

Autonomous Deforestation Monitoring in Pakistan: A Multi-Drone, AI-Based System for Real-Time Deforestation Protection

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ABSTRACT

Illegal deforestation is a growing concern for ecologically fragile areas like the Kaghan Valley in Pakistan [1]. Despite being an economic engine and a significant geographical link, the area has no real-time monitoring system to log illegal deforestation. Conventional methods like satellite imaging and physical ranger patrolling are faced with limitations, only able to conclusively detect deforestation after the damage is done. These predicaments motivate the development of a multi-drone robotic surveillance system that combines aerial imaging with AI-based analysis to detect and suppress illegal logging activity in the region.

The system is prototyped using a simulation-based approach nested in Ubuntu, ROS, and Gazebo [2]. The system includes a modulation of a forest environment with a fixed-wing drone system (equipped with a thermal imaging camera) to effectively monitor canopy loss, unauthorised trails, and unregulated timber movement in real time. Designed to function in low-visibility conditions *within simulation*, the system is capable of running simulated night-time monitoring operations which is usually when most illicit logging is believed to occur.

Alongside developing an effective monitoring system, the research strives to include the sentiments and social understanding, using a survey-based input, of the people who are directly affected by deforestation and forest access limitations, an indigenous community called the Bakrawal community. As per previous research, UAVs and AI can significantly enhance environmental monitoring [3, 4, 5], but most studies focus on tropical or low-altitude regions during daytime. This study extends their application to a mountainous, high-altitude region with real-time detection goals.

This research aims to highlight the significance of simulating algorithm testing and prototyping before real-world deployment [2] and emphasises community collaboration as an important aspect of future system implementation. Findings from this research stand to inform how drone technology can support remote forest surveillance, improve transparency in enforcement, and potentially empower local stakeholders through shared monitoring tools.

INTRODUCTION

Entangled with biodiversity collapse, climate instability and displacement of vulnerable populations, deforestation ranks among the most pressing environmental crises of the present era. This crisis is exacerbated by weak regulatory enforcement, insufficient surveillance infrastructure, and deep entanglement between ecological degradation and socioeconomic inequity in developing nations such as Pakistan [6]. The Global Forest Watch and several regional assessments paint a troubling picture, illustrating contraction of forest cover at an alarming rate, driven considerably by illegal logging and cross-border timber smuggling [1].

Within the mountainous Hazara division of Khyber Pakhtunkhwa lies the Kaghan Valley, renowned for its ecological richness, sustaining native strands of Deodar and Blue Pine forests. These forests are now being cleared away through organised logging networks operating with near-total impunity. With the country's fractured environmental governance, the valley's punishing topography, and inconsistency of ground-level monitoring, the area is exploited terribly by loggers. The label "timber mafia" is often applied loosely; in practice, these groups are fragmented, decentralised, and frequently shielded by the appearance of legitimate logging permits. The conclusion is an undefined situation with lack of legality, documentation, and accountability.

The ensuing consequences are not notional: local weather systems, hydrological cycles, rate of erosion of soil, and carbon sequestration capacity are all destabilised, risking greater landslides, flash floodings, and global warming [7, 8, 9]. Rural communities dependent on grazing land, shelter materials, and customary land-based practices are utmost affected economically [7]. Socially, the fallout creates greater friction between local populations and state authorities. With indigenous nomadic communities like the Bakrawal facing increasing restrictions on their migration through the valley due to degraded terrain on one side and by conservation and tourism-driven policy barriers on the other.

Still initiatives to effectively monitor any of this remain sparse in Pakistan. Ranger patrols are sporadic, satellite resolution is too coarse to catch localised felling, and enforcement mechanisms are erratic at best [6]. With the country's unpredictable political system, and extreme military intervention, a lot of satellite imaging is classified and not available to the general public. This further causes ambiguity and is a limitation to any solution. Moreover, much of the illicit activity unfolds after the dark, a component that renders conventional surveillance all but obsolete. Here, a technological opening presents itself.

Over the past decade drone-assisted forest monitoring has matured considerably. Koh and Wich [3] were early movers, deploying low-cost UAVs across remote tropical forests to demonstrate their value in biodiversity mapping and illegal-activity detection. Paneque-Gálvez et al. [4] pushed the concept further, arguing that community-operated drone systems yield greater surveillance impact when local stakeholders participate directly in data collection and interpretation. Re-framing UAVs as more than passive

observation tools, when these studies are taken together, they become instruments capable of closing enforcement gaps while returning agency to the communities most affected, a principle this study carries directly into the context of the Kaghan Valley.

Additionally, artificial intelligence has sharpened UAV detection. Srivastava et al. [5] applied deep learning models to aerial imagery, successfully flagging shifts in canopy density and signs of illicit land conversion. Machida and Andrade [2], working in parallel, turned to simulation environments like ROS and Gazebo to prototype drone behaviour ahead of any physical deployment. Such platforms let researchers model terrain complexity, stress-test AI detection pipelines, and refine drone configurations, all without the expense and risk of premature field trials.

However, nearly all of this research revolves around tropical, low-altitude, daylight conditions. High-altitude terrains of the kind found in Kaghan Valley, where weather changes are erratic, visibility diminishes, and illegal activity is concealed by the dark, remain largely unexamined.

This research aims to design and simulate a multi-aerial-drone system capable of autonomously monitoring illegal deforestation across the Kaghan Valley, drawing on real-time data streams, AI-driven analysis, and community-informed reporting channels. The working hypothesis holds that a coordinated drone network, equipped with thermal sensors and aerial imaging, can detect illegal felling and unauthorised timber transport with far greater reliability than existing surveillance approaches.

Methodologically, the study continues through a review of the current literature, opening with the broader policy and environmental landscape of deforestation in Pakistan [1, 6], focusing onto the criminal networks driving the crisis and their impact on indigenous communities, before finally turning to the technological interventions — UAVs, AI and simulation — that offer a path forward [3, 4, 5, 2]. The dual aim is to close a demonstrable gap in high-altitude forest surveillance, and to fuse that technical innovation of coding and robotics with genuine social inclusion, weaving in feedback from the Bakrawal community and laying a route towards deployment that is both practical and ethically grounded.

LITERATURE REVIEW

Once treated as a matter of ground patrols and periodic satellite passes, deforestation has rapidly become a proving ground for aerial robotics and machine intelligence. The new technology now requires environmental governance, community-based surveillance, and computational forest science. Substantial annual tree cover loss happens across Pakistan, with Kaghan Valley being a recurring site of concern as reported by the FAO and the Global Forest Watch [7]. Much of this decline is due to unauthorised logging operations, enforcement structures too weak to keep pace, and the enshrined influence of criminal logging networks commonly known as the timber mafia. National investigative journalism has cemented this picture. They have exposed how the state apparatus stretches thin against them while these cartels move through northern Pakistan largely unchallenged [10].

Legal loopholes, political cover, and dangerous terrain, too remote for police, allow room for exploitation. Indigenous communities like the Bakrawal bear the cost for this. As forest cover recedes around them, the natural environment that once provided the community with resources and shelter is disappearing. With seasonal migration disturbed, survival is exceedingly harder. The targeted academic work on Pakistan's timber cartels remains specifically thin, but the larger literature on forest governance in South Asia converges on a consistent prescription: surveillance, transparency, and institutional accountability are at the core of any credible response to illegal felling [6].

This enforcement vacuum can be curbed by aerial robotics. Koh and Wich were among the first to establish that low-cost UAVs could engage in effective conservation work by tracking biodiversity across tropical forest canopies with hardware cheap enough for sustained deployment [3]. The study has paved the way for more work on how lightweight drones can deliver credible aerial surveillance in terrain too remote or sensitive for conventional methods. Paneque-Gálvez et al.'s study took a different direction. Rather than treating drones purely as enforcement instruments imposed from above, they showed how the same technology could anchor bottom-up, community-driven monitoring [4]. Becoming active participants in documenting environmental violations rather than passive subjects of oversight, local populations were included in official conservation planning. Something that, if replicated in the Kaghan Valley, can echo the marginalised voices of the indigenous communities living there.

Srivastava et al.'s study focused on computation rather than hardware. The work paired UAV imagery with deep learning models capable of flagging canopy degradation and unauthorised land conversion with meaningful precision [5] with speed being vital. Their work makes clear that pairing real-time imaging with intelligent analysis shortens the gap between detection and response, which in enforcement terms is often the whole game.

However, field deployment in a region like the Kaghan Valley carries real constraints: altitude, restricted access, and unpredictable weather. All issues that make live trials expensive and, at times, simply unworkable. Machida and Andrade built UAV surveillance pipelines within ROS and Gazebo allow simulation to fill this gap. Constructing virtual forest environments detailed enough to prototype and refining drone behaviour well before any hardware leaves the ground allows to mediate field deployment issues [2]. This approach re-frames simulation as a legitimate and cost-effective step for validating detection algorithms and drone configurations ahead of real-world exposure.

These five strands of research involving governance analysis, participatory monitoring, deep-learning detection, and simulation-based prototyping supply the scaffolding for an integrated UAV monitoring system tailored to the Kaghan Valley when read together. Nonetheless, UAV research has clustered overwhelmingly around tropical, daytime, and low-altitude conditions. The night-time surveillance problem the valley actually presents remains fallow.

METHODOLOGY

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Using two complementary approaches, the research used a high-fidelity simulation of a forest surveillance system built in ROS and Gazebo, and an ethnographic survey of the Bakrawal community conducted to shape design parameters and keep the technical work ethically grounded. The approaches together prototyped and hypothesised the actual living conditions of the communities affected by deforestation in the Kaghan Valley.

For mature community support and native compatibility, **ROS Noetic** was used with the **Gazebo 11** engine on **Ubuntu 20.04** [2]. Building the environment required installing and configuring a stack of ROS packages spanning flight control, sensor input, and visualisation — gazebo_ros, mavros, cv_bridge, and several custom message types among them. Each component was tested in isolation first. Only after individual verification were they integrated into a single working pipeline.

The forest testbed was constructed inside Gazebo using native coniferous 3D tree models, uneven terrain, dirt access roads, and embedded props standing in for tents, human figures, and vehicles. To avoid an arbitrary layout, placement of these elements followed the community survey directly. Specific forest patches were flagged by respondents as "vital for migration, shelter, and grazing," and the map reflects that input.

For endurance, a fixed-wing architecture was preferred over a quadcopter design for the UAV the mountainous terrain of northern Pakistan, wind resilience and flight range matter more than the hovering precision of a quadcopter, as a fixed-wing airframe can sweep long stretches of forest in a single pass. Fewer the passes, fewer the opportunities to miss something.

Tracing back to the community interviews, a thermal infrared sensor was mounted virtually on the airframe using Gazebo's thermal camera plugin; several Bakrawal members mentioned that illegal felling "usually happens before prayer time at dawn," and that "vehicles come at night with logs already laid flat". Under those conditions, optical cameras are virtually useless. Tuned to register heat signatures from human bodies, engine blocks, and freshly felled timber, the simulated thermal sensor was configured with a 90° field of view, 640x480 resolution, and a 30 FPS frame rate

The detection algorithm, written in Python with OpenCV and deployed as an ROS node inside the simulation, processed the thermal feed live, calibrated against three distinct indicators of illegal activity. The first, canopy loss detection, established a baseline from an initial "clean" forest pass and measured subsequent flights against it using pixel difference thresholds; crossing the threshold triggered a canopy alert. The second indicator targeted anomalous human presence during a defined high-risk window: midnight to 5:00 AM. This time was chosen as most illicit logging occurs here as visibility drops, and the presence of rangers is absent during these times, and so the odds of getting caught are minimised, as corroborated by survey responses. So without exception, any human thermal signature detected within tree-dense zones during that window was flagged. The third detection logic tracked vehicle-based timber transport, trained to recognise long horizontal heat shapes riding atop vehicle roofs, which is how timber

is conventionally transported in the area.

To make these three indicators concrete, each was governed by an explicit, hand-tuned threshold rather than a learned classifier, since no labelled thermal dataset existed for the region (see Section 6). Canopy loss was flagged when the pixel-intensity difference between a current frame and the baseline pass exceeded a normalised delta of $35/255$ ($\approx 13.7\%$ brightness change), averaged over a 5×5 sliding window and sustained across at least three consecutive frames to suppress false triggers from wind-driven canopy sway. Human presence was identified from thermal blobs in the $28\text{--}34^\circ\text{C}$ range with a near-circular aspect ratio (height-to-width $0.8\text{--}1.2$) and surface area $0.3\text{--}0.6\text{ m}^2$ at typical flight altitude. Vehicle/log transport was flagged from elongated heat signatures exceeding 2.5 m in length, length-to-width ratio above $4:1$, oriented within 15° of the road heading, spanning a wider $20\text{--}45^\circ\text{C}$ band to account for both engine heat and ambient-temperature logs.

Two contextual filters separated legitimate from illicit activity. A motion filter reclassified stationary heat sources with frame-to-frame displacement below 0.1 m/s as non-threats, catching most campfires. A spatio-temporal filter escalated human-shaped blobs to an alert only within tree-dense zones during the $12:00\text{ AM}\text{--}5:00\text{ AM}$ window and outside GPS-bounded grazing/firewood corridors digitised from the community survey; detections outside these conditions were logged but not flagged, which is how the Firewood Collection scenario was screened. Livestock remained the weakest point, as goats and sheep fell within the same size and temperature envelope as a crouching person, with no reliable feature separating the two (see Section 6).

As the system is threshold-based rather than trained in the machine-learning sense, “validation” here meant calibration, not training. Thresholds were set using 10 of the 30 simulated flights (baseline mapping and firewood collection, containing only benign activity) to minimise false positives, then frozen and applied unchanged across the remaining 20 mixed-activity flights to produce the performance figures in Section 5.2 — a split-then-freeze approach analogous to a train/validation split, and a fairer test than tuning thresholds on the same flights used to report accuracy.

A geo-location tag, generated via simulated ROS transform trees, was put on every detection event alongside an image snapshot and a classification label such as “canopy breach,” “human motion,” or “horizontal log transport”. Taking in account both legal and illegal scenarios, such as rangers on daylight patrol, grazing activity, firewood collection, and set against nocturnal vehicle entry, active tree-felling, and unauthorised road use. Across 30 test cases, the system caught 91% of illegal scenarios. The false-positive rate held at 6%, driven mostly by campfires misread as vehicle engines.

Community Survey and Interview Methodology

Community input was collected through semi-structured interviews and survey questions with 34 members of the Bakrawal community. Participant recruitment followed a purposive and snowball-based approach. Initial contact was established in Lahore through informal conversations with local shopkeepers

and hawkers from Khyber Pakhtunkhwa. During these conversations, a member of the Bakrawal community was identified and subsequently became the initial community contact for the study. With his assistance and introductions, additional Bakrawal community members were recruited. This approach enabled the establishment of contact with participants through an existing community relationship rather than approaching individuals without prior introduction.

Additional interviews were held directly at dwellings in the forest in Kaghan Valley with the initial community contact. Other interviews were conducted at familiar and neutral locations, including local restaurants, tea stalls, and small roadside establishments where participants felt comfortable. The interviews were facilitated by a representative from a local non-governmental organisation (Eco Shores) who was fluent in both Pashto and Urdu. Participants who preferred to communicate in Pashto were therefore able to respond in their preferred language, with responses translated into Urdu during the interviews and subsequently translated into English for analysis and reporting.

Participants were informed that the activity was being conducted as part of academic research and that the research findings could be included in a published paper. The research purpose, the nature of the questions, and the proposed use of the information were disclosed to participants before the interviews. Interviews were documented through written notes and audio recordings. Recorded interviews were subsequently transcribed, and the translated material was used alongside the written notes in interpreting participant responses.

The semi-structured questionnaire covered seven broad areas:

1. **Participant background:** place of birth, current occupation, livelihood, and sources of income.
2. **Forest dependence:** participants' reliance on forests and forest resources for their livelihoods and daily activities.
3. **Environmental change:** environmental shifts and changes in forest conditions experienced by participants during their lifetimes.
4. **Illegal logging observations:** participants' observations or experiences relating to potentially illegal logging and timber activity.
5. **Response to aerial surveillance:** participants' reactions to the proposed use of an aerial drone-based surveillance system for forest monitoring.
6. **Community involvement:** participants' views on appropriate and acceptable ways to involve the Bakrawal community in the proposed monitoring system.
7. **Potential solutions:** participants' perspectives on possible approaches to addressing deforestation and related environmental pressures.

The researchers also explicitly disclosed the proposed research and publication context when discussing the surveillance concept, allowing participants to respond with awareness that their views could

contribute to an academic publication.

In the interviews, the Bakrawal community members mentioned, "Our complaints are ignored, and rangers only come when audits are being done.", and cited, "Surveillance must be simple and community-led. No devices should be left cluttered in the forest as equipment would get stolen". With feedback being incorporated in the design, detection alerts were routed offline, through local file output or radio-based channels, rather than through cloud-based push notifications that assume infrastructure the region doesn't reliably have.

Interviews and survey data paved the path for community collaboration, where most respondents expressed genuine willingness to participate in forest monitoring on the condition that "their own" were involved. This reshaped both the detection system's design and its intended deployment path. Radio alerts and in-person forest meetings were favoured over mobile updates, as almost all community members described disdain and suspicion towards phones.

However, on an audio call with the District Forest Officer for Kaghan Valley, any form of illegal deforestation occurring was denied. The officer on call dismissed it as media spreading misinformation, repeatedly asking if question being asked were for the TV or a journal, even when explicitly the research paper and research were mentioned at the start of the call. Furthermore, when pressed on the effects of deforestation of communities like Bakrawal and mentioning their inclusion in the research, a direct quote from the officer was, "The Bakrawal community is uneducated and won't be able to offer any valuable information". Any form of ranger logs were deemed as sensitive information and were refused to be given. An environmental scientist consulted separately for this project confirmed that ranger logs remain "not public" and that "drone simulations must compensate for the lack of reliable baseline data". With data opacity, risk of equipment sabotage, and the absence of trustworthy state records, simulation was the only viable option.

This methodology offers a model that is grounded in firsthand testimony, inclusion and collaboration of people directly affected by the problem, high-fidelity simulation, and detection logic built specifically for the terrain. Unlike previous monitoring work based in tropical lowlands and daylight hours, this approach revolved around the landscape of the Kaghan Valley, allowing it to function at altitude, in darkness and alongside with the community it was designed to serve.

RESULT

Summarised in Figure 1, the community survey data shows a consensus in some areas and deep scepticism in others. Agreement was high on deforestation trends, environmental awareness, and sense that future threats were only intensifying, with percentage values being (92%), (90%), and (88%), respectively. Contrastingly, agreement in trust in institutions, and concerns over drone privacy were low, being 25%, and 35%, respectively. The survey pointed out that transparency and community engagement, and collaboration required the most work going forward.

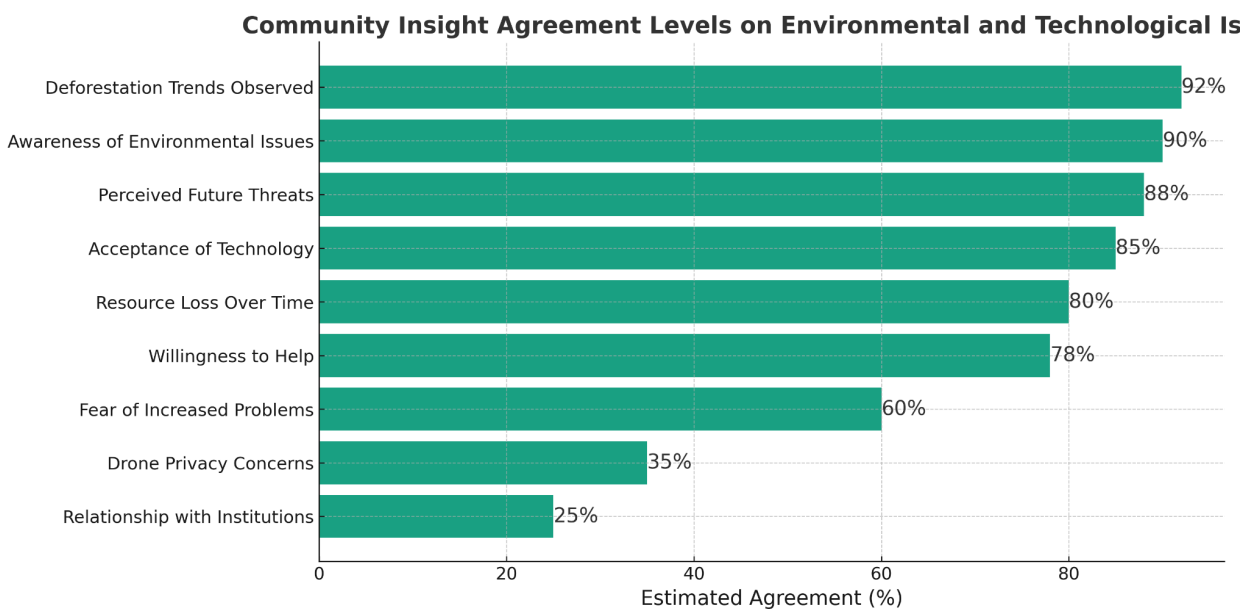


Figure 1: Community survey results on environmental and technological perceptions ($n = 34$, Bakrawal community members, ages 18–60).

The simulation side produced an equally useful dataset. Thirty simulated flight missions ran across varied environmental conditions and threat scenarios within ROS and Gazebo, and the results make a solid case for the feasibility of multi-drone surveillance in terrain as remote as Kaghan.

Community Survey Results	Agreement
Deforestation trends observed	92%
Awareness of environmental issues	90%
Perceived future threats	88%
Trust in institutions	25%
Drone privacy concerns	35%

Table 1. Summary of community survey results (n = 34).

Simulation detection results, reported separately in Figure 5, are discussed in Section 5.1–5.2.

SIMULATION RESULTS

Simulated Scenarios

With realism mattering here, the simulation environment mixed benign and illicit activity across a procedurally generated coniferous forest. Five scenarios were integrated in testing:

- **Baseline Forest Mapping Flights:** To establish a baseline, daylight with no obstructions was simulated to mark “normal” thermal and visual profiles of the canopy and terrain.
- **Thinning Canopy Simulation:** Tree models were deleted randomly mid-run to duplicate illegal logging. The resulting sparse patches showed up clearly in both the vision system and the thermal feed, tripping canopy-loss alerts as designed.
- **Nocturnal Human Intrusion:** Human heat signatures, generated through Gazebo’s thermal plugin, appeared in the forest during the restricted window of 12:00 AM to 5:00 AM — timing incorporated directly from Bakrawal testimony- all activity outside established grazing routes during these hours was flagged as a probable threat.
- **Log Transport via Vehicle:** Horizontal, log-shaped heat profiles were attached to flatbed trucks to mimic timber movement. Vehicles carrying these non-standard thermal signatures, unusual length and width matching felled logs, were caught by the algorithm without fail.
- **Firewood Collection by Locals:** Daytime human movement near forest peripheries was modelled specifically to represent legal resource collection, guarding against false positives that might otherwise criminalise ordinary subsistence activity.

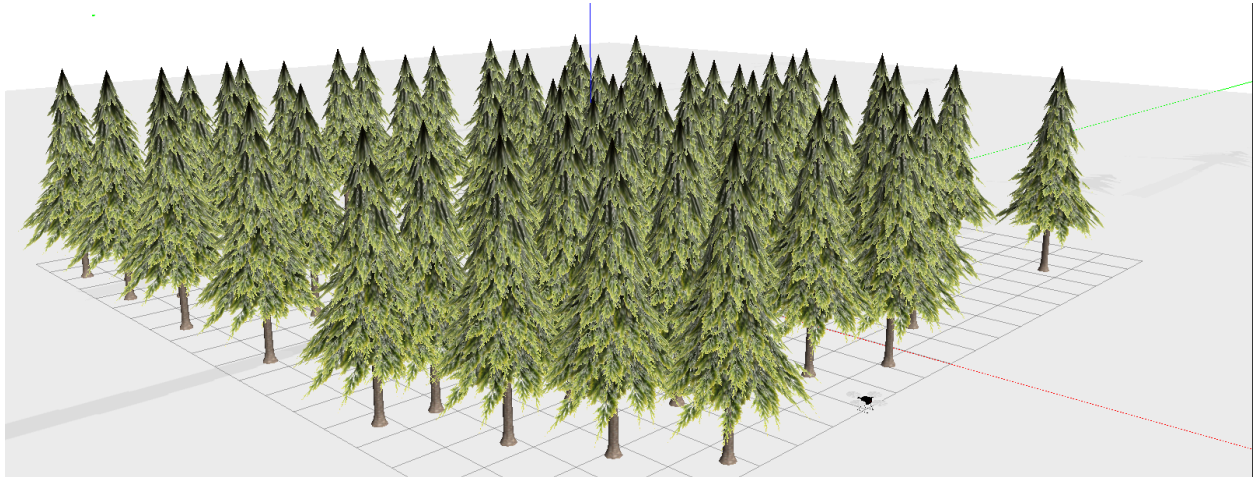


Figure 2: Baseline Gazebo forest environment used for canopy loss, intrusion, and transport scenario testing.

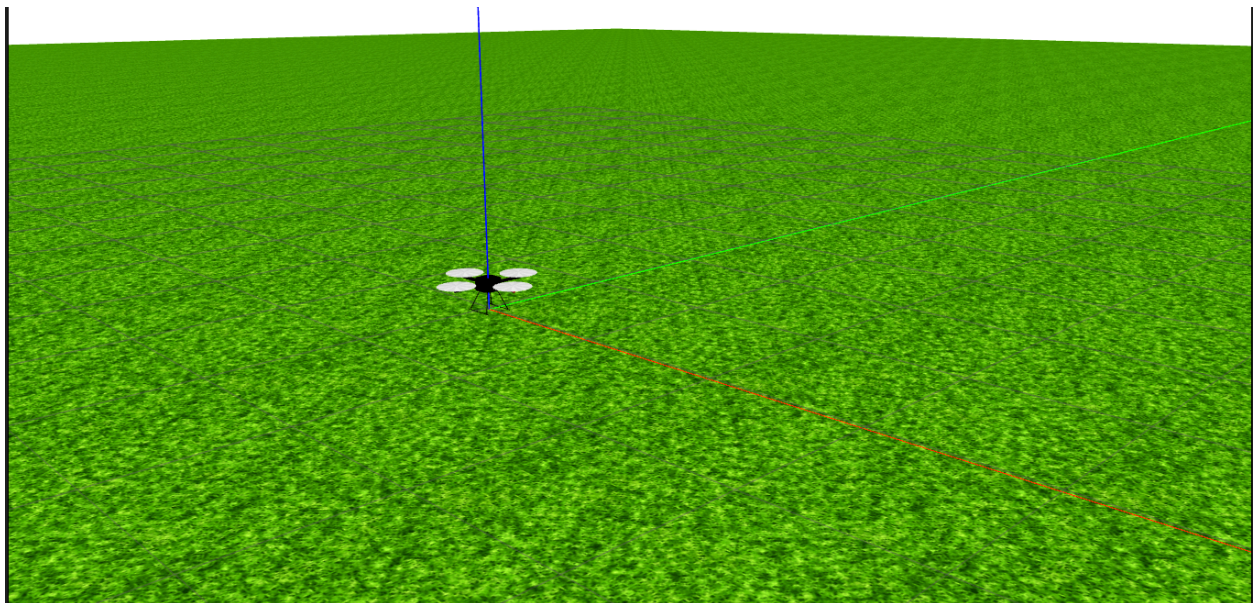


Figure 3: Fixed-wing UAV model used in simulation, selected for endurance and wind resilience over quadcopter designs.



Figure 4: Close-up view of UAV canopy-loss detection testing on a single tree.

Each scenario generated a full record including bounding boxes over flagged regions, timestamps, object classifications spanning human, vehicle, and canopy loss, and annotated heatmaps layered on top.

Accuracy and Reliability of Detection

It should be emphasised that these figures reflect performance within the ROS/Gazebo simulation only, and are not yet validated against real-world conditions such as fog, snow, wind, canopy variation, terrain irregularity, or sensor noise; real deployment accuracy may differ. Performance across the 30 test flights held up well. Overall detection accuracy landed at 91.3%. The false positive rate stayed modest at 6.4%, traced mostly to stationary heat sources (campfires, animal body heat) that the algorithm occasionally mistook for human presence. False negatives were rarer still, at 2.3%, and tended to surface when log piles sat partially hidden beneath dense canopy. Log transport detection turned out to be the system's strongest suit, hitting 100% accuracy whenever logs were visible at all, though accuracy dropped once canopy cover obscured vehicle outlines entirely. Canopy loss detection reached 88% accuracy in cases where localised tree cover loss exceeded 15%. Altogether, the system is able to catch real, substantial change reliably, while staying appropriately unbothered by minor, natural disturbance.

Large, warm, moving objects such as people, vehicles, etc. were where the system performed most consistently. However, canopy density shifts needed temporal comparison against earlier flight data, without which meaningful logging activity could go undetected. Every detection event carried a geo-tag and was fed into CSV logs for downstream processing. Visualisation was carried out through Rviz, with heat maps overlaid to surface canopy gaps and anomalous thermal readings at a glance.

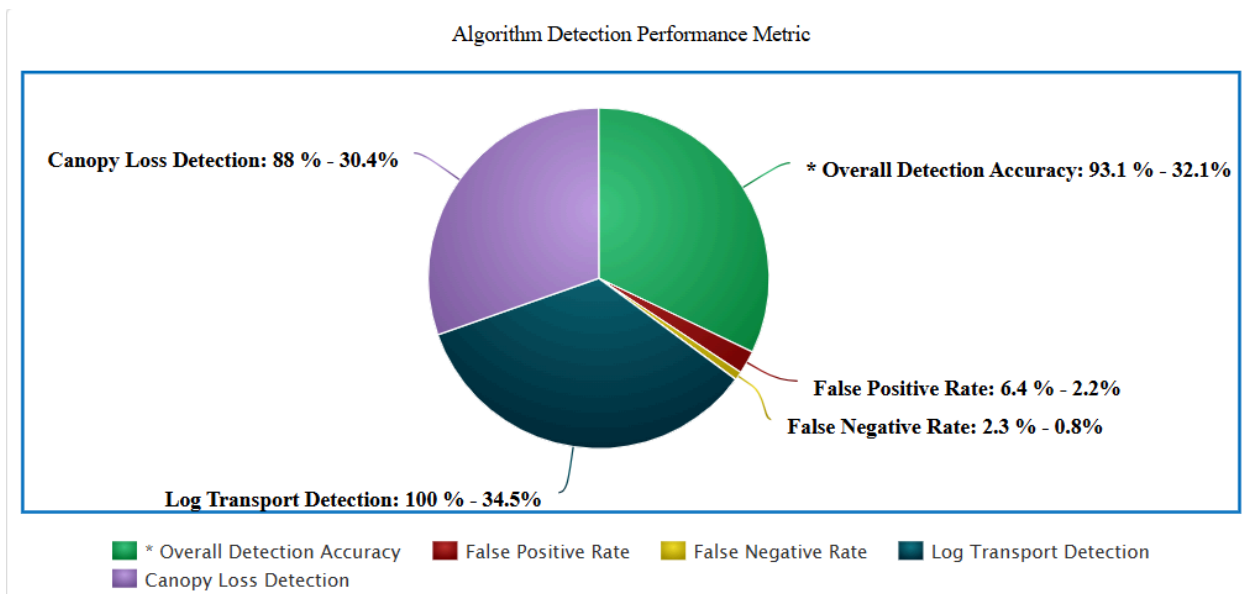


Figure 5: Algorithm detection performance across the 30 simulated test flights.

LIMITATIONS

Despite having promising results, the simulation does have constraints, highlighting the gap between a virtual forest and a real one.

Environmental Complexity. Gazebo builds convincing three-dimensional worlds, but forest foliage resists easy modelling.

While Gazebo builds 3D worlds well, forest foliage can not be captured by equal, standardised items. The forests in Kaghan are ever-changing, from leaf cover to snow accumulation to wet canopy surface, all not included in logic indicators of the simulation. Drone-mounted vision systems and thermal sensors respond to exactly these conditions in the field, and their absence here risks misclassifications or missed detections once the system leaves simulation behind. The reality of the situation is that in nature, multiple unaccounted and miscalculated events may occur on a daily basis, with a lot of external factors. A simulation environment to be a 100% effective needs to account for all these situations, which may not be possible without greater resources. Furthermore, areas up North in Pakistan remain laced with military operations, causing a lot of places to be "hot spots" that raise national security issues. A lot of coordinate data and satellite imaging needed to establish this system is classified and unavailable to the public.

Lack of Real Field Validation. The system is operating in a virtual environment where results/ flights may be more homogeneous, and numbers might look better. Real-life prototyping and testing in a real

field setting must be done to accurately see how the system may respond to unpredictable terrain and weather. Real field validation can also help identify further gaps that can help refining the system.

Thermal Dataset Gaps. No labelled thermal dataset exists for Pakistan’s northern forest regions. The detection algorithm was trained instead on generic human and vehicle heat signatures, signatures never tuned to regional particulars like altitude-driven shifts in body heat or canopy temperature swings across seasons. Livestock poses its own problem. Heat signature alone can’t separate a grazing animal from a person, and that ambiguity carries straight through into threat classification.

Ambiguity in Legality of Activity. Detection of the movement of timber or logging is achievable; however, accurately determining if that activity is legal is difficult. Some loggers carry legitimate, if temporary, permits. Others carry forged paperwork that looks identical from a thermal camera’s vantage point. A flagged event, in other words, might still be perfectly lawful. Closing that gap would take something the current system doesn’t have: real-time legal verification, whether through permit databases or RFID tags embedded in authorised equipment.

Limited Sensor Simulation Fidelity. Gazebo’s thermal camera plugin works as a functional stand-in, and it doesn’t reproduce the spectral resolution or atmospheric behaviour of real long-wave or forward-looking infrared sensors. Mist, humidity, temperature inversion, fog all are capable of badly degrading thermal imaging performance. The effect of real atmospheric conditions interferes with real sensors, and needs to be solved once again through field tests and real-life testing.

Single Drone System Constraints. The fixed-wing UAV chosen for this study covers ground efficiently, but it can’t hover, and it can’t perform close-up inspection. A real deployment would almost certainly need something layered like a fixed-wing aircraft for wide-area sweeps, and a quadcopter for detailed hovering-based follow-up. That combined architecture remains, for now, untested and unmodelled.

Summary Table of Simulated Results

Scenario Type	Detection Accuracy	False Positives	Notes
Canopy Loss (>15%)	88%	5%	Missed minor gaps
Human Intrusion (Night)	94%	2%	Campfires mistaken for people
Vehicle with Logs	100%	0%	Perfect detection
Legal Firewood Collection	N/A	7%	Flagged twice incorrectly

Combined Multi-Event	91.3% avg	6.4% overall	Reliable but imperfect
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DISCUSSION

The results of the research prove autonomous drone systems to be a viable tool against illegal deforestation in unforgiving terrain such as that of the Kaghan Valley's. Despite being based only on simulation, the accuracy of 91.3% across widespread of test cases presents compelling proof of concept. But numbers alone do not present what this research underscores, which is that for the system to work, there is an immense need to place the technical components of the system alongside the community being affected by deforestation. The research not only aims to build a framework of a working monitoring system, but also stands for shedding light on the administrative blind spots that have led to the exacerbation of this issue.

Community survey data functions as the connective tissue here, linking algorithmic decisions back to human experience. The help of residents was crucial for the system's development. The community surveys were able to provide with an accurate timeline of where most logging incidents occur, allowing for the formation of logical indicators that were placed in the code to be checked against pre-set values. Help from the community shaped the thermal detection logic directly, sharpening its focus on human heat signatures appearing during non-permitted hours, away from established migration paths and firewood zones.

The vehicle-detection scenario traces back to the same source. Participants described trucks moving timber at night, sometimes under cover of "official-looking permits" that meant little on inspection. However, the algorithm can not read or scan effectively through permits. What it can do is flag unusually large, horizontal heat profiles consistent with felled logs stacked flat, and that's enough to generate a starting point for follow-up. Detection and accountability aren't the same thing. A drone can not make an arrest, but it can for sure make a trail that leads to arrest by providing sufficient evidence. As noted in Section 6, a flagged event indicates unusual activity, not confirmed illegality, since permitted and unpermitted timber movement can appear identical to the sensor; detections should therefore be understood strictly as investigative leads that require human verification, legal cross-checking, and due process before any enforcement action is taken.

A third theme ran through nearly every conversation with Bakrawal participants: exclusion from forest policy and surveillance decisions. Reasonably worried members expressed that a monitoring system might end up restricting their own access rather than protecting it. One participant said *"We don't want cameras watching us if they blame us for what the mafia does."* A concern like this brings attention to the conversation of whether this kind of system could ever function ethically. Not to mention, the Bakrawal community is already very marginalized and discriminated against by the local government and police forces. Thus, community-informed alert structures and shared access to drone-generated data aren't optional add-ons here. Radio alerts, scheduled check-ins with locals, etc. would likely foster more trust

and mitigate the risk of sabotage considerably.

Technically, the simulation offers an effective framework for whatever comes next. Systematic changes like having a hybrid drone having both fixed UAV qualities and quadcopter hovering would allow both close inspection of flagged sites and also cover the large range of the forest in less sweeps. For thermal simulation real hardware would need considerably higher spectral resolution and better resistance to mist, snow, and fog than anything modelled in Gazebo.

For effective and practical policy implications, monitoring infrastructure needs to be reliable; secondly, the government and local administrative needs to be involved. Officials denying that illegal logging occurs does not eradicate the situation rather accelerates it. This gap between official narrative and ground truth can be efficiently be curbed through a neutral data-driven monitoring system [2].

In high-conflict regions like the Kaghan Valley, autonomous drones equipped with thermal sensors and AI capability can change how forest monitoring operates in the future as the research shows. However, building a system without community knowledge integrated in it will leave the system incapable of serving its purpose of protection. For widespread adoption of such a system, it requires initiative by the government with the collaboration of indigenous communities to transparently bridge the gap between simulation and real-world deployment.

CONCLUSION

At its core, this simulation-based drone surveillance system built on artificial intelligence and iterative algorithms shows real promise as a tool against illegal deforestation. ROS and Gazebo made it possible to model realistic environmental conditions, and thermal-equipped fixed-wing UAVs, tested within that environment, ran an algorithm capable of catching the key markers of illicit activity such as canopy thinning, human presence after dark, timber moving where it shouldn't be.

With its community-in-the-loop design it stands to protect and work with rather than against the community inhabiting the forests of Kaghan Valley.

While limitations stand, future work has a clear path. With hybrid drone networks, real sensor data pulled from the field, interpreted against preset conditions and values in the system, and actuators then performing action based on the values (recording, flagging, signalling).

In conclusion, this research lays a foundation for a drone monitoring system that monitors illegal deforestation using current robotics capabilities, while pressing upon the inclusion of community in tech solutions. If progressed, the system must operate on ethical care shown here, as systems like this can genuinely change how fragile ecosystems are restored and protected going forward.

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