AI and Computer Vision for Park Studies in Abu Dhabi: Understanding Urban Parks Through Large-Scale Image Analysis

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Abstract

We present an interdisciplinary study that applies computer vision to analyze urban parks in Abu Dhabi. Leveraging a dataset of approximately 12,000 user-generated images sourced from Google Maps, we built a pipeline to clean, process, and interpret visual information from green spaces, encompassing metadata filtering, geolocation curation, duplicate removal, and semantic outlier detection. Using YOLOv8* object detection, spatial density maps, temporal trend analyses, and behavioral heatmaps, we examine how parks are used and perceived by the public. Our findings reveal distinct spatiotemporal rhythms of park use, including strong evening peaks reflecting climate adaptation and weekend surges tied to family-oriented activity. Frequently detected objects such as palm trees, other trees, flowers, and fountains capture the ecological character of these spaces, with natural elements consistently dominating visual prominence and serving as proxies for the social and restorative functions parks fulfill. Spatial density maps further identify certain parks as primary centers of activity. We also reflect on the challenges of applying pretrained AI models to heterogeneous, user-generated data, including sampling bias and model transferability. This work contributes to broader Nature-Based Solutions (NBS) efforts and supports evidence-based urban green space planning in rapidly urbanizing contexts.

Keywords: urban parks, computer vision, object detection, urban ecology, Abu Dhabi

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Introduction

Rapid global urbanization has led to a significant decline in human well-being, often manifesting as a profound disconnection from nature and an increase in stress-related disorders (Bornioli et al., 2018; Jiang et al., 2024; Rahnema et al., 2019). In this context, studies have shown that urban green spaces can be described as restorative environments, defined as settings enabling recovery from a depleted psychological state. Abu Dhabi presents a particularly compelling context for this research. As a rapidly urbanizing Gulf city operating under extreme climatic conditions, it has invested heavily in green infrastructure as part of its broader sustainability agenda.

Urban parks in Abu Dhabi serve not only as recreational spaces but as ecological interventions — cooling islands, biodiversity refuges, and connectors within wider Nature-Based Solutions (NBS) frameworks. Understanding who uses these parks, when, and how they engage with these symbolically and functionally distinct environments is therefore a question of both social science and urban ecology.

In this study, we apply computer vision techniques to approximately 12,000 images of urban parks in Abu Dhabi, developing a comprehensive pipeline that addresses challenges in heterogeneous user-generated datasets through metadata cleaning, geolocation curation, duplicate removal, and semantic outlier detection. Using YOLOv8 object detection alongside spatial density mapping, temporal trend analysis, and behavioral heatmaps, we quantify visual ecology, visitation rhythms, and feature prominence to reveal how parks function as ecological and social spaces. In doing so, we contribute to methodological debates at the intersection of geography, ecology, AI, and digital humanities. The following sections detail our reproducible preprocessing pipeline and analytical workflow.

Related Work

Bornioli et al. (2018) discuss the two theoretical frameworks that ground the definition of restorative environments: Ulrich's Stress Recovery Theory (SRT) and Kaplan and Kaplan's Attention Restoration Theory (ART). SRT focuses on the emotional and physiological recovery from stress, relating restorative effects of natural environments with humans' innate evolutionary inclination toward nature. Conversely, ART focuses on cognitive recovery from "directed attention fatigue", suggesting restoration occurs when an environment provides a mental break through "being away" or "soft fascination". Urban parks are also recognized as components that deliver critical ecosystem services and serve as Nature-Based Solutions (NBS) to protect human well-being and ecological resilience against rapid urbanization (Jiang et al., 2024; Plieninger et al., 2022).

Several methods are usually employed in the study of park use, varying in cost, accessibility, and experimental control. They can be split into two categories: on-site and off-site (Xiang et al., 2021). On-site methods include Visitor-Employed Photography and on-site interviews and surveys. Visitor-Employed Photography (VEP) involves tasking participants of the experiment with taking pictures of scenes they "liked" and "disliked", accompanied by a photo-log explaining their choices. This method allows for capturing real-time on-site interactions and subjective meanings but can be highly resource-intensive and sensitive to potential bias introduced by participants' pre-existing beliefs (Jiang et al., 2024; Lee & Son, 2017; Sun et al., 2019). While on-site interviews and surveys provide researchers with an opportunity to interact directly with participants in the field, not only do they require extensive processing time but are also susceptible to external influences by uncontrollable factors and unexpected incidents (Xiang et al., 2021).

On the other hand, off-site methods include Virtual Reality and Photo Elicitation. Virtual Reality (VR) technology offers high degrees of experimental control and the ability to provide participants with the feeling of being physically present through the virtual environment (Gao et al., 2019). The experience of “being there” is a complex perception formed through an interplay of multisensory information and various cognitive processes. Therefore, Gao et al. (2019) show that participants using VR devices displayed different sensory perceptions and even adverse physiological reactions that compromise VR presence, further resulting in different effects of perceptions. Photo Elicitation involves participants evaluating 2D images in a controlled indoor setting, individually or in a group, accompanied by interviews, questionnaires or oral questions. While Photo Elicitation has historically been used in small-scale participatory research, recent work has extended the concept to large-scale computational analysis, using automated methods to interpret the content and context of photographs at scale. This method offers a low-cost and accessible way to study public perception but limits participants’ direct interaction with the spaces they are evaluating (Gao et al., 2019). In addition, research shows the limited range of view and the composition of the photographs can affect visual preferences (Lee & Son, 2017; Xiang et al., 2021).

Beyond these participant-centered approaches, the proliferation of digital photography, street-level imagery, and crowdsourced data, combined with advances in deep learning, has enabled the study of urban landscapes at unprecedented scales. Convolutional Neural Networks (CNNs) and object detection models like YOLOv8 now quantify visual features such as green view indices, object prominence, and streetscape characteristics from massive image corpora, providing scalable proxies for human perception and park usage patterns (Ibrahim et al., 2020; Liu et al., 2017; Sun et al., 2019). Geographic Information Systems (GIS) further support objective modeling of visual geometry, while emerging biometric and generative techniques like eye-tracking and Generative Adversarial Networks (GANs) offer complementary insights into attention and design potential (Manning et al., 2023; Qiu et al., 2023). This transition from resource-intensive manual methods to automated, large-scale analysis addresses key limitations in traditional perception studies, enabling city-wide assessments that inform planning without relying on small-sample surveys or subjective judgment (Zhang et al., 2022).

Pipeline Overview

Our pipeline was designed to transform a raw, heterogeneous image collection into a structured dataset suitable for computational analysis and interpretation. We began with approximately 12,000 images depicting a variety of Abu Dhabi parks, with diverse content and metadata. Like many user-generated corpora, the dataset suffered from missing or corrupted EXIF fields, absent GPS coordinates, intra- and inter-folder duplicates, and content outliers (e.g., unrelated images accidentally included). We implemented a sequential four-step preprocessing workflow.

Data Infrastructure and Synchronization

The image corpus is hosted on Google Cloud Storage (GCS), which serves as the primary storage backend for the project. Access to the storage layer is controlled through authentication keys and secure credentials. During experimentation, challenges emerged regarding public access permissions through Hugging Face Spaces interfaces, particularly concerning authenticated retrieval of remote assets. To facilitate collaborative access and experimentation, a public-facing interface was deployed through Hugging Face Spaces: https://huggingface.co/spaces/XavierF/ADParks12K. This interface provides visualization and prototyping capabilities for the dataset and associated computer vision workflows.

Rather than relying on static ZIP archives, the project adopts an automated ingestion strategy. A Python-based synchronization script connects directly to the GCS backend and programmatically downloads images and metadata. While compressed ZIP exports can be generated for archival or offline use, automated scripted retrieval remains the preferred access method. The synchronization pipeline was designed for server-side deployment rather than purely local execution. This architecture enables continuous ingestion and updating as new images are added to the remote storage infrastructure, ensuring that the dataset remains a living and evolving corpus instead of a fixed snapshot.

Core Preprocessing Workflow

We implemented a stepwise preprocessing workflow comprising four principal stages:

1. **Metadata extraction and quality filtering:** EXIF[1] fields such as timestamps, device type, and resolution were extracted using Python's PIL library. Images with more than 50% missing metadata or poor resolution were excluded, ensuring baseline quality. A temporal quality check revealed sparse coverage before 2017 (< 50 images/year), insufficient for robust trend analysis of park interactions. Accordingly, all subsequent processing used only images from 2017 onwards.
2. **Geolocation curation:** Park locations were manually geocoded from Google Maps based on folder names, introducing moderate spatial uncertainty. This step allowed us to associate each photo with a specific park and facilitated subsequent spatial analyses.
3. **Duplicate detection and removal:** Perceptual hashing (pHash)[2] using the ImageHash library in Python was employed to identify both exact and near-duplicate images. This sequential approach eliminated redundancy while retaining sufficient coverage for spatial and temporal analysis, leaving only unique images.
4. **Semantic outlier detection:** Image embeddings were generated using the pretrained OpenAI CLIP[3] (Contrastive Language–Image Pre-training) model (ViT-B/32). Cosine similarities were computed between each image embedding and the dataset centroid. Outliers were detected using a robust Median Absolute Deviation (MAD) approach: the median similarity served as the central tendency, with the threshold set at median minus three times the MAD. Images falling beyond this threshold were flagged as potential outliers (e.g., unrelated indoor scenes or advertisements) and removed after manual verification.

Integration With Downstream Processing

After synchronization and preprocessing, the cleaned images are integrated into a broader computer vision processing pipeline combining object detection, semantic tagging, and spatial analysis workflows. Experimental deployments and visualization interfaces were prototyped

[1] EXIF (Exchangeable Image File Format) is a standard for storing metadata—such as date, time, camera settings, and location—directly within digital image files.
[2] Perceptual hashing (pHash) is an algorithm that generates a fingerprint of an image based on its visual content, allowing for the detection of near-duplicates even if they have been compressed or slightly edited.
[3] CLIP (Contrastive Language–Image Pre-training) is a neural network trained on a vast variety of (image, text) pairs, enabling it to understand and represent visual concepts using natural language.

using Hugging Face Spaces and Google Colab environments. Within this pipeline, images are processed, annotated, and enriched with spatial and temporal metadata to support downstream analyses, including geospatial mapping, environmental perception studies, and behavioral interpretation of urban park usage.

Each of these steps was automated where possible, but supplemented by human validation to ensure reliability. The resulting dataset is both cleaner and more representative, with georeferenced images that can be systematically explored across space and time. This foundation enables robust quantitative modeling (e.g., density maps, heatmaps, object frequency trends) while preserving qualitative interpretability (e.g., experiential analysis of photographed features).

Dataset Accessibility and Reproducibility

To encourage reproducibility and future collaboration, the project infrastructure was designed around modular and remotely accessible components. Data synchronization scripts, cloud storage interfaces, and experimental visualization environments allow the dataset and associated analyses to evolve continuously as new imagery becomes available. This architecture supports future scaling toward larger urban datasets and additional Nature-Based Solutions (NBS) applications.

Technical Stack

The collection and preprocessing layer was primarily implemented in Python, leveraging the Google Cloud Storage API for remote data access and synchronization. Hugging Face Spaces was used for interface prototyping and collaborative experimentation, while server-side execution enabled continuous ingestion and automated updates of the evolving dataset.

Computer Vision Methods

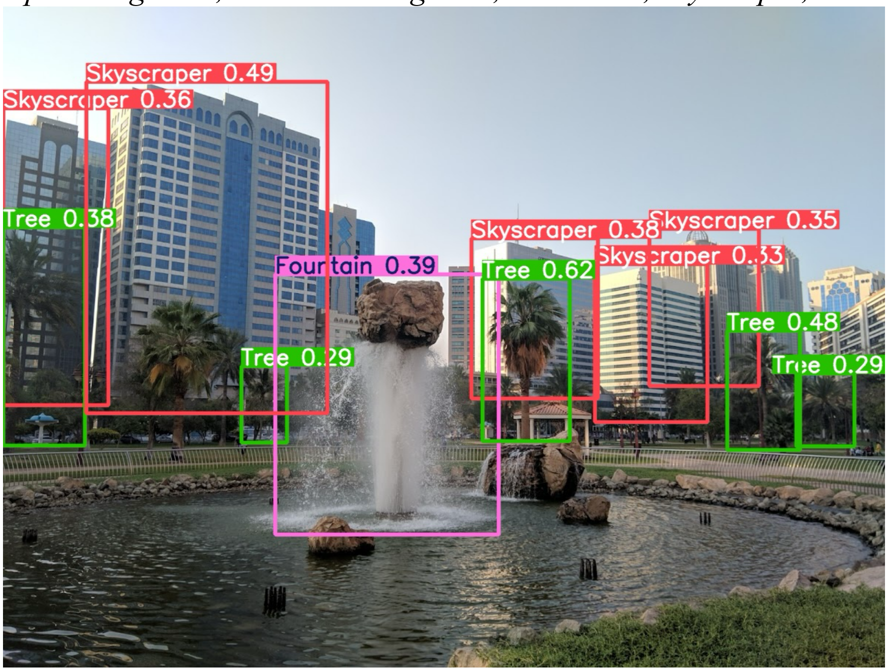
With the cleaned dataset of georeferenced park images, we next applied object detection to quantify visual content and enable spatiotemporal analyses.

YOLO Object Detection

The YOLOv8m model from Ultralytics, pretrained on Open Images V7 without fine-tuning, was employed as the primary object detection framework. The model was configured with default settings. Object detection provided bounding boxes, confidence scores, and approximate pixel areas for items such as trees, benches, play areas, and people. Of the processed images, approximately 350 lacked valid detections due to low light, occlusion, or domain shift between the Open Images training data and Abu Dhabi park imagery. By focusing on the ten most consistent labels, we constructed longitudinal profiles of visual prominence across years. Figure 1 illustrates an example detection on a photograph from Abu Dhabi Corniche Park.

Figure 1

Example YOLOv8m Detections on a Photograph of Abu Dhabi Corniche Park. The Model Returns Bounding Boxes, Class Labels, and Confidence Scores for Categories Drawn From Open Images V7, Here Including Tree, Palm Tree, Skyscraper, and Fountain.



Spatial and Temporal Visualization

We built a visualization suite to uncover spatiotemporal patterns in the cleaned image dataset:

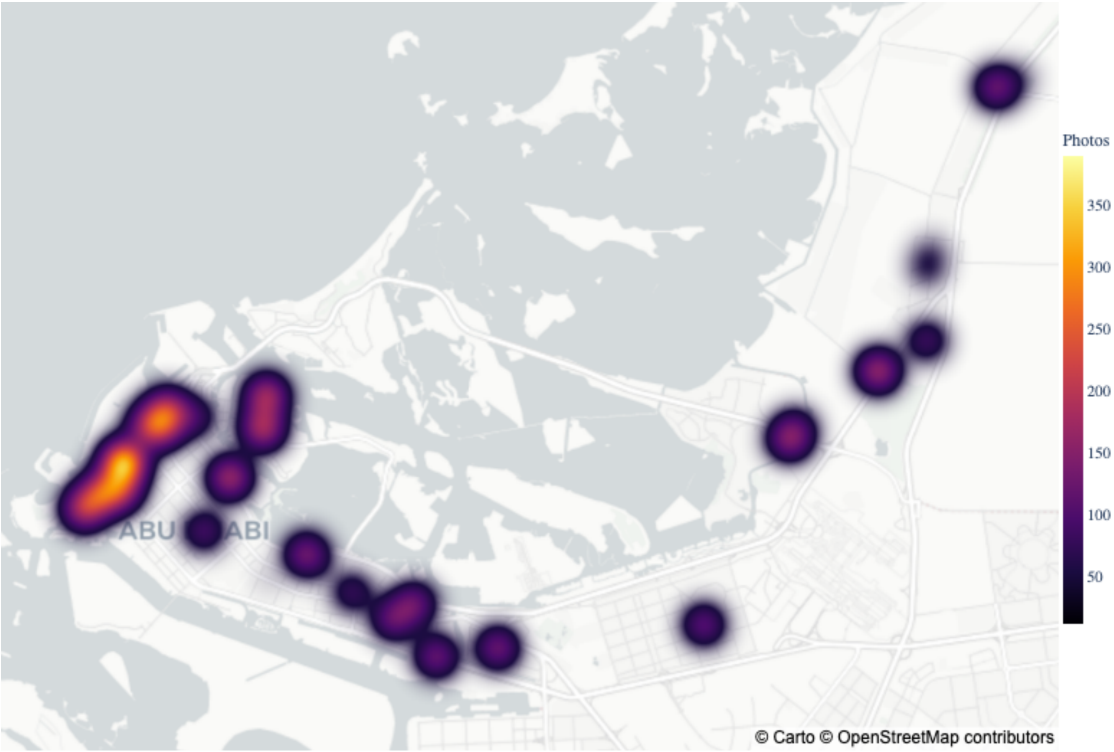
Spatial density maps: Georeferenced images were projected onto a city-scale map of Abu Dhabi, with kernel density estimation used to generate continuous density surfaces representing the concentration of photographs across the urban landscape. These surfaces serve as proxies for photographic attention and, by extension, visitation intensity. As shown in Figure 2, Corniche Beach Park, Khalidiyah Park, and Reem Central Park dominate the distribution, reflecting both their size and their cultural prominence as preferred destinations.

Temporal bar charts: Yearly photo counts were computed per park and visualized as stacked bar charts, enabling longitudinal comparison of photographic activity. Growth patterns are visible across the dataset, linked to park renovations and expansions, local public events, and the broader adoption of smartphones and social media platforms — all of which increased both photography and image-sharing behavior over the observation period.

Behavioral heatmaps: By extracting timestamp information from image metadata, we constructed weekday × hour heatmaps that map the temporal distribution of photographic activity across the week. These heatmaps reveal consistent patterns of park use: strong evening visitation peaks between 17:00 and 19:00 are present across most parks, reflecting the adaptation of outdoor leisure to Abu Dhabi's extreme daytime heat, particularly during summer months. Friday and Saturday show the highest evening intensities of the week, consistent with concentrated weekend leisure during the UAE weekend.

Figure 2

Spatial Density Map of User-Generated Photographs Across Abu Dhabi Parks. Smoothed Point Density Estimation Reveals Concentrations at Corniche Beach Park, Khalidiyah Park, and Reem Central Park.



Analyses

The integrated analyses highlight several findings:

- **Visual ecology:** Natural elements capture significantly more visual focus than artificial objects, facilitating "soft fascination" that reduces mental fatigue (Bornioli et al., 2018; Qiu et al., 2023). Urban backdrops (skyscrapers, streetlights) frequently appear, providing "legibility" and "place identity" that connect parks to Abu Dhabi's skyline while offering symbolic historical grounding (Bornioli et al., 2018; Rodríguez et al., 2019; Tveit, 2009). As shown in Figure 3, trees dominate detections across all ten most-photographed parks, while skyscrapers cluster in Reem Central Park and Abu Dhabi Corniche Park.
- **Temporal rhythms:** Figure 4 confirms strong evening peaks (17:00–19:00) during cooler hours, reflecting biometeorological adaptation and cultural leisure practices (Rahnema et al., 2019; Xiang et al., 2021). Abu Dhabi's climate drives visitation timing, with temperature/humidity mediating landscape perception alongside ephemeral events like optimal sunset lighting (Lee & Son, 2017). These patterns align with primary park motives—recreation, social relations, and seeking calm—revealing parks' embedded role in local temporal routines (Rahnema et al., 2019).

Figure 3

Top Five Detected Object Labels Across the Ten Most-Photographed Parks. Trees Dominate Detections Across All Parks, While Skyscrapers Feature Most Prominently in Reem Central Park and Abu Dhabi Corniche Park, Reflecting the Park–City Interface Charac.

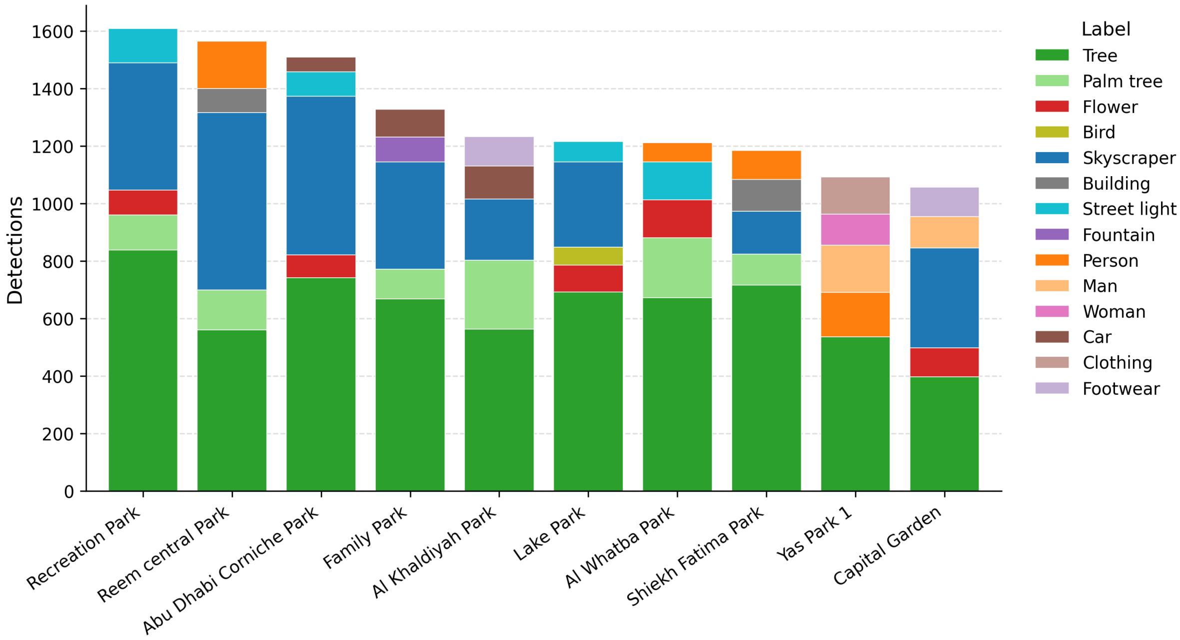
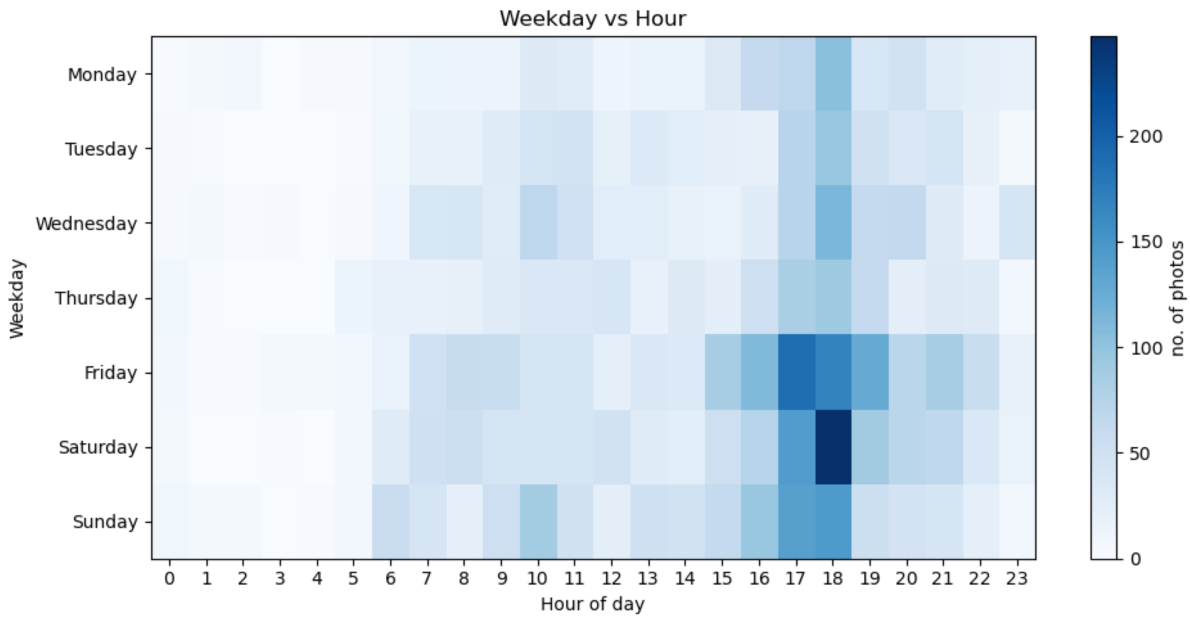


Figure 4

Weekday × Hour Heatmap of Photographic Activity Across the Corpus. Evening Peaks (17:00–19:00) Dominate the Week, With Friday and Saturday Evenings Showing the Highest Intensities.



- **User engagement:** Frequently photographed items like shade structures, water features, and playgrounds, suggest both practical and affective drivers of visitation, supporting links between restorative perceptions and material park features. Shade-providing trees offer cooling and regulating services while supporting soft fascination and Prospect–Refuge preferences for protected viewpoints (Lee & Son, 2017;

Plieninger et al., 2022; Qiu et al., 2023). Water features serve as tranquility-inducing visual anchors that boost perceived naturalness and attract intense observer attention (Rahnema et al., 2019; Sun et al., 2019). Playgrounds address core social/recreational motives, while all three elements mediate between physical landscape qualities and psychological restoration (Rahnema et al., 2019). These patterns confirm user-generated photography as a proxy for human–environment interactions.

These findings provide evidence that user-generated photography, while biased, can serve as a valuable proxy for ecological attributes and human–environment interactions.

Limitations

While our results demonstrate the potential of computer vision for studying urban parks, several important limitations constrain interpretation and generalization.

Sampling bias: As in many studies of user-generated imagery (Jiang et al., 2024; Sun et al., 2019), our dataset reflects the behaviors of individuals who choose to photograph parks and share their images. This introduces systematic biases: younger, more digitally engaged demographics are likely overrepresented; informal or habitual park users who do not photograph their visits are invisible in the data; and certain types of activity (picnicking, children's play) may be more photographically salient than others (quiet sitting, reading, walking). These biases lead to uneven representation across demographic groups, times of day, and park types, meaning that some ecological or social features will be underrepresented.

Metadata reliability: Missing or inaccurate EXIF fields — particularly geotags — reduce the precision of spatiotemporal analyses. Although manual geotagging and metadata-based filtering helped mitigate this limitation, the absence of complete and systematic metadata remains a challenge for reproducibility and limits the temporal precision of the behavioral analyses.

Model transferability: Pretrained object detection models such as YOLOv8, trained largely on global image datasets, encounter domain shift[4] when applied to Abu Dhabi parks. Misclassifications (e.g., shade structures mistaken for buildings) underscore the need for local fine-tuning using park-specific annotated training data (Lee & Son, 2017; Zhang et al., 2022).

Contextual gaps: Image-based analyses provide limited insight into the motivations, emotions, and perceptions of park visitors without supporting data from surveys, weather records, or cultural event calendars (Bornioli et al., 2018; Qiu et al., 2023). A photograph reveals that a visitor was present and what they chose to document, but not how they felt, why they came, or what they did beyond the camera's frame. Bridging this gap requires integrating the visual dataset with contextual sources.

Future Directions

To address these limitations, future work will pursue several directions:

- **Fine-tune object detection models:** Develop park-specific training sets to improve detection of local features such as palm trees, majlis seating, and shade structures.

[4] Domain shift refers to the performance degradation that occurs when an AI model, trained on one type of data (the source domain), is applied to data from a different environment or context (the target domain) that follows a different distribution.

- **Integrate contextual data:** Link photographic patterns with weather data, public event calendars, and demographic indicators to refine interpretations of temporal trends.
- **Develop emotional tagging datasets:** Annotate subsets of images with affective labels (e.g., restorative, playful, aesthetic) following frameworks in environmental psychology (cf. Gao et al., 2019; Sevenant & Antrop, 2009), enabling the development of predictive models for emotional response to park environments.
- **Interactive dashboards:** Build web-based platforms to visualize park use for stakeholders, policymakers, and researchers. The pipeline discussed in this paper provides a foundation for this, with future development aimed at stakeholder-facing interfaces that bridge AI analysis and urban governance.

Together, these efforts will help connect quantitative computer vision results with qualitative insights from landscape perception studies, strengthening the integration of AI methods with geography, ecology, and social sciences.

Conclusion

By applying computer vision to the study of urban parks in Abu Dhabi, this paper offers a replicable and scalable methodology for analyzing the ecological and social functions of green spaces in rapidly urbanizing contexts. The pipeline we developed — from raw image collection through preprocessing, object detection, and spatiotemporal visualization — demonstrates that large-scale visual data can be transformed into structured analytical outputs that reveal patterns of park use, visual ecology, and visitor engagement that would be difficult or impossible to capture through traditional observational methods alone.

This interdisciplinary work supports the development of Nature-Based Solutions (NBS) and aligns AI with urban planning, ecology, and human well-being. Beyond the analytical contributions, this work also demonstrates the feasibility of combining cloud-based storage infrastructures, automated synchronization pipelines, and open experimentation platforms such as Hugging Face Spaces and Google Colab to support continuously evolving urban environmental datasets.

Author's Note

YOLOv8 (You Only Look Once) is a state-of-the-art real-time object detection model that uses a single neural network to predict bounding boxes and class probabilities directly from full images.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used AI-assisted writing tools to improve the language and readability of certain passages. All scientific content, analyses, interpretations, and conclusions are the sole responsibility of the authors.

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