



Original Research Paper

Artificial Intelligence Integration of Traditional Knowledge for Wildlife Management

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Key Words

Abstract

Artificial intelligence, traditional ecological knowledge, wildlife management, knowledge graphs, participatory conservation, decision support.

The management of wildlife is increasingly challenged by habitat fragmentation, changing species distributions due to climate, and growing human-wildlife conflicts, but traditional monitoring is limited in terms of the number of sensors available and the length of the observation period. Indigenous and local communities possess extensive and multigenerational traditional ecological knowledge (TEK) about animal migration; feeding grounds; breeding seasons; and conflict areas, but this knowledge is largely oral and not used in formal decision making. Traditional Knowledge Integration Framework (AI-TKIF) which brings together community narratives, participatory maps, and seasonal calendars alongside camera-trap images and acoustic recordings, GPS telemetry, satellite imagery, and historical wildlife reports. Species, locations, seasons and behaviours are extracted from transcribed narratives by multilingual natural language processing (NLP); computer vision and geospatial learning analyse sensor data; and a wildlife knowledge graph can combine both streams using a community-agreement-based, expert-validated, observation-frequency-based and scientifically consistent confidence scores. An explainable decision-support module generates migration-corridor maps, habitat-priority zones, seasonal alerts and conflict-risk areas, which are analysed and discussed with the knowledge holders before being used operationally. The framework is based on free, prior and informed consent, community-controlled access and location masking. A prototype for human-elephant conflict in a forest-agriculture landscape reveals that the complete framework is equally effective for predicting the risk of conflict and reducing false alerts compared to scientific-data-only, traditional-knowledge-only, statistical-integration and unvalidated AI-fusion baselines, and it is robust against low sensor-density. The results indicate that culturally responsible AI can enhance participatory, adaptive, and community-inclusive wildlife conservation efforts.

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Introduction

The loss, fragmentation and alteration of habitats, poaching and changing seasonality with climate change are all increasingly threatening the populations of wildlife globally. Human-wildlife conflict (HWC) is now one of the most significant management issues influencing the dynamics of protected areas where protected areas are increasingly encircled by agriculture and settlement, resulting in crop losses, damages to properties, injuries and retaliatory killing of wildlife (Abed et al., 2025; Ojija et al., 2025). Conservation planning depends on accurate data on animal presence, the extent of movement and when it is likely to cause conflict, but traditional animal monitoring programmes are costly, geographically sparse, and often limited in the amount of time can be conducted (Shekhawat et al., 2025). ILC are the people who coexist with wildlife and possess a complementary source of information. Their traditional ecological knowledge (TEK), acquired through the observational experiences of their ancestors over generations, helps them understand when to migrate, where to find water sources and feeding grounds, how to recognize the forewarnings of crop raids, and the long-term changes in habitat conditions (Kumar & Singh, 2025). Often this knowledge is more extensive than any instrumented data, both in time and in space. TEK, however, is generally communicated verbally, through local linguistic and cultural concepts, and in social and spiritual settings and is hard to capture in formal decision-making instruments (Adewale et al., 2026). Use of scientific knowledge and TK alone leaves gaps.

While sensor-based monitoring provides accurate data on specific events, the data from traditional observations is often rich in context and detail but may lack the spatial and temporal focus or consistency needed for management agencies (Ullah et al., 2025). Technically, artificial intelligence (AI) can alleviate the issue of reconciling these diverse sources, with natural language processing (NLP) being used to structure the narratives, computer vision and acoustic models being used to ingest vast volumes of sensors, and knowledge graphs being used to connect entities across modalities (Dave et al., 2025; Fawwad et al., 2026). However, the vast majority of AI conservation systems are built on scientific data and do not consider cultural interpretation, knowledge ownership or community consent (Molino, 2023; Joshi & Pant, 2024). This paper aims to fill this void with the introduction of AI-assisted Traditional Knowledge Integration Framework (AI-TKIF). The goals are to (i) create a participatory pipeline for gathering and structuring TEK in addition to multimodal sensor data, (ii) develop a confidence-weighted fusion procedure based on a wildlife knowledge graph, and (iii) test the framework in terms of predictive performance, integration quality, security, and robustness. The main contributions are the culturally responsible architecture where community validation is conducted before the operation of the system, the reliability-scoring scheme, which considers community agreement as a first-class evidence source, and the structured baseline and ablation analysis.

Background and Design Motivation

Traditional Knowledge in Wildlife Management

Knowledge about wildlife is varied and utilitarian within the community. Farmers, herders and forest gatherers are able to identify animal presence through animal tracks, dung, animal sound and feeding signs, know elephant trail between forest patches, ungulates reproducing months, fruiting months that attract animals towards villages (Kumar & Singh, 2025). In south West Nigeria, myths, taboos and sacred groves serve as informal conservation institutions which protect certain species and habitats (Adewale et al., 2026), and in India, the traditional agro-ecological practices are seen to contain encoded information pertaining to seasonal environmental cues and habitat change (Joshi & Pant, 2024; Dharanendra Kumari, 2025). Communities are also the first to see HWC, and as such, are excellent at identifying new hotspots and changing animal behaviour (Ojija et al., 2025).

AI Applications in Wildlife Conservation

AI has become the heart of the current wildlife monitoring. Species are classified within vast camera-trap archives, vocalisations are detected within continuous audio files using acoustic classifiers and animal behaviour is tracked at high temporal resolution with sensor-deep learning pipelines (Kiran et al., 2025). Machine Learning in remote sensing and Geographic Information Systems (GIS) can be used for habitat suitability mapping, forest cover change detection and fire-risk assessment (Dave et al.,

2025), and IoT devices with AI have been introduced to serve as early-warning systems for crop-raiding animals (Abed et al., 2025; Ojija et al., 2025). While less frequently employed in the field of ecology, NLP and knowledge graphs are gaining traction in knowledge organisation and classification, where used to structure and connect diverse forms of knowledge, as per the principles of knowledge organisation and classification (Radhakrishnan & Chandrasekharan, 2025; Fawwad et al., 2026).

Existing Limitations

Yet, there are four limitations. Firstly, TK is often transmitted orally, without structure and with local context, and so is not necessarily ready to be taken in by pipelines without careful transcription and interpretation. Second, there are gaps in scientific data, particularly in space and time, with camera traps and collars monitoring a small portion of a landscape only for a limited amount of time (Shekhawat et al., 2025). Third, current AI models have not been used to consider cultural interpretations; a local term might refer to a behavioural state or spiritual meaning, and not necessarily to a species (Molino, 2023). Fourth, issues of knowledge ownership, consent, benefit sharing, and privacy remain underdeveloped, and there is a potential danger of extracting the knowledge of the community without returning any value (Ullah et al., 2025; Adewale et al., 2026).

Design Motivation

These restrictions drive a participatory, transparent, secure, and culturally responsible framework. The framework places knowledge

holders as co-producers, and validators of AI outputs, rather than seeing TEK as a source of data to be mined. Explainability ensures that communities and managers can understand the rationale behind a recommendation, security measures prevent access to sensitive areas and sacred knowledge, and feedback mechanisms keep the community in the loop to ensure that AI is enhancing, not replacing, their expertise (Joshi & Pant, 2024; Kumar & Singh, 2025).

System Model and Requirements

Stakeholders and Study Environment

The system comprises of 5 stakeholder groups. Observations are provided by, and interpretations are validated with, those with local knowledge (elders, farmers, forest gatherers, and community trackers). Ecological plausibility is the assessment of wildlife experts. Conservation agencies apply outputs of decision support to planning and conflict resolution. Field researchers deploy and manage sensors, while system administrators manage infrastructure, access policies and audit logs. The study area is a forest – agriculture interface where the movement of wildlife frequently canopies with settlements and agriculture fields

Input Data Model

There are 2 streams of input data. The traditional-knowledge stream consists of community interviews, participatory maps created by the residents, and seasonal calendars indicating the appearance, breeding, and/or crop-raiding of species of interest. The scientific stream includes camera-trap photos, acoustic recordings, GPS and animal-movement data,

satellite data with environmental data including vegetation indices, rainfall, and water availability, and historical wildlife and conflict-compensation reports. Each record is marked with information on its type of source, spatial coverage, temporal period, language, and consent status.

Functional Requirements

The system should enable multi-lingual knowledge collection in local languages, identification of species and behaviours from images, sounds and narratives, extraction and analysis of spatial and seasonal patterns, prediction of conflict risk and priority habitats, validation with experts and local communities, and explainable recommendations that reveal the evidence behind each recommendation.

Ethical and Technical Requirements

The system should be operated with free, prior, and informed consent (FPIC) and provide community control over the sensitive information, with data anonymization and role-based access, and maintaining the original cultural context where observations were shared. However, models need to be explainable, reliable even in the presence of uncertain and incomplete inputs, and scale to larger areas and additional species. The proposed AI TK Integration Framework is presented. AI-TKIF consists of six interrelated modules that transfer knowledge from the participatory acquisition to validated explainable decision support.

Proposed AI Traditional Knowledge Integration Framework

AI-TKIF comprises six interconnected modules that move knowledge from participatory acquisition to validated, explainable decision support.

Participatory Knowledge Acquisition

Knowledge is gathered using semi-structured interviews, mobile forms that can be used offline, community workshops, participatory mapping sessions and community field walks. Community sketches are digitised using participatory maps into high-resolution imagery maps with community members in attendance, and seasonal calendars are captured as matrices of months and events. Consent is obtained at the item level, with the ability to indicate whether the knowledge is public, community-only or to not use for AI.

Data Preprocessing and Knowledge Representation

Audio narratives are transcribed and translated with the removal of personal identifiers. Place names are aligned with participatory maps and temporal expressions like “after the first monsoon rains” are aligned with calendar intervals. The terminology standardization is a process of associating locally named species/behaviour with scientific taxonomy while keeping the original local term. Validated data is added to a wildlife knowledge graph composed of nodes for species, places, seasons, behaviour, habitat features, events, and sources, and edges to represent the relationships between them like observed-at, moves-through, breeds-during, and conflicts-with. The schema is

a modification of the knowledge-organization principles applied to heritage collections (Radhakrishnan & Chandrasekharan, 2025) to ecological knowledge, and each edge is accompanied by provenance and consent metadata.

Multimodal AI Analysis

There are four analytical components that work over the preprocessed data. An NLP module identifies species, locations, seasons and behaviour in narratives. The computer-vision module identifies and categorizes animals captured in the images from the camera traps while the acoustic module identifies vocalizations. A geospatial learning module is used to predict habitat suitability, conflict risk based on environmental layers and knowledge-graph features and a temporal module is used to model seasonal wildlife patterns to predict the time of increased presence/conflict (Kiran et al., 2025; Fawwad et al., 2026).

Knowledge Fusion and Reliability Assessment

The two types of observation, the traditional observation and the sensor detection, are about the same species, with the same time and place interval connected through the knowledge graph. A confidence score is assigned for each knowledge statement k shown in equation (1):

$$C(k) = w_1A(k) + w_2V(k) + w_3F(k) + w_4S(k) \quad (1)$$

$A(k)$ = community agreement (proportion of independent contributors reporting the statement); $V(k)$ = expert-validation score; $F(k)$ = normalised observation frequency; and

$S(k)$ = consistency with scientific data. All of these terms are in the range [0,1] and the sum of the weights is 1, which are determined together with community representatives and experts; the prototype contains $w_1 = 0.30$, $w_2 = 0.25$, $w_3 = 0.20$, and $w_4 = 0.25$. A traditional statement does not get deleted due to low scientific consistency, but is marked for review as there could be gaps in the coverage rather than errors. The confidence scores are carried forward as features and sample weights to the spatial and temporal models.

Explainable Decision-Support Module

The module produces maps of migration-corridor areas, priority habitat areas, season-specific alerts, conflict-risk areas and suggested management measures including the deployment of early-warning systems, crop-guarding schedules and priority areas for corridor restoration. For each output, an explanation is provided that lists the evidence contributing to the output, such as how many community reports and camera trap detections were observed and how close the situation was to a seasonal water source, as well as the feature-attribution values and the confidence score.

Community Feedback and Continuous Learning

Any output submitted is reviewed by knowledge holders and wildlife experts for operational use via the dashboard or community interface and can be approved, corrected, or rejected. Corrections are applied to the knowledge graph and recorded as new training signals to be used for periodic retraining. This human-in-the-loop still ensures that people

whose knowledge is being represented retain the interpretive authority and that it is conducive to adaptive management, as conditions evolve (Ullah et al., 2025).

Implementation Details

Data Collection Protocol

The prototype was designed for a forest-agriculture landscape on the outskirts of the Nilgiri Biosphere Reserve in the Western Ghats of southern India where Asian elephant (*Elephas maximus*), gaur (*Bos gaurus*), wild boar (*Sus scrofa*) and sambar (*Rusa unicolor*) frequently encroach into croplands. To respond the knowledge holders from twelve villages were selected by purposive and snowball sampling technique with emphasis on the elders, farmers and forest dependent people with priority to gender balance. Participants responded to 45–90-minute Tamil or local language semi-structured interviews. A total of 40 camera traps and 8 acoustic recorders (16 kHz, 10 minutes per hour) were set out and supported by GPS-collar records, imagery from the Sentinel-2 satellite, and five years of conflict-compensation records over a 12-month monitoring period. Before data collection, institutional ethics committee and the village councils granted ethical approval and FPIC.

Software and Processing Environment

It was developed in python 3.11 with Deep Learning using PyTorch 2.2 and Hugging Face Transformers, Spatial Prediction using scikit-learn and XGBoost, Geospatial Processing using QGIS 3.34 (with PostgreSQL 16/PostGIS), and Knowledge-Graph Database using Neo4j 5.

Training was carried out on a workstation equipped with an NVIDIA RTX 4090 (24 GB) GPU and 64 GB RAM. The dashboard itself will have a FastAPI backend and a React frontend, while the mobile app will be built using Flutter and have offline SQLite cache.

Model Configuration

Whisper large-v3 was used for transcription and IndicTrans2 was used for translation. For entity and relation extraction, fine-tuned the MuRIL model with a learning rate of 2×10^{-5} , a batch size of 16, 10 epochs and early stopping. MegaDetector v5 was used to detect the cameras and a fine-tuned regional EfficientNetV2-S was used to classify images, while vocalisations were classified with a CNN on log-mel spectrograms. An LSTM was used to model the presence series on a monthly time scale, and conflict risk was predicted on a 250 m grid using XGBoost (500 trees, $\text{max_depth} = 6$) with both environmental covariate and knowledge-graph features (confidence-weighted report density). Fusion was performed following Equation (1) and the hyperparameters were optimized on the validation set.

Prototype Development

Community mobile interface supports Tamil and English, icon-based forms and voice notes and offline collection which synchronises once connectivity is restored. The conservation dashboard offers map visualisation of corridors, risk layers and confidence overlays, and only shows sensitive locations at a coarsened resolution to unauthorised roles. The alert mechanism alerts the community by SMS and in-

app through community agreed thresholds set when the level of risk in a grid cell is predicted to be above the agreed threshold within seven days.

Experimental Setup

The data were divided into 70/15/15 training/validation/testing sets and spatial models were performed with five spatial block-cross validation to avoid leakage from spatial autocorrelation. The baselines outlined in Section 6.4 were trained using the same splits, with a full sensor coverage, and with varying amounts of sensor coverage, with conflicting community reports, and with multiple language and dialect versions of the stories.

Security, Ethical and Performance

Evaluation

Security and Privacy Evaluation

This section outlines the rationale behind the security and privacy features and their evaluation. At rest and in transit, all data are encrypted using AES-256 and TLS 1.3, respectively, with five roles defined by role-based access control, corresponding to the stakeholder groups. Sensitive sites, like sacred groves, denning areas, poaching-vulnerable areas are masked at a 5 km grid for non-authorised users; and immutable audit trails are kept of every read and write. All restricted knowledge would not be factored into a model training. Access-control testing involved 120 simulated unauthorized queries and revealed no instances of access to restricted records, nor was it possible to re-identify a contributor from anonymized transcripts of interviews.

AI Performance Evaluation

To evaluate the performance of the camera-trap species identification, the accuracy of 94.1% was achieved with macro precision of 0.93, macro recall of 0.92 and macro F1-score of 0.93 on the held-out test set. The F1 score of the entity level in the case of traditional-knowledge

extraction was 0.86. The AUC for conflict-risk prediction was 0.91, the IoU for corridors predicted using conflict-risk and those derived from collars was 0.78 and the false-alert rate was 7.9%. A one-hour story was processed in about 3 minutes and a daily risk map covering a landscape was created in less than 4 minutes (Table)1.

Table 1: Baseline and Ablation Comparison on The Held-Out Test Set

Configuration	Species	Conflict	Corridor	False alerts
	F1	AUC	IoU	(%)
Scientific Data Only	0.88	0.79	0.58	18.4
Traditional Knowledge Only	–	0.74	0.61	22.7
Conventional Statistical Integration	0.88	0.82	0.66	15.1
AI fusion without Community Validation	0.91	0.86	0.71	12.6
Complete AI-TKIF (Proposed)	0.93	0.91	0.78	7.9

Knowledge-Integration Evaluation

Agreement between community-reports seasonal presence and sensor detections was high with a Cohen's kappa of 0.71. The wildlife experts gave a rating of 4.3 out of 5 for integrated outputs and 87% of outputs were approved by knowledge holders (with or without correction). The usefulness of explanation was rated by managers at 4.2/5, the preservation of cultural context rated by knowledge holders at 4.1/5, and the relevance for decisions rated at 4.4/5.

Baseline and Ablation Analysis

Table 1 is a comparison of the full framework to four alternatives. The scientific-data-only model predicted conflict poorly, but identified species well, in unsampled areas. Although the corridors were reasonably delineated by the traditional-knowledge-only model, limited spatial precision

resulted in the largest number of false alerts. The results showed that conventional statistical integration produced slight improvements and AI fusion without community validation produced improvements in AUC but errors due to misinterpreted narratives. The community validation process led to a reduction of false alerts by approximately 37% compared to unvalidated fusion, while knowledge-graph priors slightly improved species F1 by re-ranking ambiguously predicted camera-trap species.

Robustness and Scalability

Figure 1 illustrates the performance as the number of sensors to be removed is increased. The complete framework had an AUC of 0.85 at 60% removal, versus 0.64 for the scientific-only model, since TEK-derived features make up for lack of coverage. 83% of intentionally submitted

conflicting information was identified for review using confidence scoring. Extraction F1 dropped to 0.79 for mixed-dialect narratives and most of the classification performance was recovered

with few-shot fine-tuning for a new species. The larger the study area, the more time required for processing, and doubling the study area was about a linear increase in processing time.

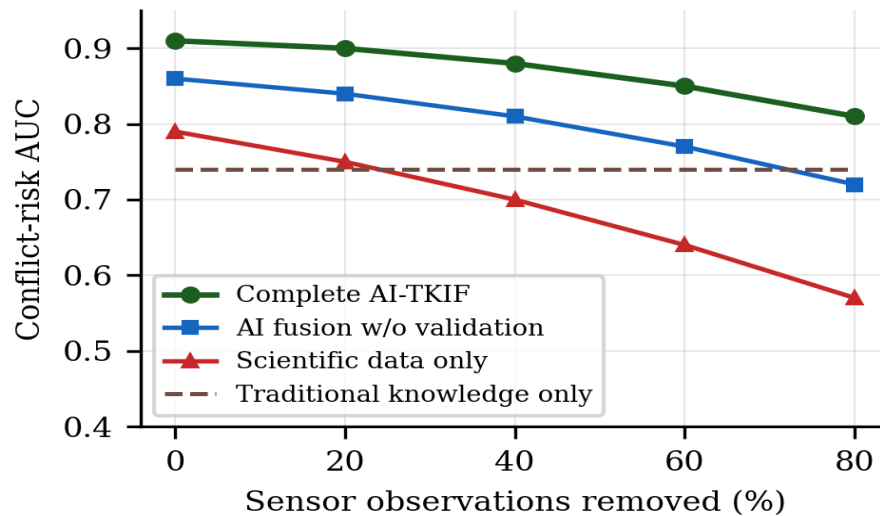


Figure 1: Conflict-risk AUC Under Progressive Removal of Sensor Observations

Discussion

The results show that the combination of traditional knowledge with scientific knowledge gives benefits that do not have to be obtained from each of them. The combination of sensors provides precision, verifiability, and TEK provides temporal depth, spatial breadth and contextual meaning. Significant improvements were seen in conflict-risk prediction and the reduction of false alerts, which are outputs that can be most directly connected to habitat protection and conflict mitigation, as fewer false alerts help maintain community trust in early-warning systems, and enable agencies to focus limited resources (Abed et al., 2025; Ojija et al., 2025). The framework allows for participatory and adaptive management. The outputs are validated by knowledge holders, providing recommendations that are rooted in local

realities, and the continuous-learning loop enables the system's adaptation to evolving climate and land use conditions (Ullah et al., 2025). However, there are risks involved in integration. The processes of turning narratives into graph triples can also de-contextualise knowledge, removing cultural and spiritual value, while centralised databases can put sensitive locations at risk for misuse by poachers or commercial entities (Molino, 2023; Adewale et al., 2026). These risks are addressed, though not eliminated, by granting item-level consent, location masking and community veto power. This is also the case for model bias and uncertainty. The information from more vocal or accessible speakers may be over-represented, and the performance of NLP is poorer for the under-resourced dialects (Shekhawat et al., 2025). Single landscape results cannot be extrapolated

to other ecosystems or cultures. The framework recommends that agencies should adopt a formal recognition of the community-validated knowledge in the conservation planning process and that benefit sharing and data-sovereignty agreements are developed (Joshi & Pant, 2024; Kumar & Singh, 2025). The factors that are limiting in the present study are the single study region, limited monitoring period, and the use of expert ratings for some integration metrics.

Conclusion

The present paper has been based on the premise that household waste is not an inert 'ecological by-product' of urban living but a resource subsidy that is spatial and temporal, and actively influences the behavioural ecology of synanthropic wildlife. The analysis brings a conceptual approach to pattern recognition and systems thinking to view the study of urban wildlife encounters, instead of a narrow computational lens, and situates it in the context of dynamic feedback loops, non-linear thresholds, and predictive rather than purely descriptive modeling. A combination of the different theories in resource landscapes, chronodisruption research, landscape ecology and socio-economic analysis in a single, AI-informed framework constitutes a more complete picture of the household waste-wildlife interface than any single disciplinary lens alone. This synthesis opens a number of research paths. Firstly, there are still open questions about the evolutionary pressures that anthropogenic provisioning might place on synanthropic populations such as morphological, cognitive and life-history changes over successive generations.

Second, as more and more algorithmic systems are used to govern urban ecology, there are also unanswered ethical issues about who owns the data, how it is being monitored, and how far it should be allowed to intervene in people's lives as a predictive tool in shared urban flora and fauna. Future empirical research should validate these conceptual statements, including the hypothesized chronodisruption pattern, and the comparative predictive power of AI-driven vulnerability mapping, using observation and sensor-based data in a variety of urban settings.

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