

AI-enabled smart forestry technologies for sustainable forest management in China's Taiwan Region: an evidence-triangulated multicase perspective

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Abstract

Smart forestry combines digital sensing, connectivity, analytics, and decision support, yet evidence of their deployment in subtropical montane forests by enterprises remains fragmented. This Perspective examines three anonymized enterprises in China's Taiwan region representing artificial intelligence-enabled natural asset analytics (Case A), satellite nonterrestrial network-based Internet of Things connectivity (Case B), and fixed-wing unmanned aerial vehicle sensing (Case C). A bilingual desk review of peer-reviewed and public institutional, partner, and corporate materials from January 2020 to June 2026 was triangulated with deidentified internal field test and operational data supplied by the three enterprises. The authors did not independently repeat or audit the enterprises' tests. Unaudited enterprise-reported results include classification accuracy of 88.0%–93.2% ($F1 = 0.91$) for Case A, an anomaly detection accuracy of 89.5%–92.5% ($F1 = 0.86$) for Case B with 15-s sensor-to-cloud latency, and a mapping accuracy of 86.2%–91.7% ($F1 = 0.90$) of Case C with 120 ha surveyed per flight hour. Cross-case analysis shows complementary roles across acquisition, connectivity, analytics, decisions, governance integration, and readiness for measurement, reporting, and independent verification. Because the test protocols were not standardized across the enterprises, the measurements support a descriptive comparison rather than a statistical ranking. We propose independently testable benchmarks and pair governance barriers with data-sharing, standardization, and subsidy measures.

Keywords: Smart forestry, Artificial intelligence, Nonterrestrial network, Unmanned aerial vehicle, Forest carbon, MRV

Citation: Zhang Y, Chen MC, Yang Q. 2026. AI-enabled smart forestry technologies for sustainable forest management in China's Taiwan Region: an evidence-triangulated multicase perspective. *Smart Forestry* 1: e018 <https://doi.org/10.48130/smartfor-0026-0015>

Introduction

Forests cover about 31% of global land and underpin climate regulation, biodiversity, and livelihoods^[1]. In China's Taiwan region, the fourth forest resource survey of the Forestry and Nature Conservation Agency (FNCA) reported 2,197,090 ha of forest and 60.71% cover for the 2008–2014 inventory period^[2]. The 2050 net-zero transition roadmap of China's Taiwan region identifies natural carbon sinks as a strategic pathway^[3]. Steep relief, typhoons, seasonal clouds, and gaps in mountain connectivity make integrated monitoring especially relevant.

As shown in Fig. 1, forest vegetation is concentrated in the central and eastern mountain ranges and varies markedly across elevation zones, whereas agricultural and urban land uses are more prevalent in the western lowlands. To capture this complexity, Lin et al. (2021) used 105 climatic variables within a machine learning framework to model the current distribution of 13 forest types. This spatial heterogeneity reinforces the need for integrated remote sensing, Internet of Things (IoT), and unmanned aerial vehicle (UAV)-based forest monitoring^[4].

Here, smart forestry means the coordinated use of digital sensing, connectivity, analytics, and decision support in forest management. Forest 4.0 is the related cyber-physical and automation paradigm; digital transformation is the broader redesign of organizational processes and governance around digital data^[5]. Forest carbon monitoring is the acquisition and estimation component. MRV (measurement, reporting, and verification) denotes the auditable chain for the measurement, reporting, and independent verification

of greenhouse gas outcomes; monitoring is an input to that chain, not a synonym for MRV.

The study asks how three complementary enterprise pathways and their company-supplied measurements can be evaluated while distinguishing enterprises' field test evidence from independent validation. It contributes a transparent public/internal evidence protocol, a literature-derived comparison matrix, and an integrated framework with falsifiable technical and governance propositions.

Literature review and analytical framework

Recent work has combined national inventories, satellite sensing, UAVs, light detection and ranging (LiDAR), open benchmark datasets, artificial intelligence (AI), the IoT, and satellite-based nonterrestrial networks (NTNs). Their operational uptake nevertheless depends on validation, interoperability, the users' needs, and governance rather than models' accuracy alone^[6–11]. As summarized in Table 1, regional deployment trajectories differ across Europe and North America, Japan and South Korea, Southeast Asia, and China's Taiwan region, revealing distinct strengths, constraints, and transferability conditions. Forest 4.0 studies likewise emphasize integration, but enterprises' case evidence often isolates one technology. We therefore evaluate data acquisition, connectivity, analytics, decision support, governance integration, and potential input to MRV processes as one linked system.

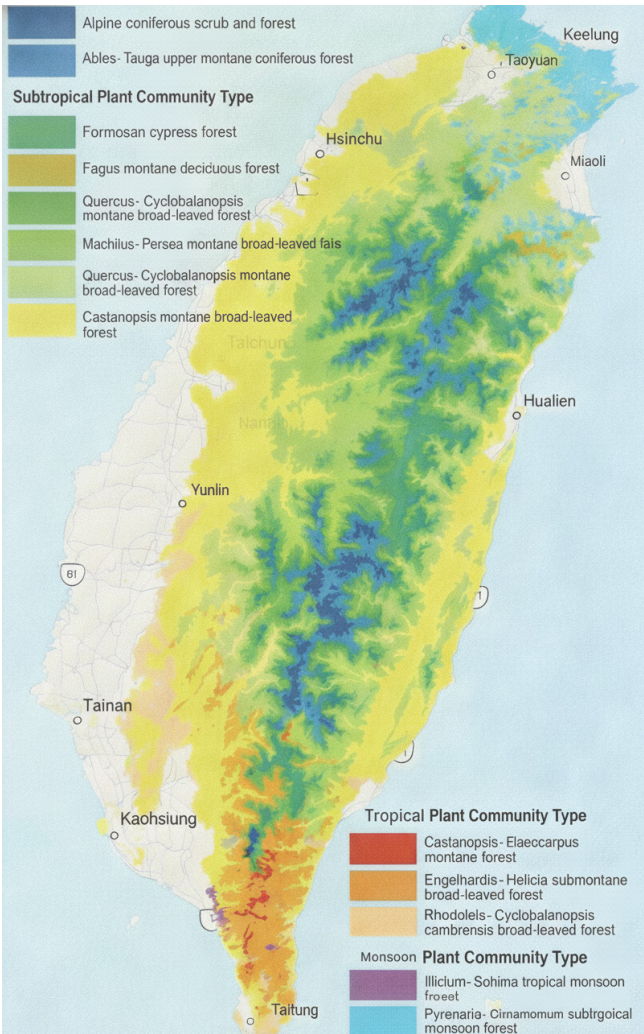


Fig. 1 Distribution of major forest vegetation in China's Taiwan region^[4].

Materials and methods

Data sources and evidence protocol

From January 2025 to June 2026, the three enterprises also supplied deidentified, aggregated internal field test and operational data on accuracy, F1 score, processing or transmission speed, coverage, efficiency, cost, staffing, and operational constraints. Evidence credibility was prioritized as follows: (1) Standards or government data, (2) peer-reviewed research, (3) independently documented deployments, and (4) the enterprises' public disclosures. Internal measurements were treated as enterprise-reported primary evidence and checked for plausibility against published ranges and documented deployments. The authors conducted no new interviews, test replications, or independent audits of proprietary records; this limitation applies to each quantitative table^[17]. Comparable market-share data were unavailable and therefore excluded. Because commercialization was the unit of analysis, universities and state forestry technology agencies served only as corroborating sources. Confidentiality requirements anonymized the enterprises as Cases A–C and removed identifying details. Table 2 summarizes the selection basis, evidence sources, enterprise-provided internal field test indicators, and validation boundaries for each case.

Case selection

The three enterprises were selected through maximum variation purposive sampling. The inclusion criteria were as follows: (1) active commercial status during 2020–2026; (2) one focal technology pathway—AI analytics, NTN/IoT connectivity, or UAV sensing; (3) documented field deployment or institutional cooperation in subtropical montane forests; (4) adequate public and enterprise-provided evidence for the 2020–2026 period; (5) regional relevance to China's Taiwan region; and (6) documented international activity or partnership. Comparable market-share data were unavailable and therefore excluded from the selection criteria. Universities and state forestry technology agencies were excluded as focal cases because the unit of analysis is enterprise-associated commercialization; their records serve only as corroborating sources. The confidentiality

Table 1. Interpretive comparison of regional smart forestry deployment patterns.

Region	Dominant trajectory	Strength	Constraint/transferable lesson
Europe and North America	Sequential: Plot inventories → remote sensing/LiDAR → AI and operational services	Long validation heritage	Interoperability and user uptake remain uneven; retain plot-based calibration ^[6,12,13]
Japan and South Korea	Policy- and sector-led integration of machinery, remote sensing, and disaster analytics	Public-program alignment	Terrain and workforce constraints favor targeted automation and shared infrastructure ^[14,15]
Southeast Asia	Project-based national inventories and remote-sensing platforms	Rapid coverage of heterogeneous forests	Connectivity and institutional capacity require open tools and regional training ^[16]
China's Taiwan region	Parallel pilots of satellite/NTN IoT, UAVs, and AI	Fast functional complementarity	Cloud, relief, fragmented data governance, and limited field benchmarks require staged validation

Patterns are nonexclusive interpretive syntheses, not rankings.

Table 2. Case selection and evidence register.

Case	Pathway and inclusion basis	Evidence used	Enterprise internal test indicators	Validation boundary
A	AI/natural asset carbon software; documented partnerships	Public corporate/partner/policy + EID-A	Accuracy/F1; processing; coverage; carbon error; cost	No independent audit; market share and MRV compliance were unverified
B	Third-generation partnership project (3GPP) NTN/IoT connectivity; institutional pilot	Public corporate/partner/government + EID-B	Accuracy/F1; latency; sensor coverage; cost; staffing	No common-site replication; interoperability unverified
C	Fixed-wing composite UAVs; mature commercial hardware	Public corporate/certification + EID-C	Accuracy/F1; area per flight; efficiency; carbon error; cost	No common-site replication or independent audit

EID-A, EID-B, and EID-C denote confidential enterprise-provided internal datasets for Cases A–C. Aggregated results are reported; proprietary underlying records are withheld. A coded source register can be supplied to the editor under confidentiality.

requirements communicated by the enterprises prohibit the disclosure of identifying details; the cases are therefore reported as Cases A–C throughout.

Analysis

A deductive matrix applied the six literature-derived dimensions to each case, followed by cross-case pattern matching. Enterprise-provided values were retained as supplied and harmonized only by label and unit; no imputation, rescaling, or significance testing was performed. Test sites, periods, sample sizes, and protocols were not uniformly disclosed, so the results are descriptive and do not constitute a standardized head-to-head trial. The technology readiness level (TRL; 1–9) remains the authors' judgment and is separated from the enterprises' measurements. Thresholds H1–H4 are propositions for independent follow-up testing, not regulatory standards.

Results

Case profiles

Case A integrates satellite, UAV, geographic, and potential ground data into vegetation, change, and carbon estimation workflows. Case B combines low-power sensors and local aggregation with terrestrial or third-generation partnership project (3GPP) Release 17 narrowband IoT over a NTN backhaul^[11]. Case C supplies fixed-wing composite UAV platforms capable of carrying red–green–blue (RGB), multispectral, thermal, or LiDAR payloads. Public records establish the functions and deployment contexts; enterprises' internal data add performance measurements, but neither source stream independently establishes compliance with the carbon credit methodology.

Enterprise-provided field test results

Table 3 compares the unaudited, enterprise-provided field test performance of Cases A–C. Because these measurements were not independently verified and the test protocols were not standardized across cases, the values are descriptive and do not constitute a ranked comparison.

Table 4 presents a descriptive comparison of enterprise-provided operational results for Cases A–C and conventional ground surveys under a nominal 1,000-ha scenario, covering the deployment time, accuracy, monitoring capacity, cost, staffing, and environmental constraints.

The reported measurements indicate different operational advantages: Case A emphasizes scalable classification and carbon estimation, Case B minimizes alert latency in low-connectivity areas, and Case C accelerates high-resolution mapping. Case A's 93.2% classification result and Case C's 8.5× efficiency gain fall within ranges reported in recent forest-related AI and UAV literature, providing a plausibility check rather than independent replication^[6,7].

Cross-case comparison

As shown in Table 5, the comparison indicates complementarity rather than a single superior case. Case A is analytics-rich but validation-dependent; Case B addresses the connectivity bottleneck but introduces operator and power dependencies; and Case C provides calibration-grade spatial detail but remains campaign-based and regulation-sensitive. Integration therefore shifts the principal bottleneck from sensing to standards, data provenance, and governance.

Strategic analysis

Table 6 summarizes the case-specific SWOT profiles and corresponding mitigation strategies. The principal opportunity is an

Table 3. Enterprise-provided field test performance results for the three cases.

Metric	Case A: AI classification	Case B: IoT monitoring	Case C: UAV survey
Primary task	Vegetation species classification	Environmental anomaly detection	Aerial forest mapping
Measured overall accuracy	88.0%–93.2%	89.5%–92.5%	86.2%–91.7%
Measured F1 score	0.91	0.86	0.90
Processing / transmission speed	2.4 frames/s (satellite imagery)	15-s sensor-to-cloud latency	120 ha/flight hour
Coverage per unit	500 ha/satellite scene	200 ha/sensor-node cluster	120 ha/fixed-wing flight
Enterprise-reported improvement	+38% accuracy vs. traditional remote sensing	72% lower data latency vs. manual survey	8.5× survey efficiency vs. ground survey
Observed operational limitation	25% cloud-affected data loss	Sensor-node battery degradation	Mountain flight restrictions

Source: Confidential internal data from the enterprises, EID-A, EID-B, and EID-C, were supplied to the authors. Values are enterprise-reported field test results and were not independently audited; the protocols were not standardized across cases. These indicators are descriptive and noncomparative; they were produced under different test conditions and should not be read as a direct performance ranking among the three pathways.

Table 4. Enterprise-provided operational results for nominal 1,000-ha deployment comparisons.

Performance dimension	Case A: AI + satellite	Case B: IoT network	Case C: UAV survey	Conventional ground survey
Initial survey/deployment	3–5 days	1–2 days	8–12 days	30–45 days
Area coverage (ha/day)	200–330	NA, continuous	80–125	22–33
Tree species accuracy	93.2%	N/A	91.7%	95.0% (limited sample)
Carbon stock error	± 8.5%	N/A	± 6.2%	± 5.0% (ground truth)
Real-time monitoring	No: batch	Yes: continuous	No: campaign	No
Wildfire-detection latency	Hours to days	< 15 min	Hours: post-flight	Hours to days
Annual cost per 1,000 ha (USD)	18,000–25,000	35,000–50,000 first year; 12,000–18,000 thereafter	22,000–30,000	45,000–60,000
Personnel	2–3 technicians	1–2 technicians	3–4 operators	6–8 surveyors
Cloud/weather impact	High: 25% data loss	None for ground sensors	Moderate: flight restrictions	None

Source: EID-A–EID-C. Enterprise comparisons used a nominal 1,000-ha deployment basis; the conventional baselines were supplied with the internal data. Results were not produced by one common-site trial and should not be interpreted as inferential rankings. The conventional ground survey baseline represents typical industry-reported ranges for subtropical montane terrain; it was not measured in a trial that was co-located with the three cases. Cross-column comparisons are descriptive only; the four columns draw on different data sources and test conditions.

Table 5. Cross-case analytical matrix and evidence status.

Dimension	Case A: AI platform	Case B: NTN IoT	Case C: UAV platform
Data acquisition	Satellite/UAV/ground inputs	Fixed environmental sensors	UAV-borne imaging and LiDAR
Connectivity	Cloud data ingestion	Long Range (LoRa)-type local links + terrestrial/NTN backhaul	Command, control, and post-flight transfer
Analytics	Classification, change, carbon estimation	Rules/cloud anomaly detection	Photogrammetry; optional downstream AI
Decision support	Maps and candidate reports	Near-real-time alerts	High-resolution survey products
Governance integration	Potential data platform	Pilot interfaces across institutions	Procurement and aviation permitting
Potential MRV input	Monitoring/estimation input only	Environmental evidence input	Calibration/validation evidence input
Performance evidence	Enterprise internal field tests; no independent audit	Enterprise internal field tests; no common-site replication	Enterprise internal field tests; no independent audit
Author-judged TRL	5–6	6–7	8–9 for base hardware; 6–7 for integrated forestry use

TRL is an author interpretation based on deployment evidence, not a measured outcome; it is analytically separate from the enterprise-reported results in Tables 3–4.

Table 6. SWOT characterization and targeted mitigation.

Case	Strength/opportunity	Weakness/threat	Mitigation path
A	Scalable analytics; demand for credible carbon information	Black box risk; unverified methodology compliance	Ground plots, uncertainty reporting, data lineage, independent verification, open export
B	Persistent remote connectivity; event warning	Single-provider, battery, and authorization risk	Multioperator 3GPP NTN; terrestrial/LoRa store-and-forward; domestic systems where authorized; replaceable power
C	Endurance and flexible payloads; precision mapping	Composite supply, operator cost, flight restrictions	Dual/local composite sourcing; modular payload bays and connectors; repairable spares; documented safety case
Cross-cutting	Multilayer fusion and policy demand	Data silos, surveillance, platform lock-in	Open application programming interfaces/portability; role-based access; community participation; procurement exit clauses

interoperable service ecosystem rather than dominance by a single vendor, whereas the main risk is dependency shifting from sensor or satellite providers to proprietary analytics and reporting platforms.

Integrated framework and discussion

Architecture and testable benchmarks

Fig. 2 links acquisition, analytics, and decisions. Two explicit feedback paths are essential: real-time IoT alerts reprioritize image tasking and change-detection thresholds; UAV and ground-plot data update georegistration, bias correction, and model calibration. Thus, the analytical layer is recalibrated rather than treated as a one-way black box.

Table 7 uses synthetic aperture radar (SAR), quality assurance and quality control (QA/QC), root mean square error (RMSE), application programming interface (API), and Intergovernmental Panel on Climate Change (IPCC) terminology. All quantitative indicators from the three cases are unaudited, enterprise-reported field-test results; they were not independently replicated or standardized and should not be interpreted as a performance ranking.

MRV, policy, and ethical governance

A carbon platform becomes MRV-ready only when its estimates enter a documented chain with approved boundaries and baselines, ground calibration, uncertainty and QA/QC, reporting controls, and independent verification. IPCC guidance requires transparency, consistency, comparability, completeness, accuracy, and uncertainty assessments^[18]. Verra and Gold Standard additionally require the applicable methodology, in addition to leakage and permanence treatment, safeguards, and third-party validation/verification^[19,20]. Neither public sources nor the enterprise's internal measurements establish that Case A satisfies these regimes; the manuscript therefore makes no compliance claim.

Three policy responses follow directly from the barriers: (1) An FNCA–local environmental bureau protocol for metadata, access roles, APIs, and incident sharing; (2) a regional subtropical smart forestry standards group led by the forestry authority with academia, operators, and communities; and (3) capital and shared-service subsidies for small forest operators deploying mountain IoT and UAV systems. Ethical safeguards must address forest data sovereignty; meaningful participation by Indigenous communities including free, prior, and informed consent where applicable; privacy and surveillance; UAV flight safety; cybersecurity; and commercial lock-in^[21].

Transferability and research priorities

Short term

Independently replicate the enterprise-reported results under common protocols for monsoon, typhoon, steep slope, and high-elevation conditions and publish a subtropical benchmark dataset.

Medium term

Compare China's mainland subtropical mountain forests, China's Taiwan region, Japan, South Korea, and Southeast Asia using common dimensions and uncertainty reporting.

Long term

Study institutional arrangements for carbon market MRV standardization, cross-border interoperability, and interdisciplinary forestry plus AI education. The parallel deployment model is transferable only after ecological, legal, infrastructure, and community adaptation.

Conclusions

The three anonymized pathways form a complementary sensing-to-governance system: UAVs and plots calibrate spatial evidence, the IoT sustains event awareness, and AI platforms integrate data for

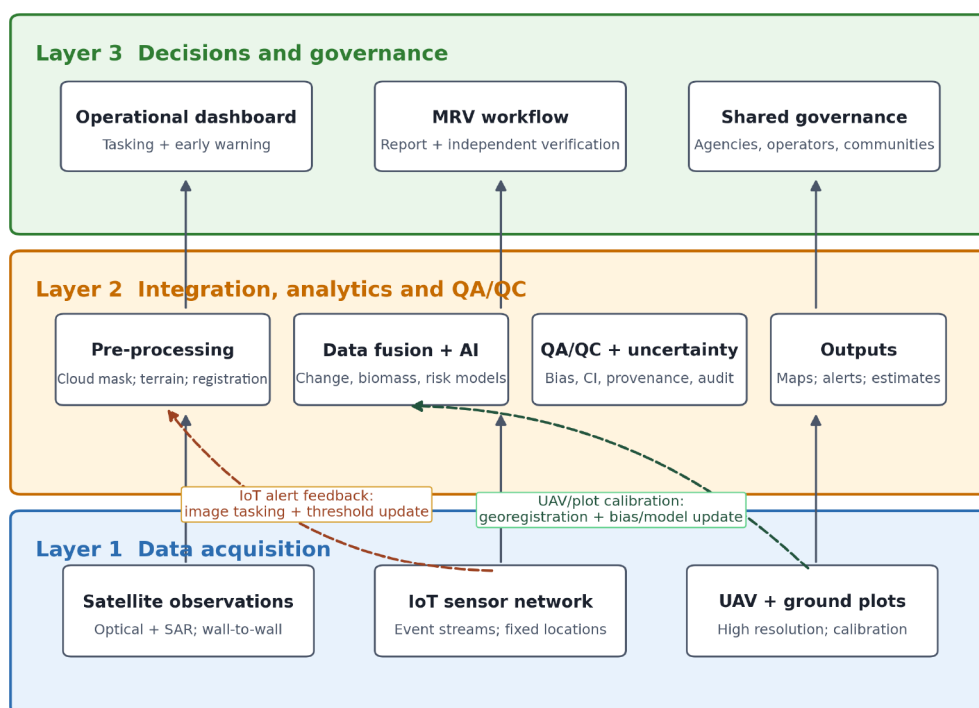


Fig. 2 Integrated three-layer smart-forestry framework with operational and calibration feedback.

Table 7. Proposed independent validation benchmarks and linked governance actions.

Layer/issue	Testable proposition (not a standard)	Validation design	Linked action
Satellite observation	H1: ≥ 1 cloud-usable optical or SAR observation every ≤ 10 days in May–October	Log usable scenes by elevation and forest type	Shared multisensor tasking and cross-agency catalog
UAV calibration	H2: Ground-sampling distance ≤ 10 cm and horizontal RMSE ≤ 20 cm	Independent checkpoints under slope/canopy strata	Shared service subsidy; common survey and flight safety protocol
IoT alerting	H3: $\geq 95\%$ of priority alerts delivered within 15 min; monthly uptime $\geq 95\%$	Timestamped logs across monsoon and typhoon conditions	Open protocols; multi-operator NTN; store-and-forward fallback
AI/carbon estimation	H4: relative RMSE $\leq 20\%$; bias and 95% uncertainty interval reported	Independent plots across elevations and forest types	Regional standard group; IPCC-aligned QA/QC; third-party verification
Governance	Metadata, audit logs, role-based access, and API conformance	Interoperability, security, and user audits	FNCA–local bureau data protocol; operator subsidies; community governance

H1–H4 are deliberately falsifiable independent-validation hypotheses, not adopted regulatory thresholds. The 25% cloud-affected data loss in Table 3 is retained only as an internal field-test result from Case A; it is not attributed to the FNCA or generalized to the region.

decisions and potential pre-MRV monitoring and reporting support. Enterprise-provided field test data indicate meaningful gains in classification, latency, and survey efficiency, although the nonstandard protocols and the absence of an independent audit limit direct ranking and generalization. By separating public facts, enterprise measurements, author-judged TRL, and independent-validation hypotheses, the revised Perspective offers a more reproducible basis for smart forestry policy and future field validation in subtropical montane regions.

Ethical statements

This study used public documents and deidentified enterprise-provided internal operational and field-test data. It involved no human participants or personally identifiable information; institutional ethical approval was therefore not required. Internal data were handled under the enterprises' confidentiality restrictions and are reported only in aggregated form. During revision, the authors used OpenAI ChatGPT (accessed 6 August 2026) for language refinement, structural editing, and enhancement of the figure and layout. The authors reviewed and edited all assisted content, verified its accuracy, and take full responsibility for the integrity and originality of the manuscript. No AI tool is credited as an author.

Author contributions

The authors confirm their contributions to the paper as follows: conceptualization, data curation, formal analysis, writing – original draft: Zhang Y, Chen MC, Yang Q; methodology, supervision, project administration: Zhang Y, Chen MC; writing – review and editing: Chen MC, Yang Q; validation: Yang Q. All authors reviewed the results and approved the final version of the manuscript.

Data availability

All cited public sources are listed below, and aggregated enterprise-provided internal field test results are reported in Tables 2–4. The underlying EID-A–EID-C datasets are not publicly available because they contain proprietary operational information subject to enterprise confidentiality restrictions. A coded source register can be provided to the editor, and further access may be considered by the corresponding author subject to enterprise authorization.

Acknowledgments

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of interest

The authors declare that they have no conflict of interest.

Dates

Received 15 July 2026; Revised 30 August 2026; Accepted 7 September 2026; Published online 10 October 2026

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