; Lingua et al., 2011; Farzalizadeh et al., 2021). These gaps, ranging from small (single-tree loss) to large (multiple-tree loss), play a vital role in ecosystem dynamics, affecting biodiversity, nutrient cycling, and resilience (Kheiri et al., 2012; Amini, 2021). In temperate forests, gaps are key sites for regeneration and renewal (Fraver, 1994; Yamamoto, 2000; Gray & Spies, 1996), reflecting forest's adaptability and health. Thus, understanding gap formation (Koosari Palangi, 2015; Nyamgeroh et al., 2018) and their spatial distribution (Wirth et al., 2001; Inoni, 2009; Wang et al., 2017; Liu et al., 2020; Rodes-Blanco et al., 2023) is essential for effective forest management and conservation.

In natural forests, gaps typically form randomly due to events like treefall, wind, disease, or wildfire. However, human activities (especially harvesting) can significantly alter these patterns (Getzin et al., 2014). Poor management may exacerbate impacts, leading to soil erosion and reduced regeneration capacity (Jedrzejewska et al., 1994; Kubo et al., 1996; Vepakomma et al., 2012; Rabins, 2019). Overall, canopy gap distribution reflects the dynamic interplay between ecological processes and human interventions.

In the context of investigating the spatial distribution patterns of forest gaps, in their study of subtropical forests in southern China, Liu et al. (2020) analyzed forest gap characteristics and spatial patterns following ice storm damage using Aerial Scanner Laser and field data across one semi-natural and two managed sites. Gap types were classified by damage origin (e.g., stem breakage, uprooting), and spatial analysis via Ripley's K-function revealed random or regular patterns at small scales (20-30 m) and clustered distributions at larger scales (beyond 65 m), especially in managed sites. Similarly, Mazdi et al. (2021) examined canopy gap dynamics over nine years in Hyrcanian forests dominated by Oriental beech. Their findings showed random gap distribution at short distances (up to 70 m), clustering at medium scales (70–380 m), and a return to randomness at longer distances. These spatial patterns were linked to topography, tree-fall mechanisms, and species-specific regeneration strategies such as crown expansion. In addition, in a separate investigation, Getzin et al. (2014) applied high-resolution UAV imagery to analyze the spatial patterns of canopy gaps in managed and unmanaged forests across two regions of Germany. They extracted all gaps within one-hectare plots and subsequently analyzed them using spatial statistics based on the pair correlation function (PCF). They hypothesized that negative correlations with size result from single-tree harvesting or the repeated formation of gaps. The results of this study demonstrated that drones are highly effective tools for mapping small gaps (less than 1 m²) and analyzing the spatial structure of the forest canopy.

In general, investigating the spatial distribution patterns of forest gaps is of great importance and requires their initial identification. Typically, data collection and gap mapping are conducted through ground-based methods, which are time-consuming and costly (Moayeri et al., 2017). Although these methods provide accurate information, they have limitations such as restricted coverage in areas with challenging topography, making it impossible to monitor the entire forest area using this approach. However, recent advancements in remote sensing science and the use of high-spatial-quality data, such as certain satellite images, UAV imagery, aerial digital images, LiDAR data, and others, have provided a suitable alternative to conventional and traditional ground-based methods (Gaulton & Malthus, 2010; Garbarino et al., 2012; Malahlela et al., 2014; Xuegang et al., 2020; Naseri & Shataee, 2024). Therefore, the utilization of modern remote sensing tools and techniques can effectively contribute to the identification of canopy gaps.

Several studies have demonstrated the effectiveness of remote sensing techniques to detect canopy gaps. Some of these researches are shown in Table 1.

Table 1. Research studies on canopy gap extraction using different remote sensing sources and methods

Research	Remote Sensing Data	Classification Methods	Study Area	Overall Accuracy (%)
Vepakomma et al. (2008)	LiDAR	Object-based	Canada – Boreal forests	96
Koosari Palangi (2015)	LiDAR	Height thresholding	Iran – ShastKalateh forest	99.11
Malahlela et al. (2014)	satellite imagery	Object-based	South Africa – Dukuduku coastal forest	93.69
Felix et al. (2021)	UAV imagery	Pixel-based	Brazil – Lavras forests	93
Jackson (2022)	satellite imagery	Pixel-based	Kenya – Submontane tropical forest reserve	94
Amini et al. (2022)	UAV imagery	Slope thresholding	Iran – ShastKalateh forest	91.7
Khalili et al. (2023)	UAV imagery	Object-based	Iran – Arab-Dagh planted coniferous stands	99

Given the above, acquiring information on forest gaps and analyzing their spatial distribution patterns can significantly aid in future management strategies and facilitate more effective decision-making toward sustainable forest management. The primary objective of this study is to investigate and precisely analyze the spatial distribution patterns of canopy gaps in managed (District 1) and unmanaged (District 2) forest stands within Dr. Bahramnia's forestry plan in Gorgan, using remote sensing data. In this research, high-spatial-resolution imagery, including QuickBird satellite images from 2007 (before tree harvesting during the second revision plan) and UltraCam-D aerial digital images from 2011 (after selective tree harvesting during the implementation of the second revision plan), was utilized for the identification and mapping of gaps using pixel-based and object-based methods. The best maps generated for each period were used to examine gap spatial distribution patterns using the Nearest Neighbor algorithm, global and local Getis statistics in both managed and unmanaged stands. Additionally, the spatial distribution patterns of small, medium, and large gaps were analyzed based on gap size. Overall, this study aims to understand how forest harvesting affects the ecological structure and spatial distribution of canopy gaps and uses remote sensing data to analyze and compare changes over time before and after harvesting, as well as to contrast these findings with unmanaged stands. This approach provides valuable insights into the dynamics of canopy gaps and contributes to inform forest management practices.

2. MATERIAL AND METHODS

2.1. Study area

The study area (Figure 1) included parcels 11, 12, 16, and 21 of District 1 (managed) and parcels 4, 5, and 7 of District 2 (unmanaged) in the Shast_ Kalateh forest, with an area of 345.04 hectares. The site is located in Watershed 85; in the south-western part of Gorgan County, between longitudes 54°24′ to 54°25′ East and latitudes 36°38′ to 36°42′ North. The minimum and maximum elevations are 313 and 697 meters above sea level, respectively. The forest stand structure comprises two to three canopy layers with relatively high species diversity. Since 1976, District 1 has been managed under an uneven-aged silviculture management plan with selective logging treatment, whereas District 2 remains unmanaged without any forestry plans and no logging. The dominant tree species in the study area included Fagus orientalis, Quercus castaneifolia, Carpinus betulus, Acer velutinum, and Alnus subcordata, occurring in certain sections. Based on the forest structure, the stands encompass a full range of developmental stages (from young trees to individuals approaching senescence). Between 2007 and 2011, legal and planned logging activities in District 1 (managed) included periodic selective harvesting of mature and over-/understory trees based on silviculture treatment. These operations were conducted under the supervision of the Bahramnia Forestry Plan, following prescribed silviculture guidelines to optimize stand structure and diversity and promote regeneration.

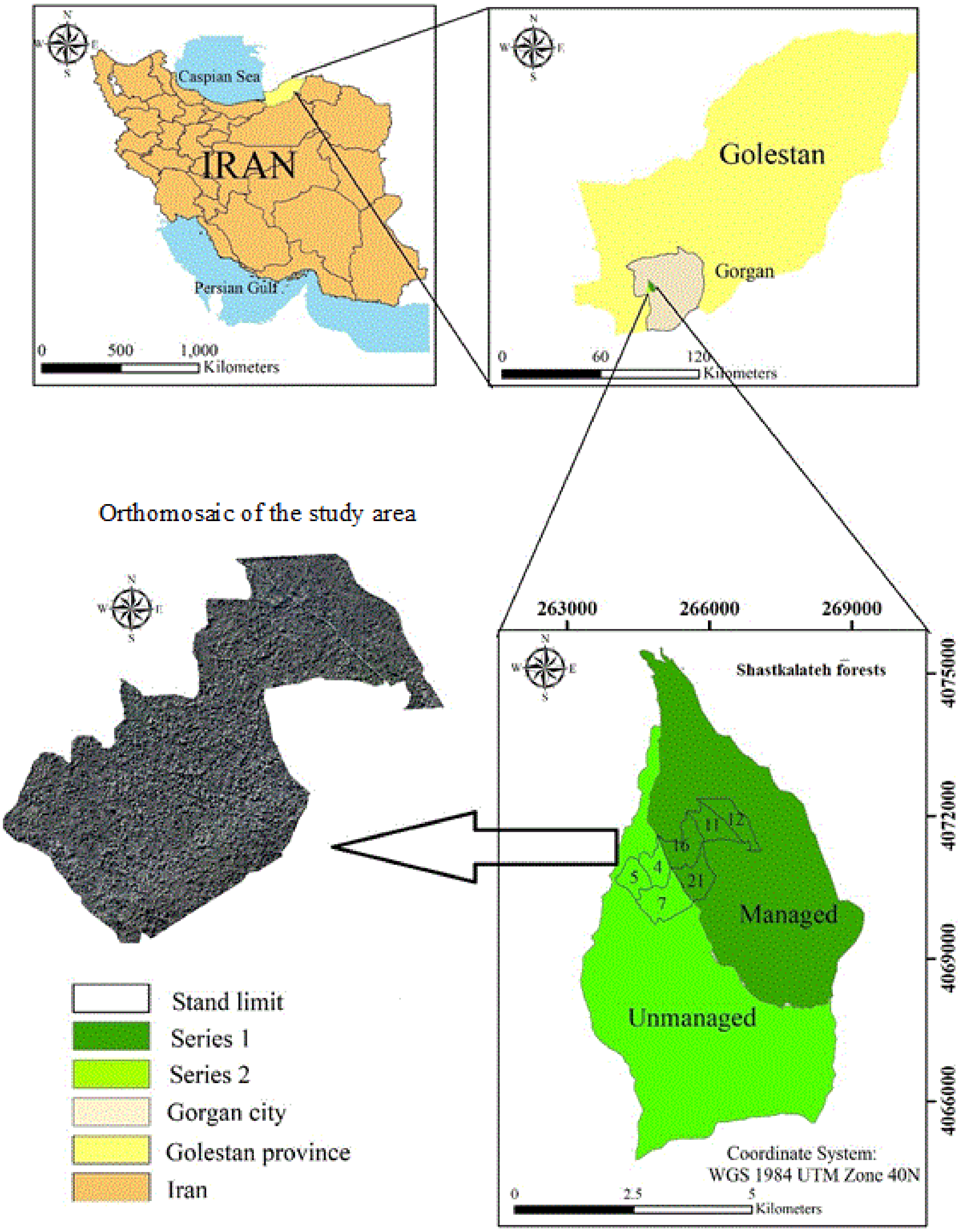

Figure 1. Location and orthomosaic of the study area in Shastkalate forests, Golestan Province, Iran.

2.2. Remote sensing data

In this study, a QuickBird satellite image from 2007 was utilized, featuring a spatial resolution of 0.61 m for the panchromatic band and 2.44 m for the multispectral bands (Table 2). Additionally, UltraCam-D aerial digital images with a spatial resolution of 0.15 m, acquired in 2011 from the Iranian Mapping Organization, were employed (Table 2). Generally, this type of satellite and aerial imagery provides extensive information regarding vegetation cover, environmental conditions, and the nature of phenomena, making it highly suitable for interpretation, analysis, and classification of such phenomena (Mohammadi et al., 2017).

Table 2. Specifications of the QuickBird and UltraCam-D images (Naseri et al., 2020)

Parameter	Images	
	QuickBird (2007)	UltraCam-D (2011)
Spatial resolution	0.61 m in Panchromatic mode	0.07-0.15 m in Panchromatic mode
	2.4 m in multi-spectrum mode	30-60 cm in multi-spectrum mode
Radiometric resolution	11Bits	12 Bits
Bands (nm)	Blue: 520-450	Blue: 420-475
	Green: 600-520	Green: 455-580
	Red: 690-630	Red: 635-675
	Near infrared: 900-760	Near Infrared: 700-805
	Panchromatic: 900-450	-

2.3. Data pre-processing

To enhance the spatial quality of the multispectral bands of the QuickBird satellite image, the Brovey fusion method was applied using ENVI 4.8 software. Consequently, the fused color images with a spatial resolution of 0.60 m were extracted by merging the panchromatic band with the green, red, and near-infrared bands. The UltraCam-D aerial digital image (2011) was processed in ArcGIS 10.8 to produce a multi-band dataset, including blue, green, red, and near-infrared bands. To ensure compatibility between the datasets used in this study, the QuickBird satellite image (2007) was georeferenced based on the UltraCam-D aerial image (2011) using PCI Geomatica 2016 software and its Engine Ortho module. For this purpose, in addition to the 2011 imagery, a Digital Terrain Model (DTM) derived from LiDAR data provided by Mohammadi et al. (2017) with resolution of 1 m was utilized for elevation corrections. Thus, 70 well-distributed ground control points (GCPs) were identified across the study area. Their precise geographic coordinates were obtained from the 2011 image, while their elevation data were extracted from the LiDAR-derived DTM. The QuickBird image of 2007 was georeferenced using these points with the mean error rate of 1.61 m.

2.4. Ground truth sampling

Due to the spatial resolution of the used images, ground truth samples of gap and non-gap areas were visually interpreted and delineated as polygons for the years 2007 and 2011. To improve the reliability of gap detection and ensure accurate delineation of gap boundaries, non-gap samples were deliberately selected adjacent to gap areas using high-resolution imagery corresponding to each period. This sampling strategy was adopted to enhance the classifier’s ability to distinguish subtle transitions between gap and non-gap zones, particularly along their shared boundaries. Ultimately, 70% of these samples were randomly selected to serve as training data for classification, while the remaining 30% were used for testing purposes (Figure 2). Specifically, for the year 2007, a total of 115 training samples and 49 test samples were used for the gap class, and 104 training samples and 45 test samples for the non-gap class. For the year 2011, the gap class included 106 training and 45 test samples, while the non-gap class consisted of 106 training and 45 test samples (Figure 2).

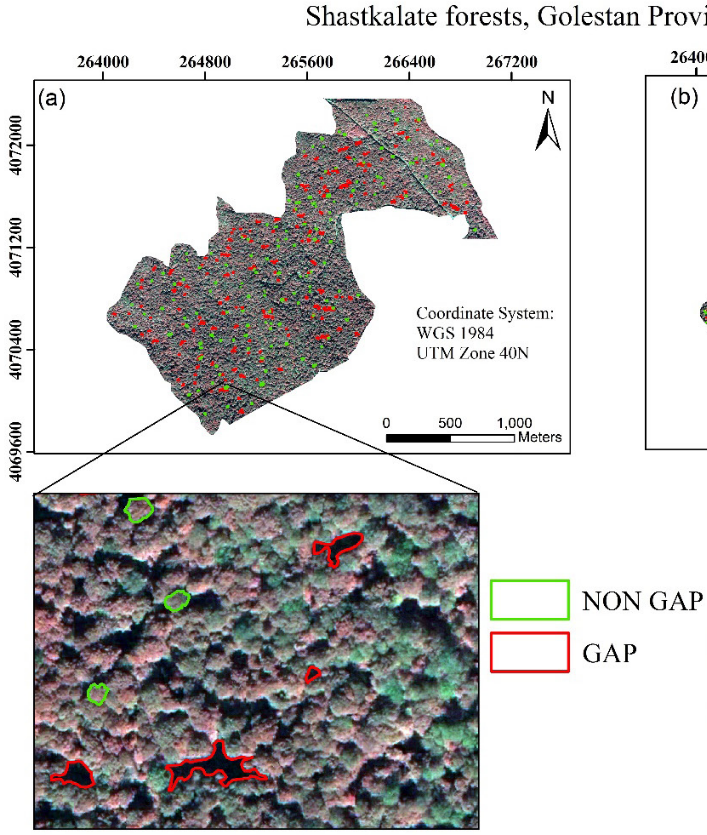

Figure 2. Location and distribution of ground truth samples (in Shastkalate forests, Golestan Province, Iran): a) 2007 and b) 2011.

2.5. Classification

Classification aims to generate thematic maps that represent the spatial distribution of various phenomena across the Earth's surface (Naseri et al., 2020). The classification process involved dividing image pixels into different classes based on spectral, spatial, and temporal features (Richards, 2020). To ensure methodological robustness and to evaluate the performance of different approaches under varying forest conditions and image types, we applied both pixel-based and object-based classification methods. Therefore, for the years 2007 and 2011, pixel-based classification methods were employed using ENVI software with SVM (Hearst et al., 1998) and ML (Cox et al., 1996) algorithms. These algorithms were selected due to their proven effectiveness in handling high-resolution satellite imagery and their widespread use in forest mapping applications. Additionally, object-based classification was conducted using eCognition Developer software with SVM, RF (Breiman, 2001), NN (Cover & Hart, 1967), DT (Quinlan, 1986), and Bayes (Hart et al., 2001) algorithms. The use of multiple algorithms in the object-based approach allowed us to compare classifier performance across different feature extraction strategies and segmentation outputs. In the object-based classification, the initial segmentation was performed using the Multiresolution Segmentation algorithm (Salem, 2008) with a scale parameter of 30, shape factor of 0.6, and compactness of 0.4 for the 2007 QuickBird imagery, and a scale of 350, shape factor of 0.9, and compactness of 0.1 for the 2011 UltraCam imagery. These parameters were selected based on visual inspection and iterative testing to optimize object delineation in relation to canopy gap boundaries. Subsequently, classification was accomplished using the aforementioned algorithms by incorporating the mean and standard deviation of the bands from the images of each period as features. The produced maps, both pixel-based and object-based classification methods, were assessed using the test samples and overall accuracy and Kappa coefficient indices.

2.6. Analysis of canopy gap spatial distribution patterns

To investigate the spatial distribution patterns of tree canopy gaps, the best-classified maps for each period were utilized. Initially, canopy gaps with areas less than 20 square meters were merged into the non-gap class (Amini et al., 2022). The Nearest Neighbor method (Clark & Evans, 1954) was then employed to determine the type of spatial distribution pattern for all gaps in both managed and unmanaged stands for the years 2007 and 2011. Subsequently, cluster grading was analyzed using the Global Getis-Ord statistic (Ord & Getis, 1995), and spatial distribution maps of gaps (Hot Spot and Cold-Spot maps) were generated using the Local Getis-Ord statistic (Ord & Getis, 1995). In the next step, the spatial distribution patterns of gaps based on their sizes were examined. Following the methodology of Amini et al. (2022), canopy gaps for the years 2007 and 2011 were categorized into three classes: small gaps (areas less than 150 square meters), medium gaps (areas between 150 and 300 square meters), and large gaps (areas greater than 300 square meters). The spatial distribution patterns of these gap size categories were analyzed for managed and unmanaged stands.

3. RESULTS

3.1. Pixel-based classification

The results of the pixel-based classification of QuickBird (2007) and UltraCam (2011) images demonstrated that the SVM and ML algorithms achieved high accuracy in both study areas periods (Table 3). Among the algorithms used, in 2007, the ML algorithm provided slightly better results with an overall accuracy of 96.54% and a Kappa coefficient of 0.927 compared to the SVM algorithm. However, in 2011, accuracy assessments revealed that the SVM algorithm performed marginally better with an overall accuracy of 98.90% and a Kappa coefficient of 0.976, surpassing the ML algorithm. The classified maps corresponding to the gap and non-gap classes for the years 2007 and 2011 are presented in Figure 3.

Table 3. Results of the accuracy assessment of pixel-based classified maps for 2007 and 2011

Year	Algorithm	Overall Accuracy (%)	Kappa Coefficient
2007	SVM	96.54	0.927
	ML	98.76	0.974
2011	SVM	98.90	0.976
	ML	98.75	0.973

SVM: support vector machine; ML: maximun likelihood.

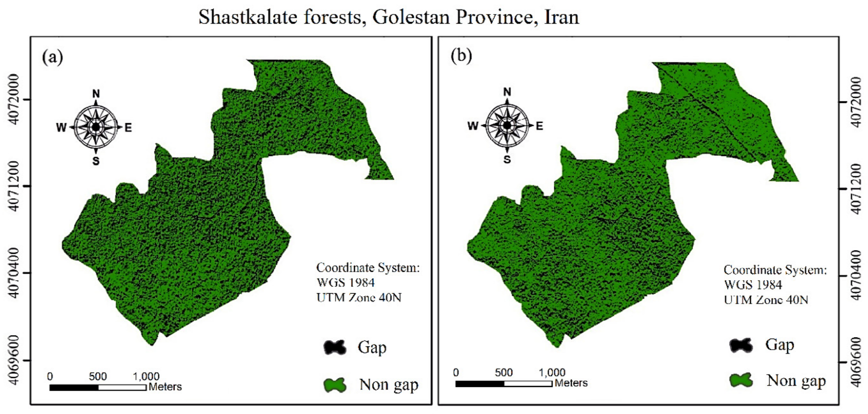

Figure 3. Maps of the best pixel-based classification (in Shastkalate forests, Golestan Province, Iran): a) 2007 (Maximum Likelihood algorithm), and b) 2011 (Support Vector Machine algorithm).

3.2. Object-based classification

The results of the object-based classification for the images from 2007 and 2011 showed that the utilized algorithms provided acceptable overall accuracies and Kappa coefficients (Table 4). Among the used algorithms for 2007, the DT algorithm achieved slightly better performance in producing gap and non-gap maps, with an overall accuracy of 94.05% and a Kappa coefficient of 0.877 (Figure 4-b). The accuracy assessment of classified maps for 2011 indicated that the SVM algorithm outperformed the others with a marginal difference, achieving an overall accuracy of 98.17% and a Kappa coefficient of 0.961 (Figure 4-a).

Table 4. Results of the accuracy assessment of object-based image classification for 2007 and 2011

Year	Algorithm	Overall Accuracy (%)	Kappa Coefficient
2007	SVM	93.88	0.873
	RF	93.87	0.872
	NN	78.83	0.568
	DT	94.05	0.877
	Bayes	93.87	0.874
2011	SVM	98.17	0.961
	RF	97.60	0.949
	NN	98.16	0.961
	DT	98.08	0.959
	Bayes	98.11	0.960

SVM: support vector machine; RF: random forest: NN: nearest neighbor;DT: decision tree; Bayes: bayesian classifier.

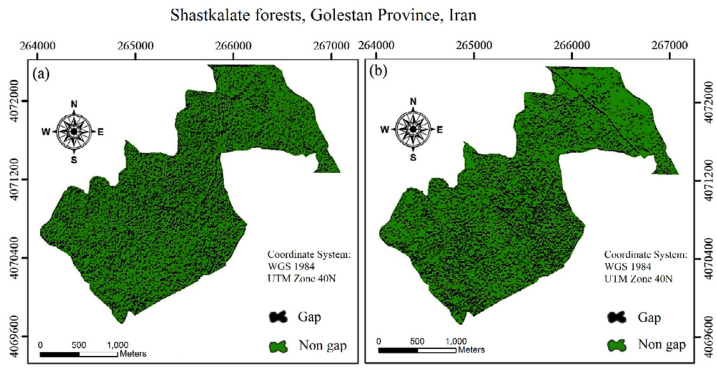

Figure 4. Maps of the best object-based classification (in Shastkalate forests, Golestan Province, Iran): a) 2007 (Decision Trees algorithm), and b) 2011 (Support Vector Machine algorithm).

3.3. Spatial pattern analysis using Nearest Neighbor index

For this purpose, the best-classified maps from 2007 and 2011, which provided the highest overall accuracy and Kappa coefficient, were utilized for spatial pattern analysis. For the year 2007, the map generated using the ML algorithm in the pixel-based method was selected, while for 2011, the SVM algorithm yielded the most accurate classification results. The spatial distribution analysis of all canopy gaps (without considering gap size) was conducted using the Nearest Neighbor algorithm for both managed and unmanaged stands. In 2007, gaps in both stands exhibit a regular distribution pattern, whereas in 2011, the distribution pattern of gaps in both stands is dispersed (Table 5). When gap size classes (small, medium, and large) were considered, the Nearest Neighbor analysis revealed distinct spatial patterns across years and management methods. In 2007, all gap classes in managed stands exhibit a clustered pattern. In unmanaged stands, small gaps displayed a random pattern, while medium and large gaps showed a regular distribution. In contrast, the 2011 results indicate that in managed stands, small and medium gaps are clustered, while large gaps are randomly distributed. In unmanaged stands, the spatial distribution patterns of small, medium, and large gaps are clustered, random, and dispersed, respectively (Table 6).

Table 5. Nearest Neighbor Index results for all gaps (without size classification) for 2007 and 2011

Year	Stands	Z-Score	P-Value	Pattern
2007	Managed	3.0138	0**	Dispersed
	Unmanaged	15.651	0**	Dispersed
2011	Managed	5.425	0**	Dispersed
	Unmanaged	17.117	0**	Dispersed

Significance levels: **: 99% confidence level. In general, the Z-score (or standard score) indicates how far a data point is from the mean of the distribution, in terms of the number of standard deviations. The Z-score value helps us understand how much the observed dispersion pattern deviates from a random pattern.

Table 6. Nearest Neighbor Index results by gap size class (small, medium, large) for 2007 and 2011

Year	Stands	Gap Size Classes	Z-Score	P-Value	Pattern
2007	Managed	Small	-8.806	0**	Clustered
		Medium	-4.656	0**	Clustered
		large	-2.535	0.011+	Clustered
	Unmanaged	Small	-0.604	0.545	Random
		Medium	1.891	0.058+	Dispersed
		Large	3.549	0**	Dispersed
2011	Managed	Small	-10.8434	0**	Clustered
		Medium	-4.3915	0**	Clustered
		Large	0.9938	0.32 n.s	Random
	Unmanaged	Small	-2.5695	0.01*	Clustered
		Medium	-0.4432	0.65 n.s	Random
		Large	7.1764	0**	Dispersed

Significance levels: **: 99% confidence level, *: 95% confidence level, +: 90% confidence level, n.s: not significant. In general, the Z-score (or standard score) indicates how far a data point is from the mean of the distribution, in terms of the number of standard deviations. The Z-score value helps us understand how much the observed dispersion pattern deviates from a random pattern.

3.4. Clustering degree analysis using Global Getis-Ord statistic

The results of the Global Getis-Ord statistic were used to assess the clustering degree of canopy gaps in both managed and unmanaged stands. In 2007, the spatial pattern of all gaps (without considering their size) is random in managed stands and low-clustered in unmanaged stands at the 99% confidence level. Similarly, in 2011, the distribution pattern of all gaps is the low-clustered in both stand types at the same confidence level, indicating weak spatial aggregation across the landscape (Table 7). When gap size classes were considered, the analysis revealed more detailed spatial behaviours. Based on the results (Table 8), in 2007, small gaps (less than 150 m²) in both managed and unmanaged stands show low clustering. Medium-sized gaps in managed stands are randomly distributed, while in unmanaged stands they exhibit high clustering. Large gaps in unmanaged stands also show the strong clustering. In 2011, small gaps in both managed and unmanaged stands again show the low clustering. Medium and large gaps do not exhibit statistically significant clustering in either stand type, suggesting a more random or dispersed spatial arrangement. Specifically, medium and large gaps in managed stands are randomly distributed, while in unmanaged stands, no consistent clustering pattern is observed (Table 8).

Table 7. Global Getis-Ord clustering results for all gaps (without size classification) for 2007 and 2011

Year	Stands	Z-Score	P-Value	Clustering Degree
2007	Managed	-1.597	0.11$^{n.s}$	Random
	Unmanaged	-10.327	0**	Low Clusters
2011	Managed	-16.974	0**	Low Clusters
	Unmanaged	-14.680	0**	Low Clusters

Significance levels: **: 99% confidence level, n.s: not significant. In general, the Z-score (or standard score) indicates how far a data point is from the mean of the distribution, in terms of the number of standard deviations. The Z-score value helps us understand how much the observed dispersion pattern deviates from a random pattern.

Table 8. Global Getis-Ord clustering results by gap size class (small, medium, large) in 2007 and 2011

Year	Stands	Gap Size Classes	Z-Score	P-Value	Clustering Degree
2007	Managed	Small	-2.181	0.029*	Low Clusters
		Medium	1.606	0.108$^{n.s}$	Random
		Large	0.061	0.951$^{n.s}$	Random
	Unmanaged	Small	-3.185	0.001**	Low Clusters
		Medium	1.668	0.095^{+}	High Clusters
		Large	2.033	0.042*	High Clusters
2011	Managed	Small	-4.050	0**	Low Clusters
		Medium	-1.525	0.127$^{n.s}$	Random
		Large	-0.324	0.745$^{n.s}$	Random
	Unmanaged	Small	-2.303	0.021*	Low Clusters
		Medium	-1.325	0.184$^{n.s}$	Random
		Large	0.422	0.672$^{n.s}$	Random

Significance levels: **: 99% confidence level, *: 95% confidence level, +: 90% confidence level, n.s: not significant. In general, the Z-score (or standard score) indicates how far a data point is from the mean of the distribution, in terms of the number of standard deviations. The Z-score value helps us understand how much the observed dispersion pattern deviates from a random pattern.

3.5. Hotspot and cold spot analysis using Local Getis-Ord statistic

In 2007, hotspot and cold spot analysis of canopy gaps was conducted using the Local Getis-Ord statistic. The resulting maps, generated without considering gap size classes, revealed spatial clusters of high and low gap densities in both managed and unmanaged stands. These maps are presented in Figure 5, where panel (a) corresponds to the unmanaged stand and panel (b) to the managed stand. This analysis provided valuable insights into the spatial correlations of forest structure and helped identify areas with potential for regeneration or degradation. Further analysis incorporating gap size classes showed more detailed spatial clustering patterns. The maps derived from the Local Getis-Ord statistic for small, medium, and large gaps in 2007 are shown in Figure 6. In unmanaged stands, large gaps (Figure 6-a) and medium gaps (Figure 6-b) exhibited strong clustering, while small gaps (Figure 6-c) showed more scattered hot and cold spots. In managed stands, small gaps (Figure 6-d) displayed localized clustering patterns, highlighting areas of concentrated canopy disturbance.

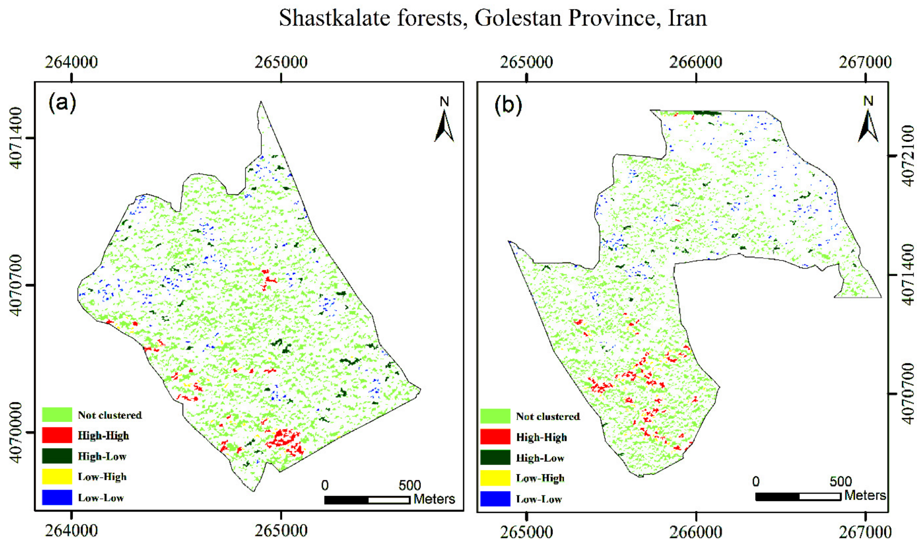

Figure 5. Hotspot and cold spot analysis maps using local Getis-Ord statistics in 2007, without considering gap size classes in unmanaged (a) and (b) managed stands.

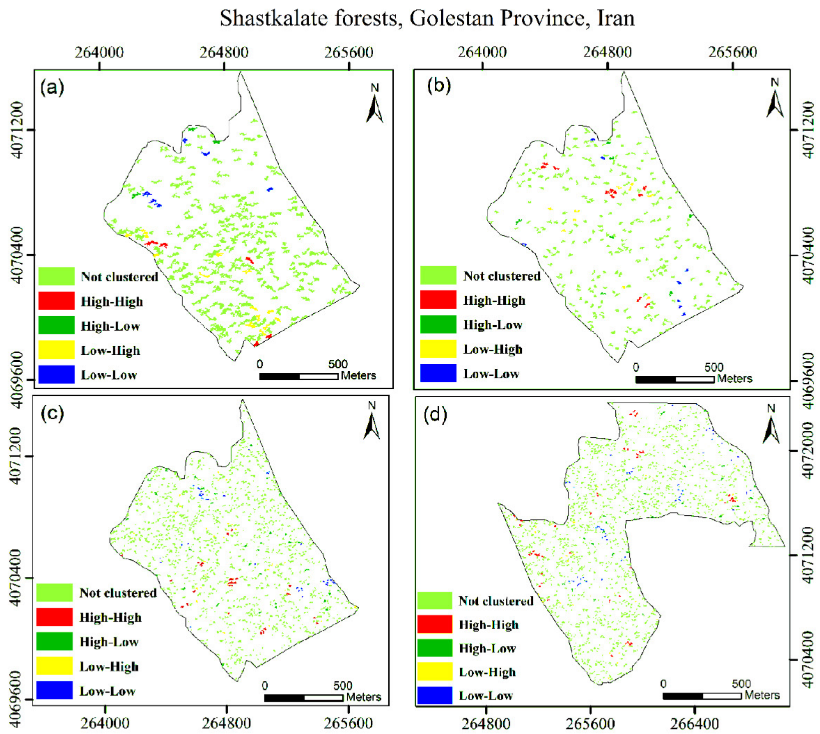

Figure 6. Hotspot and cold spot analysis maps using Local Getis-Ord statistics in 2007, showing spatial clustering of canopy gaps: (a) large gaps in unmanaged stands, (b) medium gaps in unmanaged stands, (c) small gaps in unmanaged stands, and (d) small gaps in managed stands.

In 2011, the Local Getis-Ord analysis was again applied to assess spatial clustering of canopy gaps. The maps generated without considering gap size classes are presented in figure 7, with panel (a) representing the unmanaged stand and panel (b) the managed stand. These maps revealed low to moderate clustering patterns, consistent with the results of the global clustering analysis. When gap size classes were considered in 2011, the Local Getis-Ord statistic identified spatial clusters primarily among small gaps. The resulting hotspot and cold spot maps are shown in figure 7, where panel (c) corresponds to small gaps in the unmanaged stand and panel (d) corresponds to small gaps in the managed stand. These localized patterns suggest that small-scale disturbances were spatially concentrated in specific areas, potentially reflecting underlying ecological or management-driven processes.

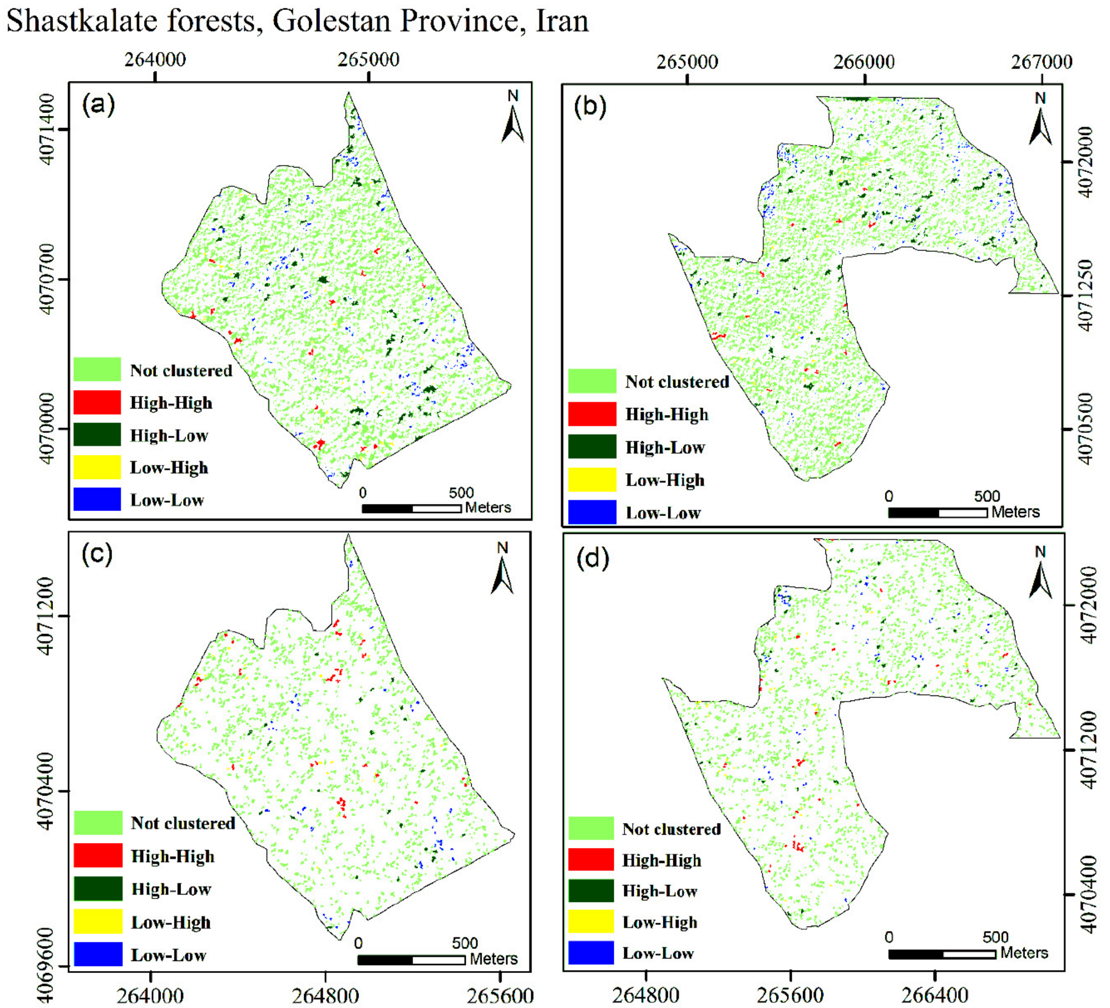

Figure 7. Hotspot and cold spot analysis maps using Local Getis-Ord statistics in 2011, showing gap distributions without size classification in unmanaged (a) and managed (b) stands, and for small gaps in unmanaged (c) and managed (d) stands.

4. DISCUSSION

This study investigated the changes in the spatial distribution patterns of canopy gaps using the classification of spectral satellite and aerial digital data in managed (harvested) and unmanaged stands and comparing pixel-based and object-based classification methods for distinguishing gap areas from non-gap areas. Based on the presented results, both pixel-based and object-based classification methods could provide acceptable results for classifying gap and non-gap regions. Although all maps generated using both methods exhibited high accuracy, the pixel-based method marginally outperformed the object-based method in producing gap and non-gap maps for the years 2007 and 2011. These findings are consistent with studies by Vepakomma et al. (2008), Malahlela et al. (2014), Felix et al. (2021), Jackson (2022) and Khalili et al. (2023), who successfully utilized high-quality remote sensing data and pixel-based or object-based classification methods to achieve satisfactory results. These studies collectively have demonstrated the effectiveness of remote sensing techniques in accurately mapping and analyzing canopy gaps across different forest types and conditions.

In the investigations regarding the spatial distribution patterns of canopy gaps in managed and unmanaged stands, the results from the Nearest Neighbor algorithm indicated a dispersed spatial distribution pattern for all gaps in both 2007 and 2011. However, upon analyzing the degree of clustering using the Global Getis-Ord statistic for all gaps in both forest stands, low clustering was observed in the unmanaged stands, while no clustering was detected in the managed stands in 2007. This suggests that tree harvesting, as part of the implementation of the first revision plan across the managed parcels, led to uniform gap distribution throughout the managed stands, with previous gaps remaining unchanged. Furthermore, the analysis for all gaps in 2011 revealed low clustering in both managed and unmanaged stands. According to the global Getis-Ord statistic, indicated that in the managed stands, selective logging after 2007 likely occurred in relative proximity, resulting in low clustering of gaps caused by tree removal. This finding aligns with the observation that selective logging treatment introduced spatial dependencies in gap formation, creating a low-clustered pattern of gaps within the managed stands post-2007.

In managed stands, the spatial distribution of small, medium, and large gaps consistently exhibited a clustered pattern, while in unmanaged stands, gap distribution tended to be random or dispersed. This result indicates that the spatial distribution pattern in managed stands which should normally be random, has been influenced by tree harvesting treatments, resulting in the creation of nearby gaps, and forming a clustered spatial distribution pattern. Based on the investigations of the first revision plan for harvesting (initiated in 1995) in District 1 (managed), it was determined that tree loggings had occurred in the studied parcels during various periods, with some parcels experiencing tree harvesting up until 2007. Therefore, it is possible that in these areas, as of 2007 (the first period of analyzing the spatial distribution patterns of gaps), the gaps created due to logging had not yet fully returned to their natural state, leading to a clustered distribution pattern observed in 2007. Over time, by 2011, the spatial distribution pattern of gaps (irrespective of size) using the Nearest Neighbor algorithm indicated a random distribution pattern in the harvested stand and a continued dispersed distribution pattern in the unmanaged stands. Additionally, when analyzing clustering degrees using the global Getis-Ord statistic for all gaps in both stand types, low clustering was observed in 2011. However, in the analysis of clustering based on gap size, clustered patterns were observed for small and medium gaps in managed stands, as well as for small gaps in unmanaged stands. This suggests that while overall clustering decreased over time in managed stands, specific size classes of gaps (small and medium) retained a clustered pattern, likely due to localized disturbances caused by selective logging treatment. These findings align with the notion that human-induced disturbances can create lasting effects on gap formation and spatial arrangement, influencing forest regeneration dynamics even years after the initial disturbance.

The analysis of clustering degrees using the global Getis-Ord statistic in 2007 revealed that small gaps in both managed and unmanaged stands exhibited low clustering. However, while medium and large gaps in managed stands showed some degree of clustering, these gaps in unmanaged stands were high-clustered within the study area. According to studies conducted by natural resource experts, severe storms before 2011 likely caused the loss of a significant number of trees in the unmanaged stands, which may explain the high clustering observed in medium and large gaps. The simultaneous removal of multiple adjacent trees leads to the formation of medium and large gaps, resulting in a clustered spatial distribution pattern, particularly due to external factors such as storms in the study region (Rodes-Blanco et al., 2023). Thus, the collective fall of trees caused by such disturbances can lead to the creation of medium and large gaps and contribute to the development of a clustered spatial distribution pattern.

5. CONCLUSION

This study analyzed the spatial distribution patterns of canopy gaps in 2007 and 2011 across managed and unmanaged forest stands using QuickBird and UltraCam-D imagery, classified through pixel-based and object-based methods. The pixel-based approach yielded slightly higher classification

accuracy. Spatial analyses revealed that, following harvesting activities, managed stands exhibited a highly clustered gap pattern in 2007, contrasting with the more natural distribution in unmanaged stands. By 2011, the spatial arrangement of large gaps in managed areas shifted toward a random pattern, indicating recovery and the effectiveness of selective logging practices. Natural disturbances also influenced spatial structure, as seen in the unmanaged stands, where gap patterns were more structured due to storm events before 2011. These findings highlight that both management and disturbance regimes shape canopy gap dynamics. Understanding these patterns is essential for developing effective forest management strategies and conserving biodiversity. Remote sensing techniques proved valuable for detecting canopy gaps, assessing forest health, and guiding targeted interventions in areas with clustered disturbances. Overall, such approaches support sustainable forest monitoring and ecosystem resilience.

Supplementary information ↑

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Supplementary material

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Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Authorship contribution statement

Omid Amiri-Karbandy: Conceptualization, Data gathering, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft.

Shaban Shataee-Jouibary: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing.

Mohammadhassan Naseri: Formal analysis, Methodology, Resources, Software, Writing – review & editing.

Jahangir Mohammadi: Methodology, Resources, Writing – review & editing.

Competing interests

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Statement on the use of Artificial Intelligence

The author(s) employed [Glosbe website] in order to translate the Abstract from English to Spanish while preparing this work. Following their use, the author(s) assumed full responsibility for the publication’s content and reviewed and edited it as necessary.

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