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Integrating Remote Sensing and Artificial Intelligence: A Review of Technological Innovations in Wild Life Crime Detection

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This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Review Article

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ABSTRACT

Wildlife crime remains one of the biggest global challenges worldwide even up to the current decade. This is even worse when it is compounded by what is referred to as the 'dark figure' where cases go unreported or are not detected by law enforcement agencies due to victim reluctance or sheer inability of the police to arrest all offenders. To address this issue, scientists have used remote sensing techniques to detect illegality using satellite and other aerial images such as drone

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and airplane images. Since the amount of remote sensing data is growing very rapidly, and increasing even more in the future, efficient computational systems and sophisticated preprocessing methods are essential for handling and analyzing these data. Artificial Intelligence(AI) has been instrumental in this area through functions like object recognition, data integration, filtering, and anomaly detection that aid the efficiency and accuracy of remote sensing exercises. Overcoming scaling challenges, enhancing engagement, and navigating privacy hurdles remain vital for the implementation of live AI-based models. This review article will also try to give a measure of the likelihood of technological solutions to prevent wildlife crimes and the overriding issue of the 'dark figure' and the expanding mass of data through a critical analysis of the literature on the respective remote sensing devices and the AI algorithms that may be used to combine them.

Keywords: Wildlife; wildlife crime; technology; remote sensing.

1. INTRODUCTION

The Unreported or undetected often referred to as the dark figure of crime poses a persistent challenge in understanding wildlife crime. Thus, making it more difficult for law enforcement agencies to uncover crimes in such isolated or hidden regions due to limited availability of resources. Human victims and witnesses might also hesitate to report such types of incidents, possibly having closer relations with perpetrators or fear (Narreddy & S, 2024). Victimization surveys, improved surveillance, and anonymous reporting mechanisms can be utilized to address such kinds of issues. Wildlife forensics along with some other law enforcement agencies had made use of the existing technologies like acoustic monitoring and remote sensing, involving imagery from drones, aircraft, and satellites to find the pinpoint locations of these wildlife crimes happening everywhere across the globe (Raihan et al., 2023).

In a study by Borgelt, et al., 2022 make a significant contribution to addressing the knowledge gap in conservation assessments concerning data-deficient species. Utilizing machine learning techniques, they estimated extinction risk probabilities of more than 7,600 species labeled as Data Deficient across various taxa. Their research reveals a concerning reality: these species are potentially more at risk than previously believed. Notably, their results indicate a high probability of threat for amphibians (85%) and significant portions of mammals and reptiles, emphasizing the urgent need to prioritize these data-deficient species in conservation strategies).Illegal hunting, or poaching, continues to be a major global issue for wildlife, primarily triggered by urban sprawl encroaching on natural habitats and the rising demand for bushmeat. While subsistence hunting still exists to fulfill local dietary needs, poaching is increasingly driven by commercial bushmeat demands. Criminal networks are constantly adapting their smuggling techniques, with the Dark Web becoming a profitable venue for the clandestine trade of wildlife. The growing international bushmeat market has intensified the commercialization of poaching, frequently leading to the unsustainable exploitation of wildlife for products extending beyond just meat (Chaber et al., 2010).

The Wildlife Protection Society of India (WPSI) oversees an extensive Wildlife Crime Database, which currently contains over 33,300 records of wildlife crime cases involving more than 400 species targeted by poachers and wildlife traffickers. This extensive repository includes information on roughly 27,000 individuals connected to wildlife crimes, such as poachers, traders, and their associates. It also holds crucial data on inter-state wildlife trade networks, smuggling routes, emerging poaching and trade techniques, and other pertinent details. Seizures, the act of confiscating illegal items, are vital for understanding wildlife crime, as they offer valuable data that aids in identifying patterns and formulating effective strategies for detecting and preventing such crimes. According to the World Crime Report 2024 by the UN, the illegal wildlife trade mainly focuses on species such as birds of prey, lizards, sea snails, pangolins, sturgeons and paddlefish, even-toed ungulates, cacti, aloes, costus root, ginsengs, rosewoods, snakes, turtles, orchids, parrots, carnivores, bivalve mollusks, elephants, and crocodilians. The most frequently seized commodities include ivory, roots, small leathers, shells, meat, medicines, live specimens, coral species, and miscellaneous items (WPSI Legal Programme, n.d.).

The third World Wildlife Crime Report explores trends and impacts of illegal wildlife trafficking, using over 140,000 seizure records from 2015-2021. There was a noticeable decline in seizures during 2020-2021, likely due to COVID-19 disruptions. To address the limitations of seizure data, the report incorporates fieldwork, market data, academic research, and expert consultations. This triangulation aims to shed light on the global wildlife trafficking landscape. Enhanced data accessibility, such as CITES illegal trade reports, benefits the report. However, seizure records have geographical gaps, focus on CITES-listed species, and miss undetected illegal trade. The analysis is enriched by considering factors like evolving trafficking methods and broader impacts beyond the number of seizures. Among the most affected species are rhinoceroses, pangolins, elephants, eels, crocodilians, parrots and cockatoos, carnivores, turtles and tortoises, snakes, and seahorses (World Wildlife Report, n.d.).

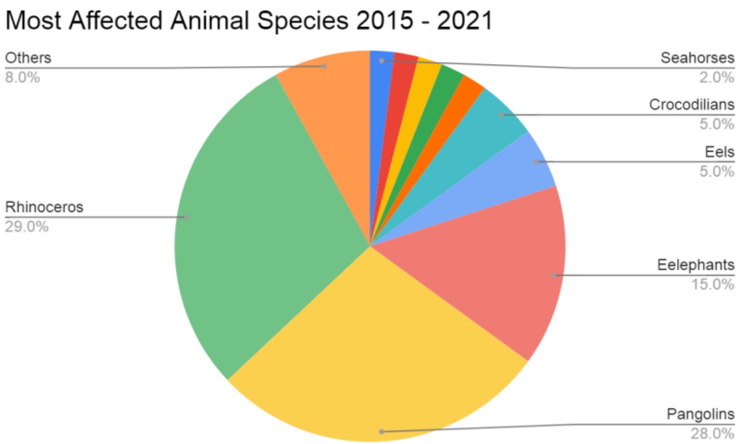

Chart 1. Trends in the standardized seizure index for all seizures and separately for animals 2015–2021

Most affected animal species 2015-2021 (2024). United Nations office drugs and crime. Retrieved June 2024, from https://www.unodc.org/documents/data-and-analysis/wildlife/2024/Wildlife2024_Final.pdf.

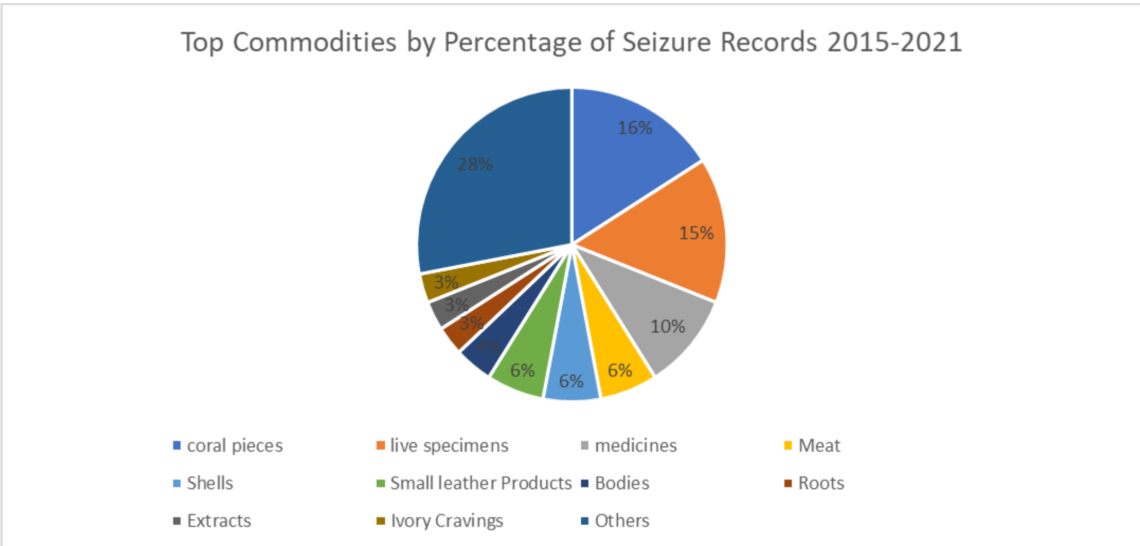

Chart 2. Illegal Wildlife Trade (2015–2021): Concentration in 15 Key Markets (Standardized Seizure Index)

top commodities by percentage of seizure record seizure 2015-2021 (2024). United Nations office drugs and crime. Retrieved June 2024, from https://www.unodc.org/documents/data-and-analysis/wildlife/2024/Wildlife2024_Final.pdf.

Table 1. A comprehensive global overview of wildlife trafficking, detailing eight key commodities, their source and destination countries, highlighting the economic and ecological impacts of illegal trade across diverse species and international markets

Commodity	Reasons for Illegal Trade	Main Source Countries	Main Destination Countries	Trends
Elephant Ivory	Valued for ornamental goods and speculative investments.	Tanzania, Kenya, Zimbabwe	China, Vietnam	Global elephant population declined by 30% in 7 years. Seizures include >40 tonnes annually, representing tonnes of thousands of elephants.
Rhino Horn	Used in traditional medicine and high-value ornaments.	South Africa, Namibia, Zimbabwe	Vietnam, China	Poaching incidents dropped from 1,349 in 2015 to 451 in 2021 in South Africa. Rhino horn can fetch $60,000/kg on black markets.
Pangolin Scales	Used in traditional medicine and exotic food markets.	Nigeria, Cameroon	China, Vietnam	Pangolins represent 20% of all illegal wildlife seizures. Over 195,000 kg of scales seized globally from 2016–2021.
Rosewood	Prized for luxury furniture and decorative goods.	Madagascar, Brazil, Nigeria	China	Accounts for 35% of global timber seizures. Export bans pushed trade to African and Latin American nations.
Sea Turtles	Harvested for meat, eggs, and shells (ornaments).	Philippines, Caribbean nations	Japan, China	Over 40,000 sea turtles harvested annually despite conservation efforts. Shells fetch $1,000/kg in some markets.
Orchids	Coveted for beauty, rarity, and use in breeding and traditional medicine.	Thailand, Vietnam, South America	EU, USA	Orchids represent 70% of CITES-listed plant species. Majority of seizures occur in EU markets due to mislabeling.
Crocodilians	Skin for luxury leather; meat for exotic cuisine.	Thailand, Cambodia, African nations	USA, Europe	Seized shipments often involve >1,000 crocodilian skins at a time. Estimated 1.5 million skins traded globally each year.
Crabs	Sought for luxury dining; overharvested beyond quotas.	Southeast Asian nations	USA, China	Luxury dining market accounts for 25–30% of illegal crab trade. Affects endemic populations in Southeast Asia.

World Wildlife Crime Report. (2024). https://www.unodc.org/documents/data-and-analysis/wildlife/2024/Cases_studies_all.pdf

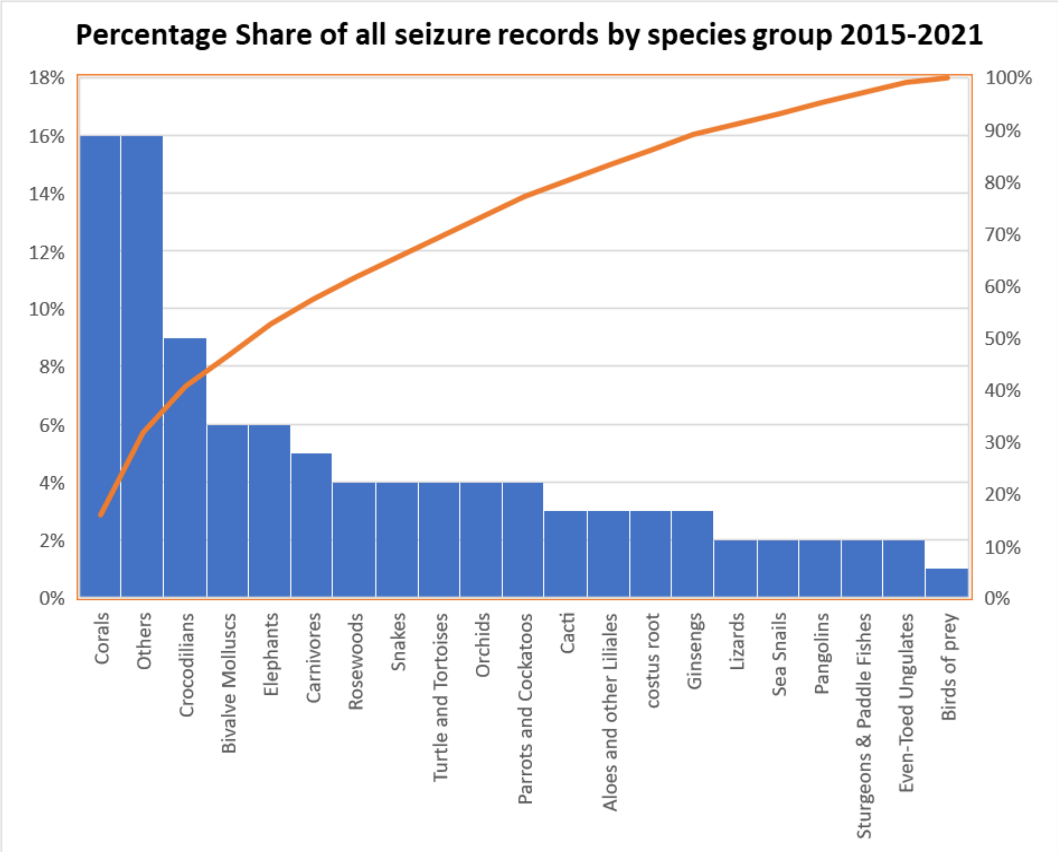

Chart 3. Trends in Percentage share of all seizure records by species Group 2015-2021

Percentage share of all seizure records by species Group 2015-2021. (2024). United Nations office drugs and crime. Retrieved June 2024, from https://www.unodc.org/documents/data-and-analysis/wildlife/2024/Wildlife2024_Final.pdf

The 2024 UN report highlights the ongoing illegal trade of endangered species such as elephant ivory, rhino horn, pangolin scales, and rosewood, driven by high demand in East Asia and Southeast Asia for ornamental goods, traditional medicine, and luxury items. Despite some progress in curbing poaching, particularly for elephants and rhinos, the report cautions against complacency, as the trade persists, involving regions like Africa and Southeast Asia as source areas. Species like sea turtles, orchids, and crocodilians are also heavily trafficked, with continuing threats from both traditional and emerging markets. Illegal wildlife trade is among the largest transnational crimes, threatening biodiversity and species survival. Historically, efforts to tackle wildlife crime include enforcement of international treaties like the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) and policy measures such as bans on ivory and rhino horn trade, penalties for trafficking, and local community engagement in conservation. Yet, the persistence of demand and weak enforcement mechanisms in source and transit countries hinder these efforts (World Wildlife Crime Report, 2024).

Wildlife crime remains a complex global challenge where policy effectiveness is intricately balanced between robust strategic interventions and significant systemic limitations. Despite comprehensive frameworks like CITES and international cooperation mechanisms, wildlife trafficking persists due to underlying socio-economic drivers, weak judicial systems, and transnational criminal networks that exploit regulatory gaps (Krämer, 2019).While technological advancements and multi-agency approaches have enhanced monitoring capabilities, the root causes—poverty, limited economic opportunities in wildlife-adjacent communities, and persistent consumer demand—continue to fuel illegal wildlife trade. The most successful policy interventions emerge from holistic strategies that integrate legal enforcement, community engagement, technological surveillance, and demand reduction campaigns, recognizing that addressing wildlife crime requires more than punitive measures but fundamental socio-economic transformation (Roe & Booker, 2019). Technological tools like AI, LiDAR, and advanced tracking systems offer promising solutions, yet their implementation remains inconsistent across jurisdictions, highlighting the need for standardized, adaptable, and locally contextualized conservation policies that balance protection with sustainable community development. The inherent complexity of wildlife crime demands a nuanced, multi-dimensional approach that addresses economic inequalities, cultural practices, and global market dynamics, transforming conservation from a reactive enforcement model to a proactive, collaborative ecological governance strategy (Wellsmith, 2011).

1.1 Role of Remote Sensing in Wildlife Crime Detection

- Remote sensing techniques are crucial for obtaining detailed information about surface and subsurface environments without direct contact. These methods are invaluable to forensic specialists and law enforcement agencies, especially in hazardous or difficult-to-reach areas. Remote sensing employs electromagnetic equipment mounted on satellites, aircraft, and Unmanned Aerial Vehicles (UAVs) to detect specific targets. This robust approach aids in various applications such as investigating environmental crimes, protecting wildlife, uncovering mining fraud, and supporting search and rescue missions. By leveraging remote sensing technologies, law enforcement and forensic professionals can gather essential data to tackle numerous challenges in diverse settings. As the volume of remote sensing data grows rapidly, advanced preprocessing techniques, like noise reduction and sensor calibration, are used to handle the massive data influx effectively.
- For instance, NASA’s Earth Science Data Systems (ESDS) reported that the Earth Data Cloud contained over 59 petabytes (PB) of data as of September 2021, with projections suggesting increases to over :”148 PB in 2023, 205 PB in 2024, and 250 PB in 2025”(Janga et al., 2023). The increasing amount of remote sensing data necessitates the use of advanced preprocessing techniques, including noise reduction and sensor calibration, to effectively manage the substantial data influx. Additionally, computer systems equipped with ample memory and parallel processing power facilitate the handling and analysis of these massive datasets, which is vital for combatting terrorism and international organized crime (Jensen, 2000).
- In tandem, the increasing quality and volume of remote sensing data necessitate efficient computational platforms and AI tools for extraction and analysis. AI is instrumental in tasks such as noise reduction, data fusion, and object detection (Mohan et al., 2021). UAVs and other platforms equipped with multiple sensors capture various energy types, facilitating a thorough analysis of Earth's surface and atmosphere. AI-driven processing systems autonomously perform tasks like calibration and anomaly detection, improving the accuracy of data interpretation (Janga et al., 2023). For the successful deployment of operational AI models, it is essential to ensure scalability, foster collaboration among stakeholders, and address privacy concerns. This review paper seeks to synthesize existing literature on remote sensing devices and provide insights into the integration of artificial intelligence (AI) with these sensors. Recent technological advancements have enabled the incorporation of AI algorithms into remote sensing devices, significantly enhancing their capabilities in data extraction, analysis, and interpretation (Zhang & Zhang, 2022).

1.1.1 Remote sensing devices

A. Passive and Active Acoustic Monitoring systems

- Acoustic Activity Monitoring (AAM) and Passive Acoustic Monitoring (PAM) are two distinct approaches used for wildlife monitoring and conservation. AAM systems actively emit sound signals, and their effectiveness depends on the target species' ability to reflect these signals, a property known as target strength. When sound waves interact with animals, a portion of the sound reflects back as echoes, a process called reverberation. These reflected echoes are analyzed to detect the presence, movement, and characteristics of the animals. AAM can detect species that do not emit sounds themselves, making it useful for monitoring a broad range of wildlife. However, its efficiency varies by species. For example, marine mammals that dive deep and experience pneumothorax (collapsed lungs) produce weaker reverberations, making them harder to detect. Conversely, species with air-filled organs, such as fish with swim bladders, generate strong echoes due to the high acoustic contrast, allowing for more efficient detection (Sharma et al., 2023).

- Contrary to AAM, PAM systems solely listen for and analyze the vocalizations and other sounds produced naturally by the target species and it is highly efficient at detecting species that can emit recognizable sounds. However, it is limited in its ability to detect silent or non-vocal species. PAM is restricted to only detecting species that are vocal or produce sound, unlike AAM which can detect species that don't emit any sound. It is exceedingly coherent in ascertaining species that emit recognizable sounds (Astaras et al., 2020).
- Acoustic traps, also known as “echo” technology are being used progressively to complement traditional anti-poaching patrols and watch for loud sounds like gunshots, chainsaws, truck engines, explosions, or airplane engines. Most systems are made up of unattended, monolithic sensors that can be installed in any part of the forests; these sensors then utilize a wireless network to locate the source of any suspicious sounds and provide exact real-time position information. Some are even equipped to automatically deploy drones or other unmanned aerial devices with GPS headings to collect evidence, photos, or infrared footage (Jachmann, 2008). The research paper from Cameroon's Korup National Park highlights the limitations of traditional, input-focused anti-poaching patrol strategies and suggests the use of passive acoustic monitoring to enhance more flexible wildlife law enforcement. Before the research period, the park game guards used tracking metrics to monitor their patrol efforts, including the distance covered and signs of hunting. However, these methods were discovered to be unreliable and inconsistent in evaluating the effectiveness of their interventions (Jachmann, 2008). Researchers installed a 12-sensor acoustic grid to gain a better understanding of the extent of gun hunting in the park. They discovered that the highest amount of hunting activity occurred annually around the Christmas/New Year season (Astaras et al. 2017).
- In response to this evidence, in 2015–2016, the park management made significant improvements to its anti-poaching patrol policy. They tripled the number of patrol days, the patrol length, and the patrol coverage area. However, despite these efforts, acoustic monitoring revealed a 15–21% increase in gunshot detections compared to previous years, indicating that poaching activities were still on the rise despite the increased patrol efforts (Jachmann, 2008). This emphasizes the significance of utilizing outcome-based metrics, such as shifts in poaching pressure, rather than solely relying on input-based measures to evaluate the impact of conservation efforts. The research highlights the valuable contribution that passive acoustic monitoring can make in facilitating adaptive wildlife law enforcement by offering rapid, reliable data to inform the timely adjustment of anti-poaching tactics (Astaras et al., 2020b).
- A wide range of sound-producing species, such as fish, amphibians, insects, and crabs, inhabit freshwater environments and create various underwater sounds. The research report highlights the potential of passive acoustic monitoring (PAM) for studying freshwater habitats. PAM can provide continuous and non-invasive monitoring of aquatic ecosystems, including their physical habitat features, spatial distributions, community interactions, and responses to environmental stressors. One of the main advantages is its ability to capture temporal patterns that are difficult to observe through intermittent fieldwork, as well as to overcome the limitations of standard optical surveys in muddy or vegetated waters. The review emphasizes the increasing importance of PAM as a powerful and adaptable tool for freshwater ecology and conservation while

acknowledging methodological challenges related to sound propagation and data interpretation (Gottesman et al., 2018b).

- In another study by Crystos Astaras and his teammate, the authors leveraged the power of passive acoustic monitoring (PAM) to shed light on a major threat facing the vulnerable European turtle dove (*Streptopelia turtur*) – illegal killing during its spring migration through the Mediterranean coast of Europe. By deploying a network of acoustic sensors at known hunting sites in the Ionian Islands, Greece, the researchers were able to estimate the scale of the poaching problem, with their data suggesting up to 57,095 turtle doves were killed or injured in this region alone during the 2021 migration season (BirdLife Internationa0l, 2019).
- This innovative application of PAM technology provides crucial, quantitative evidence to support conservation efforts for the rapidly declining turtle dove population. Whereas previous assessments of poaching impacts have relied on indirect indicators or anecdotal reports, the authors' acoustic monitoring approach offers a robust, data-driven means of directly measuring hunting pressure. Importantly, the study also demonstrates the potential for PAM to be deployed at additional known poaching hotspots along the turtle dove's migration routes, enabling a more comprehensive understanding of the scale of this threat. Overall, this work represents a significant advance in the scientific understanding and documentation of the killing crisis facing the European turtle dove. The authors rightly emphasize that these findings must now galvanize responsible authorities to take decisive action to eradicate the illegal killing of this vulnerable migratory species during its spring return to European breeding grounds. Continued acoustic monitoring will be essential for tracking the impact of such interventions and guiding adaptive management strategies in the future (Astaras et al., 2023).

B) Unmanned Aerial Vehicles (UAV)

- Unmanned aerial vehicles, or drones, are highly effective for detecting and responding to wildlife crimes due to their flexibility, maneuverability, and ability to collect high-quality photos and data. Their use is growing in conservation efforts to prevent illegal hunting of animals. Identifying the technological and environmental factors that enhance the efficiency of using drones to detect poachers is crucial for this research initiative (Doull et al., 2021).
- Historically, zoologists have used manned aircraft, kites, and balloons for aerial wildlife monitoring. However, unmanned aerial vehicles (UAVs), initially designed for military use, offer several advantages. They can access risky or hard-to-reach areas, providing a unique aerial perspective on small animal movements that are not easily visible from the ground (Wang et al., 2019). By conducting in-situ ground truthing, UAVs improve satellite monitoring. Using UAVs reduces the risk of death from piloted aircraft crashes, which are a major cause of death for wildlife biologists. UAVs reduce biases resulting from human error by enabling faster and more accurate monitoring than human observers. Advanced image processing software allows for even faster and more accurate object detection using machine learningOver the last decade, UAVs have become cost-effective and competitive in terms of coverage, making them a valuable tool for various wildlife monitoring applications (Duporge et al., 2020).
- The rise in affordable UAVs presents an opportunity for wildlife experts to monitor species abundance more accurately. These UAVs, equipped with autonomous flight capabilities and geo-referenced sensors, are increasingly used for agricultural, environmental, and wildlife monitoring. However, challenges such as regulations, costs, and public perception hinder their widespread use. A crucial barrier is the lack of advanced automated image detection algorithms tailored for wildlife monitoring. Despite this, UAVs are already being used for various wildlife management tasks, including monitoring sea turtles (*MTN 145:19-22 Unmanned Aerial Vehicles (UAVs) for Monitoring Sea Turtles in Near-Shore Waters*, n.d.), black bears (Ditmer et al., 2015), elephants (Vermeulen et al., 2013), dugongs (Hodgson et al., 2013), and birds, radio collar tracking, and anti-poaching operations. UAVs equipped with digital and

thermal sensors can capture high-resolution videos and images with minimal disturbance to animals. While they have shown effectiveness, the extensive post-processing required often offsets the time-saving benefits. To truly streamline wildlife monitoring, there's a need for improved automation in animal detection and counting from UAV imagery. Emerging research is exploring automatic classification techniques for wildlife monitoring using UAVs, showing promising solutions for conservation efforts. For instance, some studies have achieved an accuracy of 93.3% in discriminating between animal and non-animal objects using thermal imagery and advanced classification algorithms in an altitude range of 3-10m (Gonzalez et al., 2016b).

C) Camera traps

The initial use of camera traps for large mammal conservation began in the 1990s, concentrating on the tiger, Panthera tigris. Classified as endangered and one of the early “flagship” species on the IUCN red list since 1986, these studies aimed to estimate the tiger's home range and population size (Karanth, 1995). Camera traps are discreet devices, varying in size from small boxes to GPS units, used to capture images or videos of wildlife in the field (Kays et al., 2009, Franchini et al., 2022). They operate around the clock, recording thousands of images over days or weeks. Usually hidden with camouflage, they're placed individually or in groups across different habitats, often mounted on trees or rocks facing animal trails (Harmsen et al., 2017, Franchini et al., 2022). The technologies are not overly disruptive to animals as they do not require direct engagement, particularly when there is no visible flash. Due to their non-invasive nature and ability to capture otherwise difficult-to-obtain data, these technologies are favored by researchers. (Camera traps use either infrared or incandescent lighting. Infrared lighting produces color photographs during the day and black-and-white images at night, and due to its 800-950 nm wavelength, it is invisible to humans. This makes infrared cameras usually undetectable. On the other hand, incandescent lighting produces color images continuously. Incandescent cameras, which use xenon gas or LEDs, capture color pictures both day and night (Butler & Meek, 2013, Franchini et al., 2022) While primarily used for wildlife monitoring, they can also detect human presence, through software like Wild.ID can help distinguish between humans and animals, enhancing their utility for monitoring human-wildlife interactions and detecting illegal activities in protected areas (Franchini et al., 2022).

D) Satellite Imagery and GIS Mapping

- Satellite imagery provides visual data about the Earth's surface, whereas GIS mapping uses geographic data to create maps, perform analyses, and understand spatial relationships and patterns. Although satellite imagery can be a crucial part of GIS mapping, GIS involves a wider range of tools and techniques for managing geographic data.
- High-resolution satellite images have been instrumental in tracking illegal deforestation and encroachment into protected areas over the past decade. For instance, deforestation in Brazil’s Amazon has decreased by up to 78% since 1988, thanks to a coordinated enforcement strategy using satellite imagery and targeted police operations (“Emerging Technologies: Smarter Ways to Fight Wildlife Crime,” 2014, Nellemann et al., 2014). The Global Forest Watch, launched by the World Resources Institute on February 7, 2014, is an online forest monitoring and alert system. It combines satellite technology, open data, and crowdsourcing to provide timely and reliable information on forest changes, aiding in forest management (WRI, 2014, Vizzuality, n.d.)
- Satellite imagery or GIS mapping has aided in detecting illegal deforestation and invasion into the protection regions of the forests (“Emerging Technologies: Smarter Ways to Fight Wildlife Crime,” 2014, Nellemann et al., 2014). There is an online forest monitoring system that alerts us when any illegal activities are occurring in the forests. The Global Forest Watch began by the World Resources Institute on 7th February 2014. This system fuses all the data, satellite technology, and crowdsourcing to deliver punctual and reliable information about all the changes made to the forest, helping in the maintenance of the forest (WRI, 2014, Vizzuality, n.d.). Amazon Forest in Brazil has seen a decrease in deforestation by

78% from the year 1988 due to the high-resolution images sent by the satellites and also because of the organized application of plans and operations ("Emerging Technologies: Smarter Ways to Fight Wildlife Crime," 2014, Nellemann et al., 2014).

E) Electromagnetic Spectrum-Based Remote Sensing Devices

Electromagnetic (EM) sensors are a type of remote sensing devices that detect energy or functions in the electromagnetic spectrum. These sensors are designed to identify and measure electromagnetic radiation at various wavelengths, from radio waves to gamma rays. The specific application and portion of the spectrum being used determine the type of electromagnetic sensor that is utilized. Similar to optical sensors, passive sensors detect solar radiation and other natural forms of energy that the Earth reflects. On the other hand, active sensors emit energy and measure the signals that are reflected (Janga et al., 2023). These sensors enable data acquisition through satellites for global coverage, aircraft for higher spatial resolution, and drones for detailed, small-scale data collection. Here are some common types of electromagnetic sensors:

- Optical Sensors- These types of sensors can be held in hand, can be easily flown, or be space-borne, this allows them to sense and document light intensity through different wavelengths. They transfer the stored data to the ground centers or processing units, sorting it into pictures or spectral information. The materials used in these sensors help absorb and reflect certain wavelengths when sun rays interact with the Earth's surface. This allows them to make a rare spectral signature (Janga et al., 2023). In the electromagnetic spectrum, only the visible and near-infrared areas are used to collect and infer the data for this technology (Prasad et al., 2011).
- Radar Remote Sensing- This sensor works inside the microwave areas of the electromagnetic spectrum (Richards, 2009). Synthetic Aperture Radar (SAR) is advantageous for extensive forest mapping as it creates high-resolution surface photos. They are precise in identifying variations in forest cover. SAR can easily enter through vegetation and mists, delivering accurate mapping even in bad climates. They have a double polarization technology which allows them to differentiate between distinct forms of forest covering and plants, presenting a complete report of the forest arrangement and biomass. Radar remote sensing is utilized to examine signals and make maps or photos with different resolutions and views (Janga et al., 2023, *Comprehensive Remote Sensing*, 2017). It uses radar antennas to reflect microwave rhythms toward Earth or space, which takes up the echoes emitted by the objects. The echoes collect data about the objects' properties like expanse, route, size, and figure (Hanssen, 2014).
- Thermal Imaging- Infrared Thermography (IRT) is another name for Thermal Imaging. In Africa, poaching in scrub bush veld was evaluated for traditional flash techniques and was assessed for the efficiency of IRT by research studies. In the study, researchers found that inexpensive and expensive IRT tools have considerably enhanced exposure distances, unlike flash. Although the study emphasizes the ability of IRT in anti-poaching duties, more research is needed to understand its extensive use, applied practicality, and durable efficacy in real-life situations. There are aspects like field copying, sample size, and added function metrics outside the exposure distances (Janga et al., 2023). Thermal imaging mainly focuses on evaluating the temperature of objects, even animals. It uses infrared wavelengths which release and reflect to the sensitive sensors. IRT is mainly used in biological and ecological research that includes monitoring mammals and birds, recognizing hidden and night-time species, and studying the plants' physiology. Additionally, IRT has proven to be crucial in wildlife conservation, especially in poaching due to the increase in poaching cases that occur at night when the conventional monitoring tools are less operative. Other than its scientific applications, thermal imaging is important to military and law enforcement tasks, as it can easily identify warm-blooded beings, like people, even in absolute darkness, which makes it useful in conditions like hostage emergencies (Oishi et al., 2018).

- LiDAR (Light Detection and Ranging) technology- Some drones are prepared with LiDAR sensors through which significant airborne analysis can be done to map the geography, vegetation, and added factors. To gain accurate height and 3-D essential information, the drones fly above the aimed region whereas the LiDAR sensor radiates laser light towards the earth. This information is useful in evaluating biomass, tracking the health of the forest, and reviewing suitable habitats for species. The drones prepared with LiDAR sensors give complete data on the vegetation structure, which also contains shade height, density, and vertical organization (Buchelt et al., 2024). LiDAR technology utilizes laser beats to calculate the distance to the earth's surface. This technology can make thorough three-dimensional maps of the terrain, vegetation, and even the locomotion of the animals in the forest and other environments. There is a new detection method for deer crossing roads that uses 3D LiDAR technology which was created by the authors of a study called “Roadside LiDAR Sensor-based Deer Crossing Road Detection”. By innovatively using 3D LiDAR sensors and data processing tools, the system provides a precise and quick detection of deer crossings which increases the safety of roads. Through field testing, the technique proved the capability to track deer, usually at a distance of 30 m from the pavement LiDAR sensor in just 0.2 seconds. This gives drivers immediate warnings of possible deer-vehicle accidents (Chen et al., 2019).

1.1.2 Advanced AI/ML techniques in remote sensing and wildlife conservation

Machine learning and deep learning have revolutionized image recognition, classification, and object detection, particularly in wildlife conservation and environmental monitoring. These technologies offer unprecedented capabilities for addressing complex challenges in tracking, protecting, and understanding wildlife ecosystems.

- Conventional machine learning techniques like Random Forest, XGBoost, and Support Vector Machines provide robust solutions for handling high-dimensional data, though they struggle with accurate feature selection. In contrast, deep learning approaches have emerged as more sophisticated tools for intricate pattern recognition and image analysis (Alnuaimi & Albaldawi, 2024).
- You Only Look Once (YOLO): A real-time object detection algorithm that processes entire images simultaneously using a single convolutional neural network (C, 2020; Xu & Wu, 2020; Janga et al., 2023). The paper titled "Wild Animal Detection and Alert System Using YOLOv8" proposes an innovative framework for wildlife monitoring by leveraging the advanced capabilities of YOLOv8, a state-of-the-art object detection algorithm. YOLOv8 is utilized to identify and classify wild animals in real-time, addressing challenges like habitat monitoring, poaching prevention, and minimizing human-wildlife conflicts. The methodology combines deep learning with edge computing to process video streams on-site, ensuring real-time responsiveness without dependence on centralized systems. Alerts generated by YOLOv8 are integrated with the Telegram messaging platform via the Twilio API, enabling forest officers and stakeholders to take immediate action. The framework significantly improves traditional surveillance methods, overcoming issues like low-light conditions and large coverage areas by providing timely, accurate insights into wildlife activities and potential threats (Pulimi et al., 2024).
- Deep Convolutional Neural Networks (DCNNs)- The research study "Wild Animal Detection Using Deep Convolutional Neural Network" introduces a method for detecting animals in cluttered images captured through camera-trap networks. It leverages Deep Convolutional Neural Network (DCNN) features combined with machine learning classifiers such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and ensemble methods. The approach involves preprocessing images, extracting self-learned DCNN features, and classifying candidate regions as animal or background. The system achieves high accuracy (up to 91.4%) and effectively handles challenges such as dynamic backgrounds, natural camouflage, and varying illumination, making it highly suitable for wildlife monitoring in diverse conditions (Verma & Gupta, 2018b).

Another study titled as "Towards Automatic Detection of Wildlife Trade Using Machine Vision Models" explores the development of machine learning-based solutions to automatically identify wildlife trade activities. It employs advanced deep learning architectures such as Densely Connected Convolutional Network (DenseNet), Residual Network (ResNet), and Visual Geometry Group (VGG) for image recognition and classification, focusing on distinguishing captive animals from wild ones using multi-layer architectures. These models utilize convolutions and pooling layers to extract intricate patterns with high accuracy, albeit requiring computational resources and extensive labeled datasets. The study constructs two datasets with varying background complexities (data with background (data_bg) and data without background (data_no_bg)) and evaluates the models on within-distribution and out-of-distribution test sets. Training approaches include transfer learning, scratch training, and hybrid methods. Densely Connected Convolutional Network (DenseNet) and Visual Geometry Group (VGG) demonstrated superior generalization, particularly with background-inclusive data, highlighting their robustness for real-world applications. Additionally, feature visualization provided insights into the model's decision-making, ensuring accountability and aiding in tasks like object detection and semantic segmentation. This research marks a significant step towards leveraging Artificial Intelligence (AI) for combating illegal wildlife trade (Kulkarni & Di Minin, 2023).

- The AI Guardian of Endangered Species, developed by the International Fund for Animal Welfare (IFAW) and Baidu, is a breakthrough system for detecting illegal wildlife trade on digital platforms. It analyzes images of wildlife products and species, removing illicit posts with an impressive accuracy rate of 86%. The system continuously adapts to evolving wildlife cybercrime tactics, supporting law enforcement and civil society organizations in the fight against illegal wildlife trafficking (International Fund for Animal Welfare, 2020).
- every year an expanse of countrysized land is afflicted by deforestation either from illegal logging or fires, especially in growing countries like Brazil and Indonesia.In Brazil, Rainforest Connection (RFCx) works with the Tembé indigenous community to monitor illegal logging and poaching using solar-powered microphones and machine learning algorithms. This system detects sounds like chainsaws and gunshots, providing real-time alerts that help rangers act quickly and reclaim 15% of their land from illegal activities (*Rainforest Connection - Stopping Illegal Logging & Protecting Wildlife*, n.d.).
- In India’s Dudhwa Tiger Reserve, AI cameras like TrailGuard are used to monitor tiger populations and detect threats such as poachers or stray animals. These cameras process images in real time, alerting rangers to potential dangers within 30-42 seconds, significantly reducing response times and improving conservation efforts (Dertien et al., 2023).
- The intersection of artificial intelligence and wildlife conservation has unleashed transformative technologies that are revolutionizing how we monitor, protect, and preserve global biodiversity. Cutting-edge tools like CAPTURE (Nguyen et al., 2016) leverage game-theoretic models to predict poaching hotspots, while innovative platforms such as FloraGuard (Lavorgna et al., 2020b) employ natural language processing to track online wildlife trade. Recent research by (Kulkarni & Di Minin 2023, Cardoso et al. 2023, and Gbadegesin 2023) has demonstrated remarkable advancements in AI-driven wildlife protection, ranging from deep learning models that detect pangolin trafficking on social platforms to machine vision techniques for automated wildlife trade detection. The following table encapsulates five groundbreaking tools that are reshaping conservation efforts: CAPTURE uses predictive modeling to identify high-risk areas, Outland Analytics employs acoustic AI sensors for real-time threat detection, FloraGuard monitors online trafficking patterns, Terramonitor processes satellite imagery to track habitat destruction, and AI-Powered UAVs provide rapid, drone-based monitoring in challenging terrains. Tools like CITESRANGER analyze digital footprints to track wildlife trade (Salamat et al., 2022), and 3D imaging with AI-driven algorithms improves screening processes (Pirotta et al., 2022). These innovations showcase AI's transformative role in global conservation. The following table showcases five groundbreaking tools that

Table 2. AI Tools for Wildlife Crime Detection

Tool	Study and Paper Name	Methodology	Significance in Wildlife Crime Detection
CAPTURE	(Nguyen et al., 2016) Capture: A Predictive Anti-Poaching Tool	Uses game-theoretic models and machine learning to predict poaching hotspots and optimize ranger patrol deployment.	Helps focus ranger efforts on high-risk areas, improving efficiency and reducing poaching incidents.
Outland Analytics	(Shivaprakash et al., 2022) AI and Acoustic Analysis for Wildlife Monitoring	Employs AI-driven acoustic sensors to detect sounds like gunshots or chainsaws in real-time and generates alerts.	Enables cost-effective, scalable monitoring in dense forests where traditional surveillance methods are less effective.
FloraGuard	(Lavorgna et al., 2020b) NLP for Monitoring Illegal Wildlife Trade Online	Uses NLP to scrape online platforms and analyze text data for identifying illegal wildlife trade activities.	Tracks and disrupts digital wildlife trade by monitoring trafficking patterns and species names.
Terramonitor	(Raihan, 2023) AI-Based Satellite Monitoring for Conservation	Processes satellite imagery to detect deforestation and habitat encroachment, analyzing environmental changes.	Provides large-scale, consistent monitoring of habitat destruction, aiding preventive conservation measures.
AI-Powered UAVs	(Ramadan et al., 2024) Real-Time Monitoring Using AI-Driven Drones	Deploys drones equipped with AI systems to analyze aerial footage in real-time for detecting poachers or logging.	Offers rapid detection and response to threats, particularly in remote or vast landscapes.

are reshaping our approach to wildlife conservation and crime prevention.

2. CONCLUSION

In conclusion, the integration of artificial intelligence and remote sensing presents a significant advancement in animal ecology and wildlife conservation. These technologies allow for the effective analysis of large data streams to estimate populations, understand animal behavior, and combat poaching and biodiversity loss. AI and remote sensing enable habitat analysis and population censusing on a much larger scale than traditional methods. Techniques such as image classification, land cover mapping, object detection, and change detection facilitate improved management strategies for wildlife resources, ensuring a more comprehensive understanding of the relationship between wildlife populations and their habitats.By utilizing advanced AI techniques like deep learning, DCNNs, ResNets, YOLO, and Faster R-CNN, along with various remote sensing technologies, we can monitor endangered species, detect and manage invasive species, and identify ecological hotspots. These methods also help track climate change, allowing for the development of effective strategies to mitigate its impact on biodiversity. The combination of GIS, remote sensing, and AI offers a powerful toolset for biodiversity conservation, enabling the creation of targeted conservation plans to protect critical habitats and the species that depend on them. This review underscores the transformative potential of AI and remote sensing in fostering sustainable development and enhancing wildlife security services.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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