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COMBINING CAMERA TRAPS AND ARTIFICIAL INTELLIGENCE FOR MONITORING VISITOR FREQUENCIES IN NATURAL AREAS: LESSONS FROM A CASE STUDY IN THE BELGIAN ARDENNE

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KEYWORDS

Nature-based tourism - Visitor monitoring - Camera traps - Automatized image analysis - Ecosystem services Convolutional neural network

ABSTRACT

Visitor monitoring is essential for ecosystem management and the evaluation of ecosystem services. However, in natural areas without entrance fees and with scattered entry and exit points, this task can be challenging, costly, and labor-intensive. Camera traps can provide both quantitative and qualitative data on visitor frequencies, profiles, and activities in these remote areas. Manual image analysis, however, is time-consuming when dealing with large datasets. In this study, we analyzed more than 700,000 images collected by nineteen cameras over a year on hiking trails in the Belgian Ardenne. Consistent with recent studies, our research demonstrates that the use of a convolutional neural network (CNN) can achieve accurate and promising results in detecting and classifying people and non-people (dogs, bicycles). Nevertheless, automatic

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processing entails the risk of multiple counts of the same individuals, depending on camera's position, technical characteristics, and the time intervals between photos. This paper discusses the limitations and potential improvements of the monitoring methodology, from camera setup to data analysis. It concludes by the added value of this approach for the management of natural areas.

Management implications: The integration of AI with camera traps offers a practical and scalable solution for natural areas management by providing accurate data on visitor frequencies and behaviors. This approach can help site managers optimize visitor flows, reduce the impact of human activities on vulnerable ecosystems, and address user conflicts. It also supports sustainable tourism by informing decisions related to infrastructure, conservation priorities, and visitor access. Additionally, the flexibility of this method allows for site-specific adaptations, ensuring that monitoring efforts are aligned with management objectives while maintaining data transparency and privacy protection.

1. Introduction

1.1. VALUE OF OUTDOOR RECREATION AND CHALLENGES OF VISITOR MANAGEMENT

Outdoor recreation and tourism are cultural ecosystem services (ES) benefiting human wellbeing and local economies (Jones et al., 2020; Naidoo et al., 2019). Indeed, these ES and their related benefits, such as aesthetic appreciation and stress relief, are highly valued by nature visitors (Breyne et al., 2021; Doimo et al., 2020; Smith & Ram, 2017). Therefore, they can represent an important economic and political argument for conserving and restoring natural areas (Schirpke et al., 2018), especially when their financial contributions or cost savings are highlighted (Mayer et al., 2010; Schagner et al., 2017¨ ; Shanahan et al., 2016). On the other hand, over-frequentation of natural areas can also have negative impacts on the environment, such as trampling of vegetation, soil erosion, and the disturbance of wildlife (Cole, 2004; Runnstrom et al., 2019¨ ; Salesa & Cerda, 2020` ; Watson et al., 2014; Wolf et al., 2019). The COVID-19 pandemic gave multiple site managers a preview of the diverse challenges that need to be addressed within the context of growing nature-based tourism, while simultaneously highlighting the need for well-maintained natural areas for leisure activities (Derks et al., 2020; Hansen et al., 2023; Korpilo et al., 2021; McGinlay et al., 2020; Rice & Pan, 2021; Venter et al., 2020). To manage visitor fluxes and to ensure the sustainable management of natural areas, it is crucial to implement a sound monitoring of visitors, in terms of frequencies and behavior (Sievanen et al., 2008¨ ; Wolf et al., 2012).

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The number of visitors has been recognized as a principal indicator for the valuation of recreational ecosystem services, including ecotourism (de Groot et al., 2010; Mayer & Woltering, 2018; Milcu et al., 2013). Muhar et al. (2002) pointed out that the most important data to collect for visitor monitoring are (i) their number, (ii) their temporal variability of frequencies, (iii) their activity, and (iv) their density. However, in Europe, as opposed to North America or the Global South, most natural areas are public sites, accessible without passing an entry gate or paying an entrance fee (Job et al., 2021). This strongly hinders visitor monitoring and the consequent management of the area (Spenceley et al., 2021). Therefore, technical solutions should be provided to facilitate visitor monitoring.

Most information on outdoor recreation and tourism is based on extrapolations of counting events or survey data collected at specific moments, which does not allow for identifying spatial-temporal patterns in visitor frequencies and behavior (Sievanen et al., 2008¨ ; Spenceley et al., 2021). In Europe, traditional data such as accommodation statistics provide information on tourism frequencies in general but do not allow for evaluating the number of visits to natural areas. While passive tracking systems with infrared sensors, such as eco-counters, have been used for several years in outdoor areas to estimate visitation rates, it remains difficult to discriminate between persons and wildlife crossings, as well as to obtain qualitative information on the nature of visitors' activities (Fairfax et al., 2014; Pettebone et al., 2010; Spenceley et al., 2021).

Recently, innovative technologies, such as passive tracking based on mobile phone position data (Abedi et al., 2014; Ahas et al., 2008) or social media (Ghermandi & Sinclair, 2019; Pickering et al., 2023; Sinclair et al., 2018, 2020; Teles Da Mota & Pickering, 2020; Wood et al., 2013), provided detailed behavior information over a wide time span while covering larger areas (Heikinheimo et al., 2017; Kellner & Egger, 2016). However, mobile data remains dependent on the position of receiving antennas, which are generally much more dispersed in areas with low population densities of potential customers. It is hard to differentiate between a person who goes out into nature and one who does something else in large areas delimited by widely dispersed receiving antennas (Breyne, 2021). While information derived from social networking sites, such as photo analysis or the recording of hiking or trail tracks, provides accurate information on activities carried out, it only concerns a fraction of users of natural spaces (Wilkins et al., 2021).

For an accurate count of the number of people using a specific hiking route and their activities, we investigate in this article the potential of using camera traps (CTs) combined with artificial intelligence (AI) to automatically count the number of people in photos and describe their activities.

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1.2. LEVERAGING CAMERA TRAPS AND AI FOR VISITOR MONITORING

While CTs have been widely used for wildlife observation (Fisher, 2023), their use for the monitoring of outdoor recreation and tourism is less popular (Lupp et al., 2016, 2021; Staab et al., 2021). CTs allow for monitoring visitors continuously (all hours of the day and night and over longer periods of time) and cost-effectively (Roberts, 2011; Spenceley et al., 2021). They can provide quantitative data on the number of visitors passing in front of the CT by time of day, as well as qualitative data (Campbell, 2006; Spenceley et al., 2021; Staab et al., 2021). Qualitative data allows for identifying visitor activities (e.g., dog walkers, runners, hikers, itinerant hikers with big backpacks, bikers, etc.), checking group composition (e.g., alone, in groups, with children, etc.) and providing information on the revealed behavior of visitors (as opposed to the declared behavior). Moreover, it also allows for identifying potential infractions (e.g., dogs off-leash, motorized vehicles on hiker trails, nightly visits, etc.). This quantitative and qualitative information can be used to perform ES assessments or to decide about management measures related to nature-based tourism and recreation.

In the context of using CTs for visitor monitoring, two main issues remain: (i) the enormous amount of uninterpreted raw images to be processed and (ii) privacy protection (Staab et al., 2021). Previous studies using CTs mainly manually counted visitors (Arnberger et al., 2005; Bambi & Iacobelli, 2017; Campbell, 2006; Conlon, 2014; Fairfax et al., 2014; Reilly et al., 2017) or multiplied the number of pictures obtained by a correction factor estimated from manual count samples (Lupp et al., 2016, 2021) to estimate global visitor frequencies.

CT photography depends on motion detected by a passive infrared motion sensor, which detects variations in heat in the environment. When a person or an animal passes in front of the camera and emits heat, the sensor detects this difference and triggers the shot. However, the shot can also be generated by vegetation movement or variations in sunlight, which sometimes results in many empty photos on a single day (Fairfax et al., 2014). As a result, there can be significant differences over time between the number of photos taken and the number of persons who have passed in front of the camera.

The actual counting of people in all pictures remains the best solution, but depending on the number of visitors to the sites studied, this can be very time-consuming (Staab et al., 2021). It also leads to conflicts over privacy protection issues and anonymization as people can be recognized (Wilkins et al., 2021). To address this, previous studies placed the CT at knee height (Bambi & Iacobelli, 2017; Fennell et al., 2022), adjusted the settings to the lowest resolution possible (Arnberger et al., 2005) and/or blurred the lenses of the CT (Campbell, 2006; Fennell et al., 2022) to comply with privacy regulations.

Since these solutions are not ideal, as the degradation in photo quality makes counts more or less inaccurate, we counted people with AI based on convolutional neural networks (CNN) as proposed

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by several recent researches (Fennell et al., 2022; Mitterwallner et al., 2024; Staab et al., 2021). The use of AI tools to identify people or animals in CT pictures is growing fast. Staab et al. (2021) carried out a year-long study evaluating this method compared to conventional approaches, such as interviews, eco-counter pressure sensors, and manual image evaluation, at seven entrances to a protected forest area. Fennell et al. (2022) also performed a comparative study on visitors and wildlife simultaneously by using a recent open-source object detection model, focusing on identifying common mismatches and achieving better results with their model while highlighting the time gain compared to manual methods. The performance of these tools has been confirmed by Mitterwallner et al. (2024), who applied the same model to over 300,000 photos to identify people and animals in Bavaria.

A CNN is a deep learning model specialized for image analysis, using convolutional layers to detect patterns and features (Voulodimos et al., 2018). Over the past decade, several machine learning and deep learning methods have emerged to detect persons alongside hundreds of different classes of objects in images and video sequences. Recent and fast deep learning networks such as YOLOv4 (Wang et al., 2021) and EfficientDet-D3 (Tan et al., 2020, pp. 10781–10790) allow for real-time accurate detections, while much larger networks like Mask R-CNN (He et al., 2017, pp. 2961–2969) have excellent performance for object detection and instance segmentation on a large variety of classes. Contemporary researches (Fennell et al., 2022; Mitterwallner et al., 2024) used MegaDetector, another CNN algorithm widely used for wildlife monitoring images analysis (Beery et al., 2019; Microsoft, 2020), as they studied both fauna and humans.

The aim of this research is to contribute to the field of visitor monitoring by testing the potential of combining camera traps (CTs) with automated image analysis. The innovative aspect of this study lies in further exploring this combination and its related technical and analytical issues, thereby complementing the work done by Staab et al. (2021), Fennell et al. (2022) and Mitterwallner et al. (2024). This approach addresses a key challenge in using CTs for continuous visitor monitoring—namely, the labor-intensive process of manually reviewing each image—while maintaining the detail and richness of the collected data.

To be able to generalize the process in the field, we selected an open- source model (Mask R-CNN) largely used in detecting and identifying objects of interest, which can be operated by a wide range of users. In addition, we evaluate the performance of the methodology, and finally, results are used to gain insights into the spatial-temporal variability within and between different forest areas through a case study in the Belgian Ardenne where we collected photos over a year from twenty hiking trails. This case study yielded valuable insights that are crucial for informing natural areas managers and will be discussed in Section 4.5.

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2. Material and methods

2.1. CASE STUDY AREA

This study is part of the AGRETA Interreg project (Ardenne Grande Region, Eco-Tourism and Attractiveness), which brings together the institutional players in Belgian Ardenne tourism who want accurate indicators of visitor numbers in natural areas. The case study area concerns the forests of the Ardenne, located in the region of Wallonia in southern Belgium. With 6 million people living within a range of 100 km around these forests, there is a high demand for nature-based recreation and tourism (Colson et al., 2010). Ardenne visitors cited “nature” as the main reason for visiting the region, and the majority of Ardenne tourist operators name the natural environment as an essential aspect of their business (Breyne, 2021). The overall tourism sector currently makes up about 4% of the Walloon GDP (OwT, 2020). Nature-based tourism is increasingly regarded as an economic alternative to forestry and hunting activities, which strongly shape the Ardenne landscape, while potentially favoring the conservation and restoration of the Ardenne ecosystems (Filot, 2005).

Current statistics on visitor frequencies for Wallonia are provided by the Walloon Observatory for Tourism (OwT). These data are based on two main inputs: (i) accommodation statistics (registered lodgings from hotels, bed and breakfasts, campsites, guesthouses, etc.) and (ii) paid entries for attractions (zoos, museums, amusement parks, etc.). As elsewhere in Europe (Job et al., 2021), there is currently no standardized or continuous approach to monitor visitors to natural areas in the Ardenne. The scattered entry and exit points to the Ardenne forests strongly complicate the monitoring of visitor frequencies and their behavior. The only information on forest visits available for the Ardenne is provided by two studies. Colson (2009) performed phone surveys with Walloon and Brussels residents, as well as one-to-one surveys in 40 forest plots, and counted observations by forest guards. He estimated that 45% of Brussels and Walloon residents go into a Walloon forest at least once a month, and that approximately 130 million people visit the Walloon forests yearly, based on linear regression modeling. Bodson (2019) also surveyed residents from Wallonia and Brussels and similarly found that 49% of them visit a Walloon forest at least once a month. These two studies, however, are based on quite old data and do not reveal spatial-temporal patterns of visitor frequencies or detailed information about the profiles of those visitors.

The present study examines the potential of combining CTs with automated image analysis to provide site managers with more continuous, detailed, and site-specific information. Since the end of the COVID-19 crisis, the demand for "nature" has significantly increased (Hansen et al., 2023; Spalding et al., 2021; Venter et al., 2021; Yap et al., 2022). In the Ardennes, the public has diversified, and visitors' expectations have shifted toward more free activities outside the classic attractions. This shift has also generated negative reactions from forest managers and the local

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population (OwT, 2023). Therefore, to manage tourist flows correctly, it is essential to assess visitor numbers and the nature of their activities. This assessment will help validate these sentiments, which often depend on local or specific events and are not recurrent or generalizable (Spenceley et al., 2021).

Four main natural and forest massifs have been selected as pilot sites to test the visitor monitoring methodology (Fig. 1). The Natural Park "*Hautes Fagnes-Eifel*" (HF-E, 72.000 ha) includes a large peatland reserve and is highly reputed as a tourist hotspot. This area was recently closed due to an estimated over-frequentation related to the COVID-19 pandemic (Jebali & Van Oppens, 2020). The Natural Park "*Haute-Sûre Forêt d'Anlier*" (HSFA, 83.000 ha) represents the largest continuous broadleaved forest in Belgium; however, there are few recreational infrastructures present, and the forest is less known to the public. The Natural Park "*Deux Ourthes*" (PNDO, 76.000 ha) encompasses the valleys and plateaus around the Ourthe river and is situated around two main tourist cities, La Roche-en-Ardenne and Houffalize. The Great forest of "*Saint-Hubert*" (SH, 70.000 ha) lies at the heart of the Ardenne and is well known for its game presence and deciduous forests. In Belgium, natural parks are considered as category V protected areas according to the International Union for Conservation of Nature (IUCN) classification.

2.2. EXPERIMENTAL DESIGN

In the summer of 2018, twenty CTs were placed in the four aforementioned forest massifs, with a distribution of five per area. In coordination with the local forest agency *'Département de la Nature et des Forêts* (DNF)' and the administrations of the concerned natural parks, CTs were set up on some of the main trails in the area to ensure a certain visitor flux. Some CTs were placed on trails near specific points of interest, such as wildlife observation towers or well-known viewpoints.

A basic CT model was selected: the Dorr Snapshot Limited Black 5.0 ¨ S, which costs 89€ and operates on 8 alkaline AA batteries. Each CT was equipped with a 16-gigabyte SD card. This model uses infrared detection to detect moving objects within a range of 15–20 m and has a field of view with an angle of 52°. Upon detection, the CT was programmed to take two consecutive images with an approximate reaction time of 0.9 s between detection and the acquisition of the first image. Two images were preferred over one to ensure objects were captured entering the field of view after detection. The interval between two detection events was set to a minimum of 10 s to allow sufficient time for objects to move out of the capture area between events. CTs were mounted 3–5 m above ground to deter theft, and an explanatory card was included in each camera box in case it was retrieved. Vegetation obstructing the field of view or causing false detections was occasionally removed. The CTs operated for over one year, with start dates ranging from June 11, 2018, to August 21, 2018, depending on the area, and end dates from October 12, 2019, to October 24, 2019.

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Images were collected and batteries were checked once every one to three months. This resulted in a total of 734,433 images from the 20 CTs, detailed in Table 1.

2.3. DATA PROCESSING

2.3.1. DETECTION AND IDENTIFICATION

In this study, we used the Mask R-CNN algorithm (He et al., 2017, pp. 2961–2969) for object detection and identification. This CNN is among the state-of-the-art techniques for object detection in various environments (Voulodimos et al., 2018). The algorithm produces a set of predictions visualized as processed images containing bounding boxes around each detected object, as shown in Fig. 2. Simultaneously, it generates a text file per image detailing the positions, classes, and counts of the detected objects.

Fig. 1 : *Case study area with the locations of twenty camera traps (black icons) in Belgian Ardenne (yellow zone), major settlements (blue dots), primary roads (orange lines), and natural areas (green-hatched zones). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)*

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Mask R-CNN has been trained on the Microsoft COCO dataset, which includes over 1.5 million annotated objects across 90 object classes (Lin et al., 2014). For this study, three specific objects were selected for detection and identification: persons, bikes, and dogs. Objects were considered valid if identified with a confidence level greater than 70%, to avoid to miss some objects, and the consistency of these identifications was verified through manual checks. The text files generated by the model were subsequently processed using 9.4 (SAS, 2013) to obtain aggregated visitor counts and for further analyses. It is important to note that Mask R-CNN detects individual objects rather than groups. For example, it identifies a bike and a person separately, but not a biker. Consequently, visitor counts represent the total number of detected individuals, which includes a mix of simple hikers, bikers, or dog walkers.

2.3.2. TECHNICAL AND ANALYTICAL CONSIDERATIONS

In this section, we address technical inaccuracies relevant to this study. The earlier these issues arise in the process, the more downstream problems they are likely to cause.

Missing data. Despite the overall continuity of the data collection, there were some technical issues that caused gaps in the dataset. These issues included moving vegetation, poor weather conditions, and theft on two occasions. These problems resulted in gaps ranging from a few days to over a month for some CTs. Specifically, all images from "*Hérou*" (Her, PNDO) were excluded from the analysis due to an insufficient number of registered days, partly because the CT was stolen. For "*Baraque Michel*" (BM, HF-E), images from the first autumn (before August 29, 2018) were removed due to (i) the presence of a branch in the field of view and (ii) the felling of the tree to which the camera had been attached. In general, due to the large number of CTs and the total duration of the monitored period, missing data represented less than 10% of the dataset and did not significantly influence the overall relative results.

Privacy Protection. To comply with the General Data Protection Regulation (GDPR 2016/679), several measures were implemented to ensure that individuals could not be recognized in the images. Initially, three layers of transparent adhesive tape were attached to each camera lens to blur the images and address privacy concerns (Lupp et al., 2021). However, after a few months (see Table 1 for specific dates), these adhesives were removed because they caused non-detections by the model. Despite this, the position of the CTs at a height greater than 3 m and the adjustment of the settings to the lowest resolution helped prevent individual recognition. The presence of the adhesive tape in some images and its absence in others did not affect compliance with privacy regulations, but it could have impacted the performance of the algorithm. This potential impact was assessed through a paired *t*-test for each object category under study (i.e., persons, bikes, and dogs). After CNN processing, the upper part of the objects is blurred to make them anonymous like done by Fennell et al. (2022).

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False Trigger events. To demonstrate the added value of automated image analysis compared to extrapolation based on the number of images as an indicator of visitor numbers, we examined the importance of empty images (i.e., those without any targeted objects) and their variation over time (Findlay et al., 2020). This analysis was conducted using the cleaned dataset, which involved manually deleting erroneous images, such as those taken during the camera's installation, and duplicate images.

Redundancy. One of the main challenges in achieving accurate visitor counts was addressing redundancy, or the repeated counting of the same individuals. Three main issues of redundancy were managed in this study:

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Table 1 :*Overview of camera traps (CTs) deployment (n = 20) and visitor metrics across sites. Areas include: Natural Park 'Haute-Sûre Forêt d'Anlier' (HSFA), Natural Park 'Hautes Fagnes-Eifel' (HF-E), Natural Park 'Deux Ourthes' (PNDO), and the Great Forest of 'Saint-Hubert' (SH).*

Area	Site	CT code	Start Date	End Date	Start Date "non-blurred"	No. of active days	Total no. of images	No. of images/ CT/day	Total no. of images after screening	Total no. of visitors	Relative prop. of visitors	Avg. no. of visitors/image	Avg. no. of visitors/day	Total no. of bikers	Total no. of dogs
HSFA	Stand de tir	Sdt	21/08/18	23/10/19	01/04/19	428	21,085	49	1,995	3,166	4.52	1.59	7.4	512	174
	Fagne Jean Simon	FJS	21/08/18	23/10/19	01/04/19	428	10,137	24	3,082	5,977	8.65	1.94	13.96	1,98	176
	Etang Fabrique	EFa	21/08/18	23/10/19	01/04/19	389	50,920	131	20,671	34,479	58.88	1.67	88.63	2,263	1,040
	Pont	Pon	21/08/18	22/10/19	01/04/19	427	25,060	59	5,022	8,520	9.97	1.7	19.95	761	148
	Vallée	Val	21/08/18	23/10/19	01/04/19	428	18,691	44	2,640	3,118	5.64	1.18	7.29	923	120
	Total					**2,100**	**125,893**	**60**	**33,410**	**55,260**	**10.08**	**1.65**	**26.31**	**5,557**	**1,658**
HF-E	Polleur	Pol	11/07/18	12/10/19	12/02/19	327	65,732	201	18,844	39,635	12.47	2.1	121.21	382	627
	Baraque Michel	BM	11/07/18	18/10/19	12/02/19	449	121,734	271	30,192	108,748	33.69	3.6	242.2	492	593
	Pont Marie	PM	11/07/18	05/08/19	12/02/19	383	65,926	172	23,408	72,326	21.93	3.09	188.84	439	192
	Bout	Bou	11/07/18	24/10/19	12/02/19	470	41,344	88	13,380	33,015	10.39	2.47	70.24	634	200
	Botrange	Bot	11/07/18	24/10/19	02/08/18	470	73,305	156	28,337	64,006	20.14	2.26	136.18	4,055	878
	Total					**2,099**	**368,041**	**175**	**114,161**	**317,730**	**57.98**	**2.78**	**151.37**	**6,002**	**2,490**
PNDO	Cheslé	Che	12/07/18	23/10/19	28/01/19	469	7,998	17	3,174	7,644	7.62	2.41	16.3	28	95
	Hérou	Her	12/07/18	16/06/19	28/01/19	222									
	Barrage Nisramont	BN	12/07/18	23/10/19	28/01/19	405	40,180	99	18,289	35,577	35.49	1.95	87.84	75	135
	Engreux	Eng	12/07/18	23/10/19	28/01/19	469	38,501	82	16,346	44,058	42.96	2.7	93.94	383	690
	Plateau des Tailles	PdT	12/07/18	23/10/19	28/01/19	469	16,484	35	5,965	12,979	12.95	2.18	27.67	100	753
	Total					**2,034**	**103,163**	**51**	**43,774**	**100,258**	**18.29**	**2.29**	**49.29**	**586**	**1,673**
SH	Bilaude	Bil	13/07/18	10/08/19	21/03/19	394	45,530	116	9,001	18,902	25.28	2.1	47.97	878	187
	Priesse	Pri	13/07/18	23/10/19	21/03/19	468	46,603	100	12,300	23,727	29.79	1.93	50.7	571	158
	Pont Mauricy	MPM	13/07/18	23/10/19	21/03/19	468	9,494	20	3,586	8,707	10.26	2.43	18.6	409	204
	Fourneau Saint-Michel	FSM	08/08/18	23/10/19	21/03/19	442	27,354	62	8,180	18,770	25.1	2.29	42.47	501	798
	Beyoli	Bey	08/08/18	15/05/19	21/03/19	281	8,355	30	2,430	4,678	5.67	1.93	16.65	112	38
	Total					**2,053**	**137,336**	**67**	**35,497**	**74,784**	**13.65**	**2.11**	**36.43**	**2,471**	**1,385**
Total						**8,286**	**734,433**	**89**	**226,842**	**548,032**	**100**	**2.42**	**66.14**	**14,616**	**7,206**

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Fig. 2: *Example of a processed image from "Botrange" (Bot, HF-E) with bounding boxes for each detected/identified object, in this case two persons (red) and their bikes (green). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)*

(i) Some detection events were triggered less than 10 s after the previous event, likely due to a bug during image capture or metadata recording. These events were automatically removed during analysis.

(ii) Series of two images at each detection event. Ideally, each object of interest would be photographed only once. However, due to the camera's field of detection, individuals might appear partially or in full in two images. To avoid partial views of visitors, the CTs were configured to take two pictures at each detection event. The maximum number of objects per class was recorded from these two images.

(iii) The 10-s delay between two detection events was intended to allow sufficient time for objects to move out of the field of detection/vision. This interval was constant for all twenty CTs. However, the position of each camera in relation to the trail was not identical. Consequently, when the angle between the center of the image field and the trail was relatively small, the 10-s delay was not always sufficient to allow visitors to move out of the field of detection/view before a second series of photos was taken. This could lead to multiple detections of the same visitor(s). These multiple detections also occurred when individuals stagnated in front of a CT. In some cases, this stagnation was induced by the position of the CT and could have been avoided, as will be discussed. For the image analysis, whenever the detected number of visitors for a specific day and CT exceeded ten times the average number of visitors per day for that same CT, the images were manually checked to determine if these outliers were due to special events (e.g., sports events) representing true frequency rates, or if they were related to issues of redundancy (e.g., stagnating groups). If the latter was the case, the overall frequency for that day and CT was adjusted after a manual control.

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Model accuracy. Before interpreting visitor numbers and the proportions of different user profiles (i.e., walkers, cyclists, or dog walkers), it is essential to assess the accuracy of the Mask R-CNN model. Although Mask R-CNN was trained with diverse real-life examples (Lin et al., 2014), it was necessary to evaluate its performance with CT images taken under field conditions in natural areas.

A control sub-sample was manually reviewed for each CT during each astronomical season (spring, summer, fall, and winter, according to equinoxes and solstices) based on two criteria: (i) 100 consecutive images, randomly selected from each season for each of the 19 CTs, and (ii) a minimum of 50 true positive objects had to be identified. This resulted in a control sample representing approximately 1% of the total image dataset at the time of the analysis.

A confusion matrix was created for each CT, containing four categories: objects detected and correctly categorized (true positives - TP), mistakenly detected/identified objects (false positives - FP), missed detections (false negatives - FN), and correctly non-detected objects (true negatives - TN). For motion-triggered image capture tasks, calculating TN is problematic due to the uncertainty of the number of empty images collected. Therefore, sensitivity and specificity metrics (Altman & Bland, 1994) were used, calculated according to the following formulas:

$$Sensitivity(\%) = \frac{TP}{(TP + FN)}$$

$$Specificity(\%) = \frac{TP}{(TP + FP)}$$

Sensitivity and Specificity give respectively the proportion of positive and negative instances that are correctly identified. To obtain an estimation that corrects for these errors, we suggest to apply the following formula:

$$Estimation\ (no.) = N - [(1 - Specificity(\%))^{*}100] + [(1 - Sensitivity(\%)^{*}100]$$

Note that the final visitor numbers provided in the results section will be based on model outcomes and will not include corrected estimates. In addition, as mentioned earlier, the potential impact of blurring the lenses with adhesive tape during the first part of the monitoring period is evaluated for each profile through a paired bilateral *t*-test for each camera.

Camera positioning. The positioning of the CT is expected to play a significant role in the quality of the data (Campbell, 2006). However, this is not always straightforward in field conditions. The CTs were positioned at varying locations relative to the monitored trail to balance the need for support, minimize theft, and avoid altering hiker behavior. While standardizing the CT positions could have increased the stability of the results, spatial constraints and field conditions made this challenging. Nonetheless, this variation provides insights into the most effective CT positions for future visitor monitoring studies. Fig. 3 provides an overview of the 20 camera placements, showing the approximate horizontal angle of each CT relative to the monitored trail. Two specific

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issues related to CT positioning are addressed: (i) non-detections by the model, which may lead to an underestimation of visitor numbers, and (ii) redundancy, which may result in an overestimation of visitor numbers.

CNN non-detections. Objects of interest are present in the images, but the model fails to detect them (false negatives, FN). This issue is also addressed in Section 3.3. When individuals were not detected or classified by the model, the assumed causes were recorded. This check was carried out during the first months of field implementation and thus only concerned blurred images.

2.3.3. Visitor frequencies and spatial-temporal variability

Overall visitor frequencies were calculated over time and for each site. The counts for forest areas represent the sums of the CTdata from these areas. This method may lead to an overestimation of visitor frequencies if individuals make a round trip and pass by multiple CTs during the same visit.

Fig. 3 : *Example images from the 20 camera traps, showing the horizontal angle relative to the trail. The first column shows HSFA, the second HF-E, the third PNDO, and the fourth SH. Full names of the areas and camera locations are provided in Table 1*

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Such redundancy among CTs might occur in the HF-E (excluding the Pol site) or in the PNDO (between Eng and BN), though it involves routes longer than 15 km that are used by relatively few walkers. The variability in visitor numbers and the respective proportions of user profiles were evaluated over time, considering potential effects of seasons, weekends, and holiday periods, as well as the distribution of visitors throughout the day. This information was visualized using descriptive graphs. Two general linear model (GLM) analyses were performed, as this model handles non-normally distributed data effectively. The first assessed the relative influence of weekends, holidays, and seasons on visitor frequencies per site, while the second included CT positioning as an explanatory variable to highlight its relative influence compared to weekends, holidays, and seasons on frequency rates. Weather conditions were not included as explanatory variables due to their strong correlation with seasons and high daily variability, making it difficult to isolate their effects. Additionally, local administrations were consulted for an inventory of organized activities near the monitored sites during the study period. This information was compared with the frequency data to potentially explain any unusually high visitor numbers observed. All analyses were performed using the statistical software SAS 9.4 (2013).

2.4. DATA SECTION

Table 1 provides a detailed overview of the CTs deployment and overall results for each of the 20 sites. Given that the settings required each CT to capture two images in succession per detection event, this resulted in an average of 44.5 movement detections per site per day and approximately 89 images per site per day. The numbers labeled "after screening" refer to the images remaining after the removal of erroneous or empty images and the elimination of duplicate images. The total number of visitors presented is after correcting for outliers. The relative proportion of visitors refers to the proportion of each CT's data relative to the five CT of the area and each area's total data relative to the overall number of visitors. Images from "*Hérou*" (Her, PNDO) were excluded from the analysis due to the limited number of active days compared to other sites.

In total, we conducted a year-round monitoring at 20 different locations across four areas, resulting in the analysis of approximately 734,433 images (226,842 after screening) over a sampling effort of 8,286 days, yielding a ratio of 89 images per camera per day. From these images, 548,032 persons, 14,616 bikes, and 7,206 dogs were observed.

3. Results

The results section is structured into two main parts to thoroughly evaluate the effectiveness of the method and its application to a case study. In the first part, we assess the method's efficiency from camera setup to data processing. Initially, we quantify the impact of false camera triggers (3.1). Following this, we examine redundancy issues (multiple counts) based on trigger delay (3.2).

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Subsequently, we evaluate the sensitivity and specificity of Mask R-CNN on photos containing objects such as hikers, bikes, and dogs (3.3). Finally, we identify the causes of non-detection related to CT positioning and field conditions (3.4). In the second part, we apply the method to a case study in the Belgian Ardenne, conducting the first survey of this kind in the region.

3.1. FALSE TRIGGER EVENTS

Table 2 indicates the proportion of false trigger events, i.e., "empty" images without any objects of interest as identified by the model. On average, about one-third (31%) of the images are empty, but this proportion varies between 0% and 100% depending on the site and specific timing. Even though summed variances may cancel out, Fig. 4 demonstrates an important overall variation over time. On average, the proportion of false trigger events is higher in late spring and early summer when vegetation is growing and lower during the winter season.

3.2. TRIGGER DELAY AND REDUNDANCY

The selected trigger delay between detection events affects the visitor count (Fig. 5). As the trigger delay increases, the total number of people counted decreases, with a reduction of over 10% on average between intervals of 10–20 s, and over 26% between intervals of 10–60 s. While it is important to avoid counting the same individuals multiple times with too short a delay, such as less than 10 s, which is generally the time needed to leave the camera's field of detection, it is also crucial not to set the delay too long. Longer delays may result in undercounting groups of people who are more or less dispersed but following each other.

Variations in the interval can result from factors such as a group of people passing by in a short time or individuals lingering in front of the CT. Outliers exceeding ten times the average number of visitors per day and per site were manually reviewed, identifying 34 such days. Of these, 15 were confirmed as true counting events (e.g., organized trail runs or weekend snow), while the remaining 19 were classified as redundancy cases (e.g., picnics or stationary groups), leading to adjustments in the daily visitor frequency.

3.3. MODEL ACCURACY

Table 3 presents the sensitivity and specificity ratios for each object of interest. The results of the paired bilateral *t*-test, conducted per site to compare the model's performance on blurred versus non-blurred images, indicate no significant difference in specificity across any of the profiles.

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Table 2 : *Proportion of false trigger events across areas.*

Area	Avg. (%)	Median (%)	Min. (%)	Max. (%)
HSFA	40.3	35.4	6.3	95.6
HF-E	19.9	13.8	2.4	89.9
PNDO	20.4	15.1	0.1	100.0
SH	45.3	43.3	7.6	91.2
Total	31.1	26.4	4.5	93.7

Fig. 4 : *Overall proportion of empty images (false trigger events) and seasonal variation over a year. Seasons are defined astronomically.*

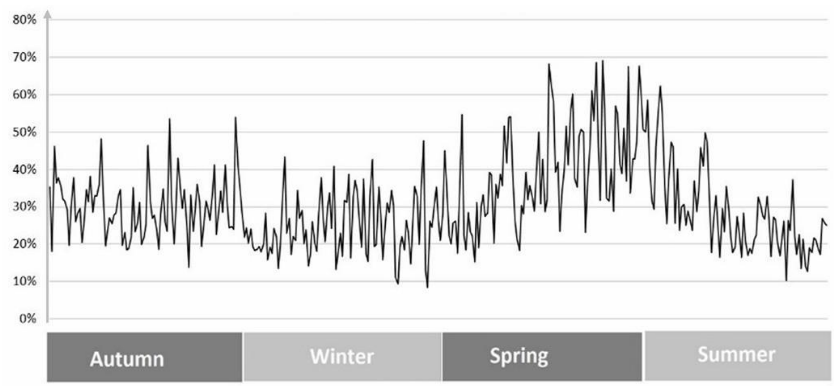
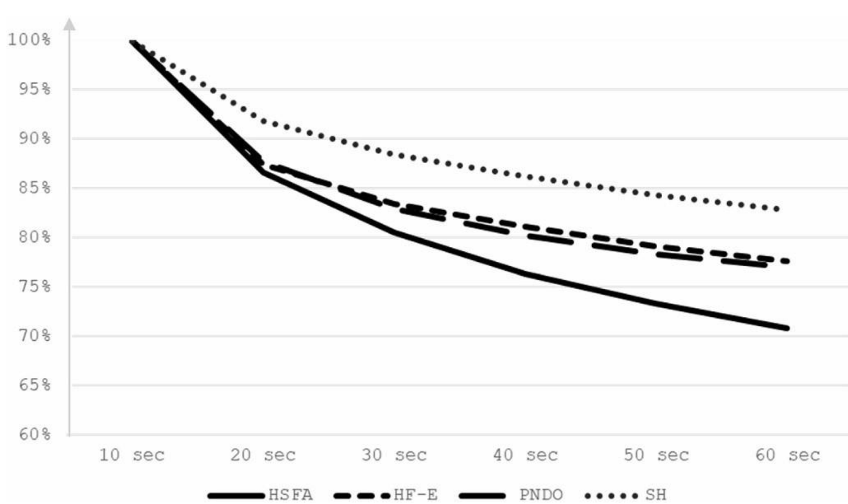


Fig. 5. *Influence of trigger delay variation on visitor detection proportions across areas.*



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However, the test does reveal a significant difference in the model's sensitivity for each object of interest. Thus, the additional blurring of images did indeed affect the model's performance.

Overall, the model demonstrates better performance in detecting and identifying persons compared to detecting and identifying bikes and dogs. Consequently, the proportions of bikes and dogs in reality are higher than those calculated by the model. Applying the correction formula, estimates for bikes are between 1.5 times (for non-blurred images) and 2 times (for blurred images) higher, while for dogs, estimates are between 3 times (for non-blurred images) and 4 times (for blurred images) higher.

3.4. NON-DETECTIONS

Two major issues contributing to non-detection events for blurred images were identified: the superposition of objects (21.7%) and excessive distance between the object and the CT (15.9%) (Fig. 6a). Fig. 6b illustrates example images for each of these known sources of non-detection.

In cases *ii* and *iii*, the horizontal angle between the center of the image and the direction of the trail is too small. This limited angle leads to two main issues: in case ii, when the trail is narrow and people must follow each other, they become overlapping in the image; in case *iii*, when combined with an open landscape, the small angle prevents people from leaving the frame within the 10-s delay, causing them to be present in the image when a nearby object triggers the camera, but not counted due to being too far away. Occasionally, these distant objects are counted under favorable conditions (e.g., good lighting), resulting in an overestimation of visitors as they are counted multiple times. Case *iv* was due to humidity accumulating between the lens and the adhesive, which severely blurred the image and rendered silhouette recognition impossible. Cases *v* and *vi* resulted from poor contrast, caused by a half-open canopy and nighttime conditions, respectively, and exacerbated by the presence of the adhesive tape. In case *vii*, the height at which the CTs were placed led to occlusion from objects blocking the view of the person (e.g., an umbrella). Due to the adhesive tape's impact on model performance, it was removed following approval from local site managers.

Table 3 *:Sensitivity and specificity ratios by object and results of paired-samples t-test. Note: ***p ≤ .001, *p ≤ .01; p ≤ .05.*

Object	Pairs	Sensitivity	Std. Deviation	Paired difference	Specificity	Std. Deviation	Paired difference
Person	blurred	0.92	0.05	**0.05*****	0.99	0.01	0.00
	non-blurred	0.97	0.02		0.99	0.01	
Bike	blurred	0.60	0.36	**0.20***	1.00	0.00	0.31
	non-blurred	0.80	0.24		0.89	0.31	
Dog	blurred	0.33	0.34	**0.26****	0.92	0.29	0.26
	non-blurred	0.59	0.17		0.99	0.03	

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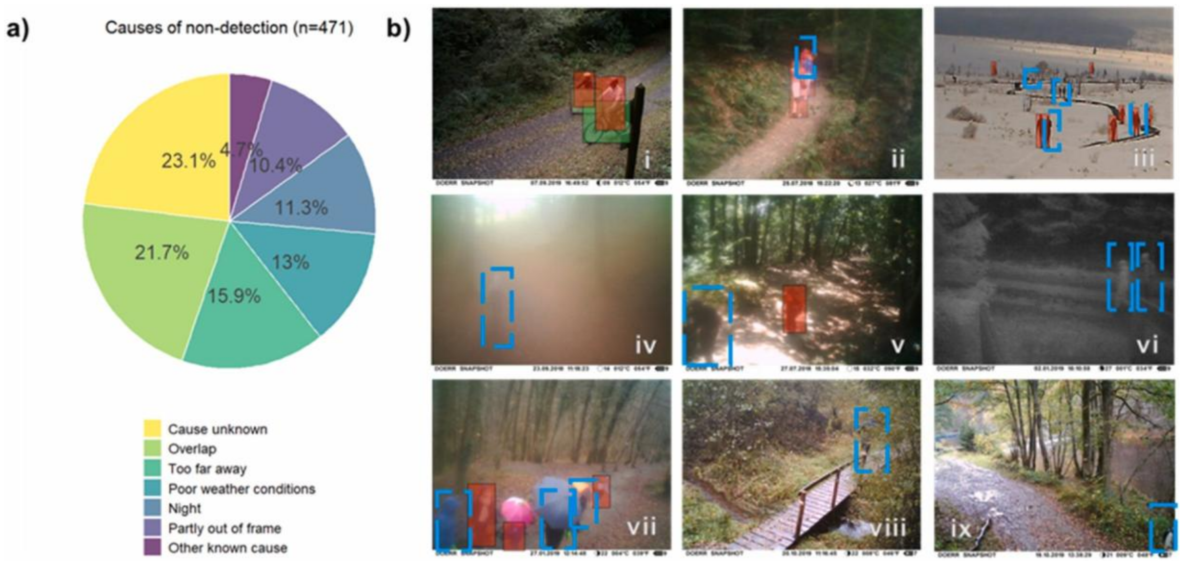
Fig. 6 : *Causes of non-detection. a) The relative proportions of causes of a non-detection of objects. b) Examples of causes of (in)correct detection: (i) Ideal conditions, (ii) Superposition, (iii) Too distant objects (zoom x8), (iv) Fog (weather conditions), (v) Poor light exposure, (vi) Night, (vii) Self-occlusion, (viii) Occlusion due to context, (ix) Object partly out of frame. Non-detected objects are marked by blue dotted lines. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)*



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For context-related occlusion (*viii*), the CT detects movement behind a partial obstruction (e.g., a bush), but the model fails to recognize the partially hidden person. In cases of objects of interest partly out of the frame (*ix*), this occurs because they are moving in or out of the frame, typically in the first or second image of the sequence, but are correctly identified in the subsequent images.

3.5. HOW MANY VISITORS USED THE MONITORED ARDENNE FOREST TRAILS ?

Number of visitors. During the entire monitored period, the 19 CTs captured data on more than 500,000 people, averaging 66 people per camera per day (Table 1). This number represents visitors passing by the monitored sites rather than the number of unique visitors in the area, as individuals might pass in front of multiple cameras on different occasions or visit the location several times. Additionally, visitors may access the forest areas without passing in front of the CT due to the high number of entrances and hiking trails in certain massifs. Of the detected visitors, hikers and bikers account for 97.35% and 2.65%, respectively, while dog walkers represent approximately 1.55%, based on the simplified assumption of one dog per person.

On average, two to three individuals were detected per image (Table 1). Group sizes were assessed based on the number of people appearing in a single image. However, this assessment was influenced by the camera's position and field of view, which introduced variability and limited the ability to draw significant conclusions from group size differences.

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Spatial variation. With more than 300,000 visitors, the HF-E area exhibited three to six times more photographed individuals compared to other areas (Table 1; Fig. 7). "*Baraque Michel*" (BM), located near the starting point of the most famous trail in the peatland reserve, is the most visited spot, whereas "*Bout*" (Bou), situated at the greatest distance from any well-known trailhead, is the least visited location.

The HSFA is the least visited area overall, but there is considerable spatial variation in visitor numbers. More than half of the visits (59%) are concentrated at "*Etang Fabrique*" (EFa), where the CT is positioned along an easy walk around a pond near one of the main villages. In contrast, other sites in HSFA are located on more remote trails within the forest. In the PNDO, the "*Barrage de Nisramont*" (BN) and "*Engreux*" (Eng) sites, both situated along a popular trail that traverses the Ardennes, show the highest visitor frequencies. "*Cheslé*" (Che), a historic site with a Celtic oppidum located at a significant distance from the car parks and the start of the trails, is the least frequented site in the PNDO, accounting for just 8% of visitors. In the SH forest, "*Priesse*" (Pri), located near a wildlife observation tower, records the highest visitor frequency, while "*Beyoli*" (Bey), situated at the far end of the forest, accounts for only 5% of the monitored visitors to the SH forest.

Temporal variations. Very high peaks in visitor frequency were most often associated with special events (such as trail running or mountain biking) or the presence of snow in the area with the highest altitude in Belgium (HF-E). The inventory of organized activities provided by local administrations corresponded with these unusual peaks in visitor frequency, as illustrated in Fig. 7.

When individual CT locations were included as explanatory variables in the general linear model, weekends remained the most significant factor ($F = 294.40$), followed by the specific CT location ($F = 128.58$), holiday periods ($F = 17.14$), and astronomical seasonality ($F = 13.20$). On average, visitor frequencies on weekends were 2.76 times higher than on weekdays, while holiday periods saw 1.38 times more visitors. Compared to winter, spring had 1.01 times more visitors, summer had 1.17 times more visitors, and autumn had 1.30 times more visitors.

Fig. 7 : *Spatial-temporal variation in the number of visitors/camera.day for each area over a yearly timespan. Seasons are defined astronomically and trail running events are referred as "Trail".*

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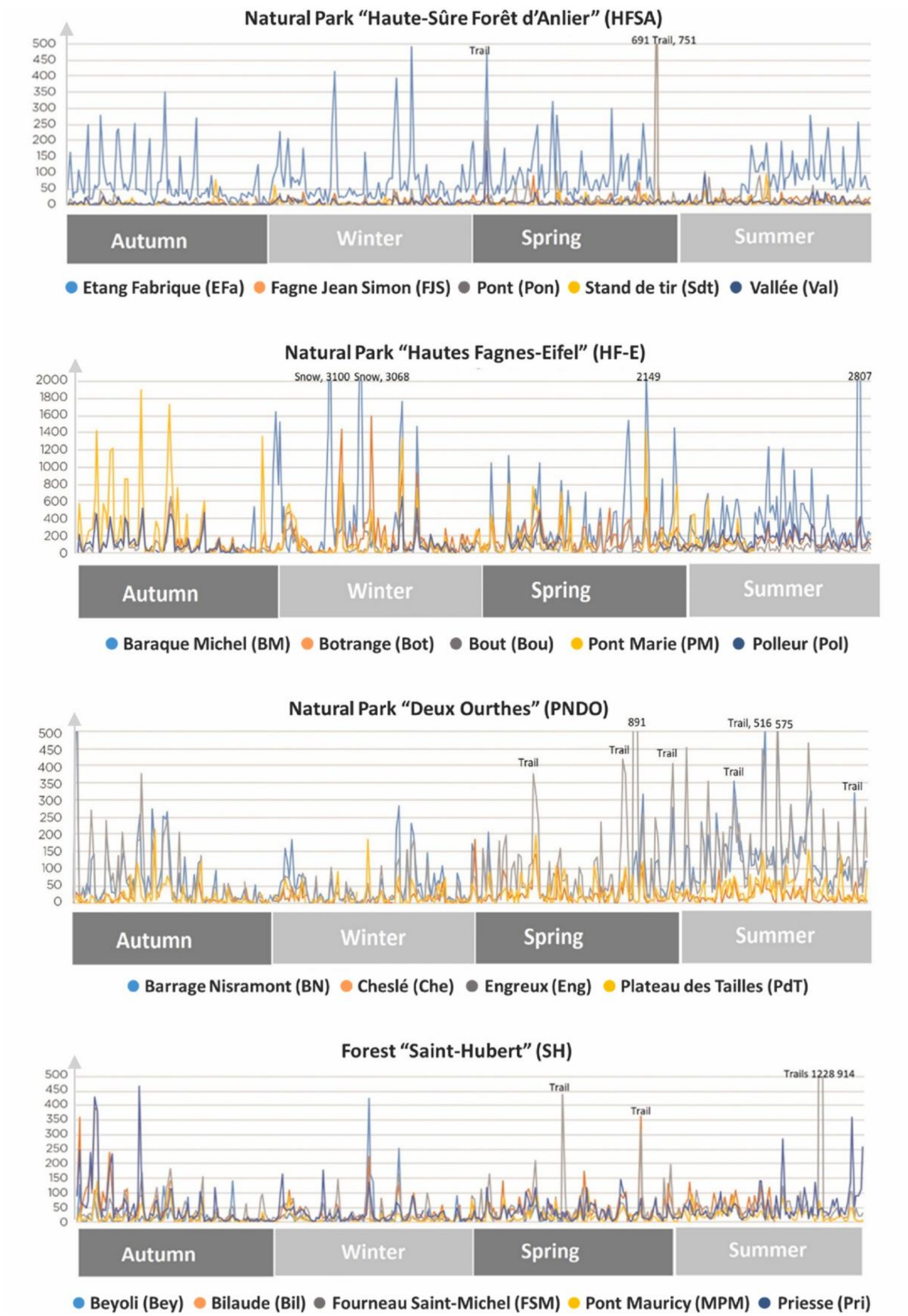

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Given the significant site effect, a site-by-site GLM was then carried out to measure the effect of temporal variables such as weekends, holidays and seasons (Table 4). Seasonal effects, weekends, and holiday periods also significantly influenced visitor numbers. Even though this influence varied across different sites in Belgian Ardenne, weekends are generally the main explanatory factor for variations in visitor frequency at natural sites. However, the relative importance of holiday periods and seasonality depended on the specific CT location. For example, seasonality was a significant factor at "*Bilaude*" (Bil, SH) due to the autumn deer roaring event, while holiday periods were more influential at "*Plateau des Tailles*" (PdT, PNDO).

When analyzing visitor attendance throughout the day (Fig. 8) for winter and summer periods, defined by the change in hours on March 31, 2019, we observed an average peak in activity for hikers and two distinct peaks in activity for bikers. However, the timing of these peaks varies slightly with the season. In winter, activity begins earlier and there is a later peak at the end of the afternoon occurring compared to summer.

4. Discussion

4.1. THE BENEFITS OF COMBINING CAMERA TRAPS AND AI FOR VISITOR MONITORING

In this study, we evaluated the effectiveness of a camera trap-based monitoring method using a CNN to improve time and work efficiency by automatically detecting, classifying, and counting visitors in open areas. Our focus included false trigger events, redundancy, model accuracy, and non-detection issues, emphasizing biases due to camera positioning, field conditions, and human behavior through a case study in the Belgian Ardenne.

We conducted year-round monitoring across four areas, resulting in the analysis of over 734,000 CT images with a sampling effort exceeding 8,000 days (Table 1). These figures are larger than those reported by Fennell et al. (2022) and Mitterwallner et al. (2024), confirming the high potential of camera traps for monitoring human activities along popular hiking trails.

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Table 4 : *Overview of F-values from the Generalized Linear Models (GLM) for each of the explanatory variables per site. CT: Camera trap location. Note: ***p ≤ .001, **p ≤ .01; *p ≤ .05*

Area	CT	Weekend	Holidays	Season	Weekend* Holidays	Weekend* Season	Season * Holidays	Weekend*Holidays*Season	R^2 (%)	Overall F-value
HSFA	Efa	94.08 ***	2.59	0.46	1.17	2.11	0.92	2.70 *	34.9	13.38 ***
	FJS	4.53 *	0.45	1.15	1.63	0.69	1.42	1.01	7.7	2.11 *
	Pon	3.84 *	0.16	2.19	3.10	0.16	0.71	1.08	8.4	2.25 **
	Sdt	9.85 ***	11.56 ***	5.49 ***	0.19	6.19 ***	2.85 *	4.00 **	22.0	6.48 ***
	Val	18.15 ***	2.01	3.82 **	2.50	2.20	0.58	1.21	16.9	4.78 ***
HF-E	BM	26.75 ***	0.43	1.44	0.26	0.91	0.58	1.94	14.1	3.73 ***
	Bot	49.20 ***	9.50 ***	7.07 ***	4.21 *	0.99	10.52 ***	9.29 ***	36.2	15.07 ***
	Bou	67.93 ***	6.06 **	9.95 ***	8.63 ***	3.44 *	4.69 ***	4.66 ***	35.1	16.14 ***
	PM	38.25 ***	3.64	8.13 ***	10.95 ***	2.14	2.30	1.51	32.8	11.01 ***
	Pol	43.07 ***	9.90 ***	2.83 *	1.67	2.40	4.16 *	7.62 ***	40.2	16.19 ***
PNDO	BN	56.53 ***	18.16 ***	15.59 ***	3.11	4.20 **	2.55	1.41	45.4	24.84 ***
	Che	77.82 ***	25.73 ***	16.02 ***	0.15	6.36 ***	3.36 *	2.88	33.7	14.02 ***
	Eng	30.31 ***	2.70	14.47 ***	0.03	3.03 *	0.37	1.33	26.3	10.58 ***
	PdT	26.71 ***	10.63 ***	2.24	0.04	1.84	0.97	1.62	17.6	5.65 ***
SH	Bey	5.77 *	0.05	0.28	5.07 *	0.14	1.80	0.52	14.7	2.36 **
	Bil	32.04 ***	0.03	7.10 ***	6.00 **	2.35	4.50 ***	0.81	24.5	8.10 ***
	FSM	29.29 ***	1.95	1.97	1.35	1.67	0.99	0.35	16.4	5.45 ***
	MPM	46.74 ***	34.07 ***	8.27 ***	1.00	4.69 ***	3.70 **	2.95 *	29.7	11.20 ***
	Pri	25.43 ***	0.74	4.80 ***	6.54 **	4.35 ***	2.45	0.48	26.6	10.58 ***

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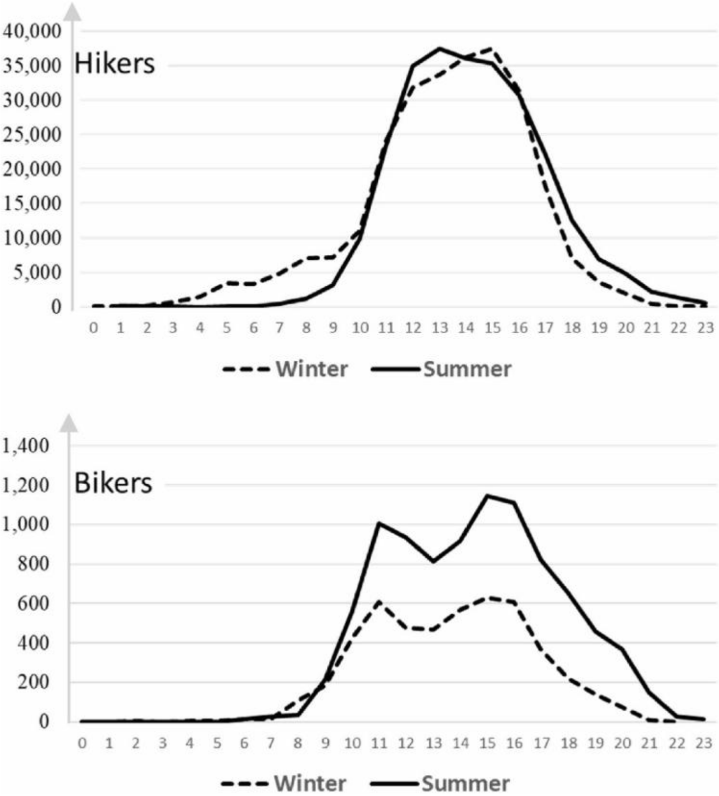
Fig. 8 : *Absolute visitor (hikers, bikers) count according to season and time of day (hours).*



Previous studies carried out a decade ago using CTs for visitor monitoring have predominantly relied on manual counting to estimate visitor frequencies (Arnberger et al., 2005; Bambi & Iacobelli, 2017; Campbell, 2006; Conlon, 2014; Fairfax et al., 2014; Reilly et al., 2017). While the manual counting method allows for precise quantitative data after analyzing sequences of several photos to give a unique visitor number and qualitative information on hiker behavior and user profiles, it is impractical to implement this method on several hundred thousand photos.

Lupp et al. (2016, 2021) proposed a method to control false trigger events by checking the number of people in a sample of photos and extrapolating the total number of visitors from the number of pictures. They assume a stable ratio over time. In our study this ratio evolves throughout the year, with more empty photos in spring and early summer due to vegetation growth or the presence of sunny areas in the camera's field of detection. Despite careful attention to vegetation evolution during periodic camera surveys, we still observed 31% of "empty" photos, i.e., without hikers, bikers, or dogs. Therefore, this cannot be a reliable estimator of the number of visitors.

To address this problem, the use of CNNs to automatically detect, classify, and count people in photos is very efficient. In our case, we achieved a sensitivity of 97% and a specificity of 99% using a low-end CT (<100 €) with low-quality shots and positioned at a relative distance from hiking trails. This is comparable to the results of Fennell et al. (2022) and Mitterwallner et al. (2024), who achieved sensitivities of 95% and 91% and specificities of 99% each, using MegaDetector (Beery et al., 2019; Microsoft, 2020), another CNN algorithm. Once the analysis process is set up, it is straightforward and can handle sets of several hundred thousand photos.

However, the analysis is less effective for bikers, with a sensitivity of 80% and a specificity of 89%, due to their speed of movement in the camera's field of view, resulting in blurred photos or partial views of the bike. As discussed below, more powerful CT and appropriate positioning can improve the detection of fast-moving objects.

Combining CTs and CNN also has advantages over other passive counting methods, such as infrared automatic counters, as images are available to verify anomalies in counts. In several cases, daily peaks were due to organized trail running events, leading to specific increases in visitor frequency. The images can identify the nature of the group activity, whether it was declared or not, and whether it led to issues such as trail deterioration or wildlife disturbance.

In several instances, CTs captured sharp daily peaks in visitor frequency at one site due to a group stopping or picnicking in front of it, causing repeated movement detections and over-counting. To accurately assess visitor numbers and count visitors, they need to be on the move to limit redundancy and avoid counting the same people multiple times. CTs should be positioned to avoid points of interest such as viewpoints and crossroads, which are likely to cause people to stop. Additionally, CTs must be positioned subtly to limit theft and avoid to draw attention.

Finally, unlike other counting methods, such as infrared automatic counters, CTs are clearly cheaper and can be easily moved to different locations if needed. These insights underline the potential of combining AI with CTs for visitor monitoring in natural areas, confirming the methodological insights obtained by Staab et al. (2021). Even if automatic counting is not 100% accurate, it is at least four times faster, which is crucial when processing hundreds of thousands of photos.

4.2. PRIVACY PROTECTION ISSUES AND ANONYMIZATION

To comply with the General Data Protection Regulation of the European Union (GDPR 2016/679) and respect the human ethics (Sandbrook et al., 2021; Sharma et al., 2020), several measures were implemented to ensure individuals could not be easily recognized. The GDPR requires the anonymization process to be guaranteed as best as possible from the moment the picture is taken and throughout the analysis process. We combined the use of layers of transparent adhesive tape (as for Lupp et al., 2021), low-resolution pictures, and the placement of CT at least 3–4 m away and not directly in the movement direction to avoid individual recognition.

The use of layers of transparent adhesive tape to blur photos impacts the quality of human silhouette recognition, with specificity dropping from 97% to 92%. However, this physical system also caused problems of CT fogging in the wettest locations, rendering some CT non- functional.

The analysis process must be highly supervised and validated by a Digital Protection Officer. The procedure stipulates, for example, that only a limited number of responsible persons can handle the files with the original photos, and that after analysis, faces are systematically blurred and the originals deleted. Various blurring techniques for the images based on frames recognized by the CNN model are available, such as the method used by Fennell et al. (2022) and Mitterwallner et al. (2024). Once the faces have been sufficiently blurred, the photos can be used to verify the AI

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results, identify particular events, or count activities or situations not automatically identified. For instance, we were able to show that barely 50% of dogs are on a leash, even though this is compulsory in the forests studied.

4.3. SPATIAL-TEMPORAL VARIABILITY

Due to the automated detection, identification, and counting method used in this study, it was possible to handle large volumes of data and ensure continuous monitoring over a one-year period. As expected, there was a clear overall effect of the type of day (weekend versus weekday) and specific periods (holiday periods, respective seasons). Overall, weekends saw approximately three times more visitors than weekdays, making weekends a more important factor in explaining visitor frequencies than holiday periods or seasonal variations. This suggests a higher influx of day-trippers residing at a relatively moderate distance from the forest areas compared to long-term holiday stays, as also observed by Job et al. (2021) in Germany.

When considering the seasonal effect, autumn appears slightly more attractive than summer. During summer, people often head to the beach or travel abroad for extended vacations, while in autumn, they prefer visiting local natural areas, similar to trends observed in some German national parks (Sinclair et al., 2020). This could be due to the combination of the colors of deciduous forests, mushroom picking, and the deer roaring during this time of the year in the monitored areas, especially SH. While weather conditions certainly influence visitation patterns, they were not analyzed in detail in this study due to their strong correlation with seasons and high daily variability. This focus on seasonal trends allowed for a clearer understanding of overall visitation dynamics.

The results also demonstrate strong spatial variability between and within sites, indicating differences in popularity and attractiveness. The "*Hautes Fagnes-Eifel*" area (HF-E) alone accounts for more than half of the total visitors. At the level of individual CT, average daily frequencies range between 6 and 242 visitors. CTs with the highest frequencies are located near specific points of interest, such as observation platforms/ towers and hideouts like "*Botrange*" (Bot, SH), "*Bilaude*" (Bil, SH), and "*Priesse*" (Pri, SH), on popular trails like "*Pont Marie*" (PM, HF-E) and "*Engreux*" (Eng, PNDO), or close to easy access points like "*Etang Fabrique*" (EFa, HSFA) and "*Barrage de Nisramont*" (BN, PNDO). More remote CTs not located near specific points of interest show relatively lower frequencies, such as "*Beyoli*" (Bey, SH), "*Pont*" (Pon, HSFA), and "*Bout*" (Bou, HF-E).

For some trails, only the weekend effect is notable (Efa, FJS and Pon from HFSA; BM from HF-E; FSM from SH), suggesting they are primarily used for local recreation and do not experience increased traffic during peak tourist periods. In contrast, other trails also receive a substantial increase in usage during holiday periods (e.g., SDT from HFSA, Bot and Pol from HF-E, BN from PNDO), indicating their attractiveness for tourists. This point-specific information can guide site managers on the pertinence of infrastructure at specific locations, the geographical designation of nature reserves, or the potential to organize tourist activities, diversifying routes to limit overcrowding on weekends. As mentioned earlier, unusual peaks in frequencies for certain CTs were due to the organization of specific events. Information obtained can be used by event organizers or local authorities for planning future events, evaluating past ones and communicating about it.

The frequentation of different user profiles (hikers, bikers, and dog walkers) over the hours of the day showed a similar peak in trail use. For certain trails or during high seasons, this might trigger tensions and conflicts between users. Several incidents between bikers and hikers have already been reported in the Ardenne region (Dehaye & Evrard, 2020; Sudinfo, 2020). CTs could objectively examine this issue in problem-solving processes. The spatial variation of the presence of different profiles seems largely due to access restrictions or physically unsuitable trails for specific types of use. For example, the "*Baraque Michel*" (BM) CT which recorded the highest overall frequency, accounts for 34% of monitored hikers in the "*Hautes Fagnes-Eifel"* (HF-E) but only 8% of bikers, as bikes are not allowed on this duckboard trail in the peatland nature reserve. These results provide an estimate of the frequency of infractions, indicating to site managers the need for revised signage or intensified field control at this location. The "*Barrage de Nisramont*" (BN, PNDO) CT shows 36% of hikers versus 12% of bikers, likely due to the very steep and rocky trail suitable for thrill-seekers.

4.4. SOURCES OF UNWANTED VARIATION

Various factors may contribute to undesirable variations in visitor numbers.

Camera Model. One important factor is the performance and quality of the CT. In our study, we chose a standard entry-level model (<€100) in 2019, with a field of view and detection range of 52°, a sensitivity distance of around 15–20 m, and a physical trigger delay of about 1 s. Staab et al. (2021) compared manual counts with CT counts. They found that CTs detect only a portion of people passing in front of them (88.4% in their case). This is likely true for the equipment we used as well. Higher-quality CTs now available have greater motion detection sensitivity and faster photo capture, making it easier to capture fast-moving visitors, such as bikers, with sharper photos that are easier for AI to identify.

Camera Position. A second factor affecting data quality is CTs positioning relative to the trail, as discussed based on the identified causes of non-detection events. One cause is the superposition of objects in the picture, where objects hide others. Superposition occurred mainly when CTs were positioned relatively frontally with an angle of nearly 0° or perpendicularly with an angle of nearly 90° to the trail. Objects passing behind or next to each other are hence superposed in the image, complicating correct identification by the model. Another parameter is the distance from the path, which can lead to objects not being detected but also to multiple counts of the same hikers. When the CT is activated due to the movement detection of a nearby object, objects situated at a greater distance are also captured in the same image. While some of these remain undetected, the model does detect these objects on several occasions, especially in good lighting conditions; this potential redundancy should be avoided.

For visual counting on CT pictures, Campbell (2006)suggests placing it such that trail users move towards or away from the camera to deal with fast-moving cyclists. In their case, Miller et al. (2017)

suggest to place the CT at a distance of 1–2m from the trail, with a 20° angle to the trail for users moving than 8 kph. This frontal position does not lend itself to automated detection methods due to issues of superposition and distant objects. In our case, the best detection ratios were found for cameras placed at an angle between 30° and 80° to the trail and at a distance of 2–5 m. Cameras positioned frontally to the trail also allow objects to stay too long within the field of view, creating redundance.

A too-great height of the CT, combined with low image resolution, complicates correct identification of low-to-the-ground objects, such as dogs (author's observation). Additionally, the Mask-RCNN model was trained on a dataset where objects were represented at about eye level (Lin et al., 2014), giving a different perspective than a bird's eye view. The closer a CT is positioned to the trail, the lower its height should be to reduce this plunging view. A height of 2 m at a distance of 2–5 m seems ideal, though this also makes the CTs more visible to visitors, making it important to protect them from theft (Meek et al., 2013) and camouflage them to avoid altering visitor behavior.

Plant and light obstructions must also be taken into account when placing the CTs. It is advisable to verify the images taken during the first days to check for potential elements causing false triggers or obstructions. Additionally, vegetation at the edge of the detection field must be regularly trimmed. As discussed before, it is advisable not to place the cameras near landscape elements conducive to stopping objects of interest (e.g., bridges, tree stumps, intersections, and hideouts), as this increases the risk of redundancy.

Camera Settings. A third factor is the CT settings. To limit potential redundancy, we set a 10-s interval between triggers of two photos. Mitterwallner et al. (2024) use no delay between triggers, while Fennell et al. (2022) analyze data with a time lapse of 5 min between events. The 10-s delay was found through field tests to be the best compromise between overestimation (0 s) and underestimation (5 min). Analyses show that successive events within a short period of 10 s are quite rare, even in the case of a group of hikers, whose members are rarely just one behind the other. As anonymized photos are always available, it is possible to check what has happened in the field and to manually correct automatic counts when groups of people follow each other continuously.

Parameters can also be set according to the camera's position relative to the path, as it is not always possible to have an ideally placed support that optimizes the shot while remaining discreet.

4.5. MANAGER USES AND CHALLENGES

The quantification and reporting of visitor frequencies in natural areas, where no site-specific data was previously available apart from subjective observations, highlights the importance of these natural areas for the general public. An accurate estimation of visitor frequencies can support a re-evaluation of the ecosystem services emphasized in a particular area, alongside adjustments to the budget allocated for sustaining those services.

Our results confirmed the general assumption that more remote trails receive lower frequencies than easily accessible, well-reputed, or sign- posted trails (Marion & Leung, 2004; Zhai et al., 2018).

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Estimating the order of magnitude of visitor frequencies to these different locations and their variation over time can guide site managers in structuring visitor fluxes through space and time, both for existing and future areas prone to nature-based tourism.

While the monitoring devices of this study were no longer in place during the COVID-19 pandemic, the "*Hautes Fagnes-Eifel*" (HF-E) was temporarily closed due to reported over-frequentation (Jebali & Van Oppens, 2020). This event triggered a public discussion on how to sustainably combine nature conservation, access rights to nature for different user profiles, and scattered/concentrated visitor frequencies. Implementing a flexible and continuous monitoring system could facilitate decision-making processes on this topic by providing reliable and objective information.

This paper contributes to the field of outdoor visitor monitoring by evaluating the potential of using CTs in combination with AI. It was shown that this combination allows for handling large amounts of data over a continuous monitoring period, correctly identifying empty images and the main objects of interest, and providing qualitative data on top of quantitative data, with the possibility to manually verify any data anomalies. Additionally, unlike other counting methods, such as infrared automatic counters, CTs are cheaper and can easily be moved to different locations if needed. All these insights underline the potential of combining AI with CTs for visitor monitoring in natural areas, confirming the methodological insights obtained by Staab et al. (2021).

Nevertheless, the feasibility and added value of implementing this method for continuous outdoor visitor monitoring depend both on fine- tuning this method on a technical and procedural level and on the monitoring context and objectives. To cope with the issues outlined in this paper, several improvements were identified for further research or field applications:

1. For comparison between CTs and depending on the objects to detect, we advise placing CTs at an angle of 30°–80° to the trail, at a distance of 2–5 m and 2 m in height.

2. Sensitivity for objects of interest other than persons can be improved through scene-specific training on images from CTs rather than an external dataset (Cioppa et al., 2019).

3. Clear regulations concerning privacy protection for CTs and the adopted analytical methodology should be established (Sandbrook et al., 2021; Sharma et al., 2020; Wilkins et al., 2021), possibly using an algorithm that automatically detects and blurs faces on-the-fly before storing the data (Farfade et al., 2015; Fennell et al., 2022; Mitterwallner et al., 2024).

4. Further research on integrating different quantitative and qualitative monitoring techniques, such as mobile phone positioning data (Abedi et al., 2014; Ahas et al., 2008), user-generated content from social media (Pickering et al., 2023), visitor surveys, and ecological impact assessments.

While one can always monitor more precisely to gather more reliable and detailed information, monitoring efforts in the context of site management, compared to research projects, should address site- specific needs, possibilities, and objectives. Site managers often have limited budgets and human resources. The monitoring protocol outlined in this paper is not yet fully automated and requires specific technical competencies and time investment from the site's management team or externalization of the monitoring activities to a (research) institution or company. Externalization can enhance exchanges between natural resource managers and scientists (Maebe et al., 2023), but transparency in methodology (e.g., on privacy matters) and accessibility of deliverables must be ensured for the monitoring outcomes to be useful for management practices.

For this paper, we focused on general visitor counting and included profiles such as hikers, bikers, and dog walkers. With the Mask-RCNN algorithm, it is theoretically possible to include other profiles or items related to those profiles, such as horsemen, joggers, backpackers, skiers, wheelchair users, prams, and children versus adults. This could provide more detailed insight into site users' profiles and their respective proportions over time, potentially allowing site managers to identify needs, set priorities, and adapt their management accordingly. However, an overload of information does not necessarily lead to better management practices. Site-specific issues and needs should determine the necessary information for improving management.

The use of CTs could foster the cohabitation of human activities and wildlife by detecting user profiles and wildlife and objectifying the impact of visitor frequencies on wildlife presence. For example, one of this study's CTs captured images of the first official comeback of the wolf to the Ardenne territory. Another potential application relates to the ongoing discussion about the cohabitation of hikers and bikers in natural areas (Rupf et al., 2014). Understanding the proportion of each user profile in different areas can help identify problematic points and nuance media reports on conflicts.

Combining information on visitor frequencies and profiles with data on visitor preferences for landscape characteristics and indices of the ecological status of the landscape can inform site management strategies and support potential shifts in management practices. Baum et al. (2017) found that ecological characteristics of a site largely explained visiting frequencies, with specific location ranked second; Simkin et al. (2020) found that the type of forest (old-growth, plantation, etc.) impacts the mental health effects on forest visitors. Such data can guide management decisions to ensure the sustainable management of natural areas.

5. Conclusions

The outlined methodology helps alleviate one of the main constraints to using camera traps (CTs) for continuous visitor monitoring, specifically the time-consuming requirement of manually verifying each image, without losing the level of detail of the available information. While this research concerned a pilot study and identified several points for improvement, it also demonstrated the potential of combining CTs with automated image analysis through AI. This method can provide insightful, site-specific, quantitative and qualitative information on visitor frequencies and profiles over a continuous time frame. This can complement information from more large-scale monitoring assessments if they exist.

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Visitor frequency data should be combined with an understanding of the drivers behind those frequencies, such as specific landscape characteristics, insights into the socio-cultural context, and the ecological status of the area, among others. This research represents a contribution to the field of visitor monitoring and ecosystem services assessments. It provides an improved tool to visualize the importance of natural areas for recreation and tourism, which in turn can foster the sustainable management of those areas.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Quentin Guidosse: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation.

Johanna Breyne: Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Anthony Cioppa:** Software, Methodology. **Kevin Marechal:** ´ Writing – review & editing, Supervision. **Ulysse Rubens:** Software, Methodology. **Marc Van Droogenbroeck:** Software, Resources, Methodology. **Marc Dufrene:** ˆ Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data will be made available on request.

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