

Article

Cooperative V2X-Based UAV Detection in Rural Transportation Corridors

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Highlights

What are the main findings?

- A calibrated simulation study indicates that sparsely deployed V2X roadside units (RSUs) can be augmented with passive RF sensing to support UAV detection in rural and semi-rural corridors, focusing on RF-emitting targets in unlicensed ISM bands.
- Cooperative processing across multiple RSUs improves detection robustness compared with single-RSU sensing, particularly under weak signals, terrain masking, and narrowband interference.

What are the implications of the main findings?

- The approach is positioned as a supplementary early warning layer intended to cue follow-on sensing and tracking, rather than to provide continuous coverage or high-precision localization.
- Low-bandwidth feature exchange and distributed correlation support a dual-use extension of existing V2X infrastructure through functional and spectral separation from standards-compliant ITS safety messaging.

Abstract

Rural transportation corridors remain weakly instrumented for continuous low-altitude airspace monitoring. At the same time, Vehicle-to-Everything (V2X) roadside units (RSUs) are increasingly deployed for transportation safety services. This work investigates whether existing RSUs can be extended with passive, cooperative RF sensing to detect small UAVs without modifying standards-compliant ITS communications in the protected 5.9 GHz band. A calibrated simulation study evaluates corridor-scale operation under realistic propagation conditions, including terrain masking and narrowband interference. All results reported in this paper are derived from simulation and do not include field measurements or hardware prototyping. False alarm performance under diverse ISM emitters is not quantified. The results show that cooperative processing across neighboring RSUs improves epoch-level verified detection coverage compared with single-RSU sensing. Bearing variability is reduced for weak or partially masked signals. These gains result from feature-level validation across spatially separated receivers rather than deterministic signal combining. RF calibration constrains detections to physically plausible kilometer-scale ranges. The resulting angular accuracy is sufficient for early warning and track initiation, but not for precise localization. Overall, the findings indicate that existing V2X infrastructure can



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support supplementary early warning capability for corridor-scale airspace monitoring while preserving primary V2X safety functions.

Keywords: Vehicle-to-Everything; roadside units; cooperative sensing; small UAV detection; rural corridors; early warning

1. Introduction

Small unmanned aerial vehicles (sUAVs) pose a growing challenge for low-altitude airspace monitoring in rural and sparsely instrumented regions. Operational ADS-B coverage datasets indicate that near-surface surveillance from a single ground receiver is typically reliable only within approximately 20 nautical miles (≈ 37 km), beyond which low-altitude coverage gaps become frequent [1]. A comparable imbalance is observed in European civil radar coverage, where dense surveillance is concentrated along major air routes at cruising flight levels, while coverage degrades substantially away from these corridors [2]. Radar-based detection of sUAVs is further constrained by their small physical size and low observability, while acoustic methods typically operate over only a few hundred meters and degrade significantly near highways. Extending dedicated surveillance systems into rural corridors would therefore require dense and costly deployments that are difficult to justify. These coverage gaps enable unauthorized UAV operations that may threaten critical infrastructure, transportation corridors, and manned aviation.

In parallel Vehicle-to-Everything (V2X) roadside infrastructure is being deployed at scale along major transportation corridors. European planning documents anticipate widespread rollout of roadside units (RSUs) along TEN-T corridors by 2030 [3], with corridor-scale pilot deployments reported in the United States and Australia [4–6]. In rural environments, deployment studies consistently report RSU spacing of 2–5 km, reflecting practical constraints on power availability, right-of-way access, and installation costs [7,8]. Although this infrastructure is designed primarily to support transportation safety and traffic-efficiency services, its geographic distribution and continuous operation motivate consideration of whether RSUs can support additional sensing functions without altering their primary role.

From an RF propagation perspective, rural transportation corridors present conditions fundamentally different from those in dense urban environments. Open terrain increases the likelihood of line-of-sight links between low-altitude transmitters and roadside receivers, while reducing multipath complexity. Limited backhaul capacity restricts centralized raw-signal processing, favoring edge-level sensing approaches in which RSUs exchange compact detection features rather than streaming IQ samples [9]. V2X messaging continues to follow IEEE 802.11 and ETSI ITS-G5 specifications [10,11]. A single RSU provides only coarse angular information, motivating cooperative processing across neighboring nodes to support detection and bearing estimation over kilometer-scale separations.

This paper examines whether existing and planned RSU deployments can realistically support distributed passive RF sensing for sUAV detection while maintaining standards-compliant V2X safety communications through functional and spectral separation. The analysis focuses on RF-emitting sUAVs operating in the 2.4 GHz and 5.8 GHz ISM bands, which are widely used for command-and-control and telemetry links by commercial platforms in the 2–25 kg class. Passive RF monitoring is implemented as a parallel sensing function at each RSU, while safety-related V2X communications continue to operate in the protected 5.9 GHz ITS band. Noise and interference characteristics are calibrated using an open V2X IQ-sample dataset to ensure physically plausible RF conditions [12].

The proposed framework combines local spectral analysis with lightweight inter-node feature exchange to support cooperative bearing estimation and trajectory filtering under kilometer-scale RSU spacing. System performance is evaluated through Monte Carlo simulations over a 200 km rural corridor instrumented with 80 RSUs under calibrated propagation and interference conditions.

The scope of this study is limited to RF-emitting UAVs operating in the 2.4/5.8 GHz ISM bands [13–15]. RF-silent platforms, sub-GHz control links, and non-RF sensing modalities such as radar, acoustic, or optical systems are outside the scope of the present analysis.

The main contributions of this work are as follows:

1. A cooperative RF-sensing framework for sparse RSU networks, combining spectral analysis, cross-correlation, and distributed bearing estimation.
2. A dual-use RSU architecture designed to preserve core ITS functions through functional and spectral separation, with sensing confined to unlicensed ISM bands.
3. Performance validation under realistic RF conditions using the IEEE DataPort V2X IQ-sample dataset for calibration.
4. A discussion of deployment trade-offs and feasibility, including scalability considerations across major international intelligent transportation system programs.

The study is conducted as a calibrated simulation-based analysis intended to assess feasibility and performance trends, rather than to propose or validate a deployable operational system.

The remainder of this paper is organized as follows. Section 2 reviews related work, Section 3 describes the system model and methodology, Section 4 presents the results, Section 5 discusses implications and limitations, and Section 6 concludes the paper.

2. Related Work

Research on corridor-scale sUAV detection using roadside infrastructure covers several partially overlapping areas. These include V2X deployment studies, cooperative perception, UAV detection technologies, RF-based sensing, and integrated sensing and communications (ISAC). While each area provides relevant technical foundations, most studies rely on assumptions that differ from sparse RSU deployments and passive sensing in unlicensed ISM bands.

V2X deployment research focuses primarily on transportation safety and traffic efficiency. Corridor-scale studies in Europe, the United States, and Australia emphasize interoperability, regulatory coordination, and spectrum coexistence in the 5.9 GHz ITS band [3–6]. Deployment analyses consistently report RSU spacing of 2–5 km as a practical compromise driven by power availability, right-of-way access, and installation costs [7,8]. Resource-allocation studies also favor feature-level information exchange over raw-data transfer due to bandwidth and backhaul constraints [9]. In this body of work, RSUs are treated almost exclusively as communication infrastructure rather than sensing nodes.

Cooperative perception (CP) extends V2X systems toward shared situational awareness through feature-level data exchange among vehicles and infrastructure [16–19]. Proposed mechanisms include message forwarding, RSU-assisted scheduling, and region-of-interest compression. Most CP evaluations assume dense urban deployments with short inter-node distances. Airborne targets and kilometer-scale RSU spacing are rarely considered. Related UAV-assisted architectures address communication coverage extension [20] but do not investigate passive RF-based detection.

Classical distributed detection frameworks (e.g., k -out-of- N fusion rules) are widely used to improve robustness under weak-signal conditions but are typically evaluated in homogeneous sensing networks rather than sparse corridor-scale RSU topologies. This mo-

tivates evaluating cooperative validation under calibrated, interference-rich RF conditions representative of roadside deployments.

Security and privacy aspects of V2X systems are typically studied separately, with a primary focus on protecting communication integrity rather than enabling sensing functionality [21]. UAV detection technologies based on radar, electro-optical/infrared (EO/IR), acoustic, and multisensory configurations have been widely studied for fixed-site monitoring and critical infrastructure protection [22–26]. These approaches typically assume controlled sensor placement and relatively dense installations. Their applicability to extended rural corridors is limited by range constraints, sensitivity to environmental conditions, and line-of-sight requirements, particularly for EO/IR and acoustic modalities.

RF-based UAV detection using software-defined radio (SDR) receives targets control and telemetry emissions in unlicensed ISM bands. Prior work shows that modulation features, spectral signatures, and RF fingerprints can support UAV classification and, in some cases, direction-of-arrival estimation [27–29]. Experimental setups commonly rely on compact receiver clusters with meter-scale baselines and relatively controlled spectral environments. The impact of dense, heterogeneous ISM-band interference is rarely modeled systematically.

Passive radar approaches exploit illuminators of opportunity such as DVB-T, LTE, or DAB transmissions to detect non-cooperative targets. Reported UAV detection ranges are typically limited to 1–2 km under favorable signal-to-noise conditions [30]. These systems are usually evaluated in single-site or small multi-site configurations. Cooperative fusion across sparsely spaced roadside receivers is not a central assumption in this literature.

Multisensory fusion and learning-based methods combine radar, RF, EO/IR, and acoustic measurements to improve robustness and reduce false alarms [23–25,28–31]. Deep-learning-based approaches can achieve high classification accuracy but often assume collocated sensors, stable propagation conditions, and significant computational resources. These assumptions limit their applicability to sparse RSU deployments along long corridors.

ISAC research provides a broader context for joint communication–sensing systems. Surveys describe waveform-level sensing techniques, cooperative ISAC architectures, and data-driven designs for future wireless networks [32–34]. Multi-node studies demonstrate localization gains through coordinated processing [35,36]. In contrast, ISAC approaches typically rely on modified physical layers or dense node layouts. Studies on V2X interference and coexistence mainly focus on preserving communication performance [37–39], with interference rarely treated as an inherent component of a cooperative sensing environment.

In summary, existing work addresses V2X deployment, cooperative perception, UAV detection, RF sensing, and ISAC largely in isolation. Their intersection under corridor-scale constraints—specifically, sparse RSU spacing, passive ISM-band monitoring, and cooperative sensing in interference-rich environments—remains insufficiently explored. This work addresses that gap by treating RSUs as cooperative RF sensors and evaluating detection performance at the corridor scale. Table 1 positions the proposed approach relative to existing studies.

Table 1. Summary of related work.

Research Area	Key Studies	Main Focus	Key Limitations w.r.t Corridor-Scale RSU Sensing
V2X infrastructure deployment	[3–9]	Corridor-scale V2X programs; RSU planning and optimization; identification of typical rural RSU spacing (2–5 km); spectrum and resource constraints.	RSUs are modeled primarily as communication infrastructure; sensing functionality is not considered.

Table 1. Cont.

Research Area	Key Studies	Main Focus	Key Limitations w.r.t Corridor-Scale RSU Sensing
Cooperative perception (CP)	[16–19]	Message forwarding, RSU-assisted scheduling, feature/ROI compression, datasets, and experiments improving shared situational awareness.	Focus on ground traffic and dense urban deployments; sparse RSU spacing and airborne targets are not central assumptions.
Air–ground communication architectures	[20]	UAV-assisted communication and space–air–ground integrated networks for coverage extension.	Address connectivity rather than sensing or UAV detection using roadside infrastructure.
Vision- and acoustic-based UAV detection	[22–26]	Radar, EO/IR, acoustic, and multisensor UAV detection for fixed-site monitoring.	Dense static installations; limited range and sensitivity to weather, clutter, and ambient noise; not suited for long rural corridors.
RF-based UAV detection (SDR)	[27–29]	RF fingerprinting, modulation analysis, and direction-of-arrival estimation using ISM-band emissions.	Compact receiver clusters with meter-scale baselines; interference and spectrum congestion are rarely modeled systematically.
Passive-radar UAV detection	[30]	UAV detection using illuminators of opportunity: system-level surveys and reported detection ranges.	Static receiver geometries; cooperative fusion across kilometer-spaced roadside receivers is rarely evaluated.
Multisensor fusion and learning-based methods	[23–25,28–31]	Fusion and machine-learning approaches combining radar, RF, EO/IR, and acoustic data.	Assume colocated sensors, stable propagation conditions, and substantial computational resources.
Integrated sensing and communications (ISAC)	[32–36]	Waveform-level sensing, cooperative ISAC architectures, and localization through coordinated processing.	Depend on modified physical layers or dense node layouts; sparse ISM-band sensing with RSUs is not targeted.
V2X interference and coexistence	[37–39]	Analysis of interference effects and mitigation strategies to preserve V2X communication performance.	Interference is primarily treated as a communication impairment rather than as part of the sensing environment.
This work	—	Cooperative passive RF sensing using sparsely deployed RSUs (2–5 km) for sUAV detection in the 2.4/5.8 GHz ISM bands under calibrated interference conditions.	Focused on RF-emitting UAVs; non-RF sensing modalities are outside the scope.

3. System Design and Methodology

This section describes the cooperative V2X–UAV sensing architecture, the propagation and SINR models, and the simulation setup used for the performance evaluation in Section 4. The focus is on how standard V2X roadside units (RSUs) are augmented with passive RF sensing capabilities and on how multi-node cooperation is modeled within a calibrated simulation framework.

All fixed scenario parameters and calibrated thresholds used throughout this section are summarized in Table 2 to ensure clarity and reproducibility.

The system considers 80 RSUs deployed along a 200 km rural transportation corridor with a uniform spacing of 2.5 km. Each RSU is assumed to support standards-compliant V2X safety communications in the protected 5.9 GHz band (ITS-G5 or C-V2X, depending

on deployment) and is additionally augmented with a passive sensing module operating in the 2.4/5.8 GHz ISM bands. Each RSU hosts two subsystems operating in parallel:

1. A communication (COM) subsystem that handles V2X safety messaging in the 5.9 GHz band.
2. A sensing (SENS) subsystem that performs passive RF monitoring, feature extraction, adaptive thresholding, and cooperative message exchange.

Table 2. Key simulation parameters and calibration settings.

Parameter	Value	Source/Note
Corridor length	200 km	Scenario definition
Number of RSUs	80	Fixed topology
RSU spacing	2.5 km	Representative rural corridor spacing (deployment studies)
UAV count	7	Multi-target scenario
UAV speed	50 m/s	Scenario definition
UAV altitude	500–1200 m	Low-altitude corridor flights
Bands monitored (SENS)	2.4 GHz, 5.8 GHz	ISM bands; separated from the 5.9 GHz ITS safety band
Time step/engagement	1 s/600 s	Simulation horizon
Monte Carlo runs	20	Independent realizations
Detection rule	k-out-of-N validation	k = 1 single-RSU; k ≥ 2 cooperative validation
Detection threshold γ	−3 dB SINR	Pre-cooperation detection gate (fixed configuration)
Mean SINR of confirmed detections (observed; not a design parameter)	~10 dB (observed after validation; indicative)	Observed output (post-validation); not a design parameter.
Cooperation radius	~7.5 km	Neighbor RSU set
Cooperative window N	3–5 RSUs	Diminishing returns beyond ~6
Interferer location	130 km	Scenario definition
Interferer EIRP	38 dBm	Scenario design (interference-limited case)
Interferer model	Structured narrowband interference (frequency-swept); 20 MHz BW; 80% duty	This section
Noise floor	−107 dBm	Receiver NF/BW assumption; calibrated
Background interference	−103 dBm	IEEE DataPort IQ dataset

Figure 1 provides a conceptual overview of cooperative sensing architecture. The illustration depicts the logical flow of information exchange between neighboring RSUs and the fusion function and is not intended to represent physical distances, antenna patterns, or exact simulation geometry.

The sensing process begins with local spectral analysis. Each RSU processes 100 ms RF windows, selected as a compromise between temporal resolution and feature stability, extracts time–frequency descriptors, and compares them against an adaptive threshold derived from calibrated noise and interference levels. When a candidate emission exceeds this threshold, the RSU broadcasts a time-stamped descriptor to neighboring nodes within a cooperation radius of approximately 7.5 km.

Neighboring RSUs correlate the received descriptor with their local observations. In this study, correlation is performed at the feature level using the descriptor fields (timestamp, center frequency, received power, and coarse bearing). This step is intended to reduce isolated local triggers by requiring cross-node descriptor agreement and reinforces marginal detections observed across multiple RSUs. Detections that pass cooperative validation are forwarded to the fusion center, where bearings from multiple RSUs are combined at 1 s resolution. Track continuity and noise suppression are achieved using

a standard Kalman filter, which provides temporal smoothing and mitigates short-term bearing fluctuations caused by fading and interference.

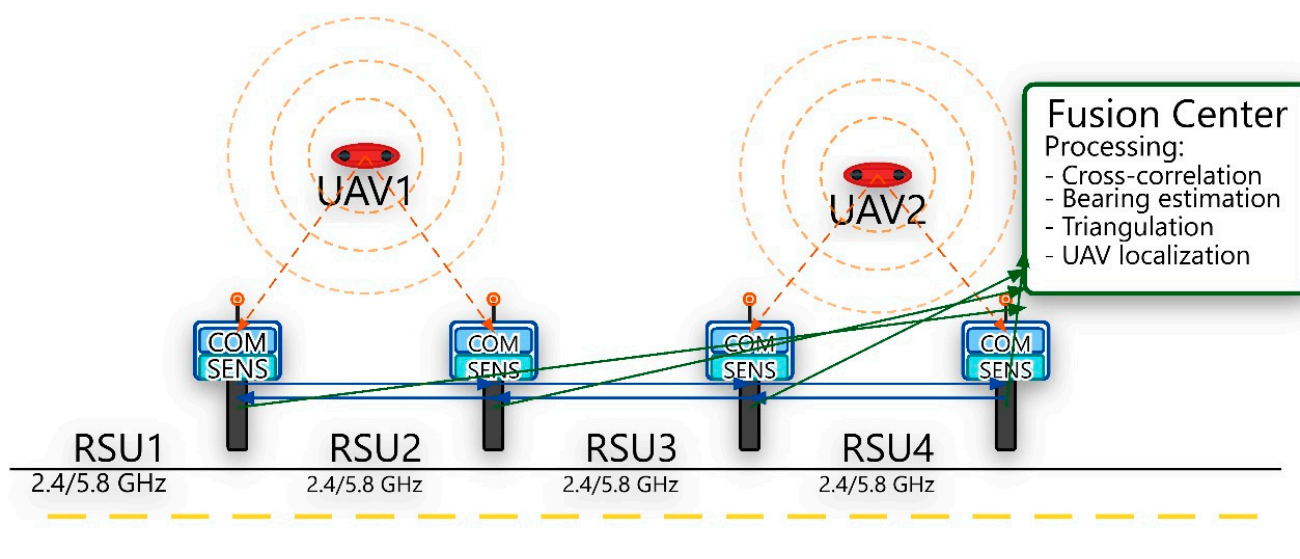


Figure 1. Logical cooperative sensing architecture. Each RSU integrates a communication (COM) module for standards-compliant V2X safety messaging in the protected 5.9 GHz band and a sensing (SENS) module for passive RF monitoring in the 2.4/5.8 GHz ISM bands. Orange dashed circles/arrows indicate UAV RF emission coverage and the passive sensing paths to nearby RSUs. Green links denote cooperative SENS information exchange (feature-descriptor sharing/correlation) among neighboring RSUs and forwarding of cooperatively validated detections to the fusion center. The blue link denotes the COM (5.9 GHz) communication flow. The figure illustrates logical information flow and is not to scale.

To minimize bandwidth usage, RSUs exchange only compact descriptors (timestamp, center frequency, power level, coarse bearing) rather than IQ samples. The cooperative workflow, therefore, consists of:

1. Local RF monitoring and feature extraction at each RSU.
2. Feature-level correlation among adjacent RSUs.
3. Bearing fusion and track filtering at the fusion center.

These processing blocks serve distinct functional roles in the pipeline. Local thresholding produces candidate events, cooperative k-out-of-N validation confirms events using multi-node evidence, bearing fusion combines bearing observations for confirmed events at one-second resolution, and Kalman filtering is applied after validation to smooth short-term fluctuations and maintain track continuity. The filter does not generate detections and should not be interpreted as contributing to detection performance. Accordingly, the reported cooperative detection gains reflect the k-out-of-N validation step rather than any downstream block. All detection metrics in Section 4 are computed at the output of the k-out-of-N validation stage.

Propagation between UAVs and RSUs is represented by a large-scale model with correction terms for extended attenuation, terrain masking, and altitude-dependent line-of-sight (LoS) effects. The total path loss is:

$$PL_{\text{total}}(d, f, h, \alpha) = \text{FSPL}(d, f) + L_{\text{ext}}(d) + L_{\text{terrain}}(\alpha) - G_{\text{altitude}}(h) \quad (1)$$

where PL_{total} represents the total path-loss in dB; d is the slant range between UAV and RSU (m); f is the carrier frequency (Hz); h is the UAV altitude (m); and α is the elevation angle.

$G_{\text{altitude}}(h)$ is an altitude-dependent excess-gain term (in dB) that reduces the effective path loss under improved line-of-sight conditions.

The free-space component is.

$$\text{FSPL}(d, f) = 20\log_{10}(d) + 20\log_{10}(f) - 147.55 \quad (2)$$

The correction terms $L_{\text{ext}}(d)$, $L_{\text{terrain}}(\alpha)$, and $G_{\text{altitude}}(h)$ represent extended propagation loss (e.g., diffraction), elevation-dependent terrain masking, and LoS improvement at higher altitudes. Residual small-scale fading and short-term channel variability are absorbed into a stochastic fading margin applied in the link budget, parameterized using the IEEE DataPort V2X dataset [12]. The calibrated RF parameters used throughout the simulation are summarized in Table 2 and are applied consistently across all Monte Carlo runs. This margin is modeled as an additive loss term (in dB) sampled per sensing epoch to capture residual link variability under the calibrated RF conditions.

The cooperative SINR is expressed as:

$$\text{SINR}_{\text{coop}} = \text{SINR}_{\text{base}} + G_{\text{coop}} \quad (3)$$

where $\text{SINR}_{\text{base}}$ denotes the single-RSU SINR and G_{coop} represents the diversity gain from neighboring RSUs. Equation (3) serves only as an analytical upper bound; in the simulation, cooperation is implemented at the decision level rather than through deterministic SINR accumulation. The cooperative gain is approximated by the following upper-bound expression:

$$G_{\text{coop}} = 2.0 + 10\log_{10}(N_{\text{adjacent}} - 1), N_{\text{adjacent}} \geq 2 \quad (4)$$

In practice, the effective gain is reduced by partial spatial correlation, unequal link geometry, and interference asymmetry.

With N_{adjacent} denoting the number of RSUs participating in cooperative validation. The logarithmic form reflects diminishing gains as the coalition size increases. Equation (4) is used as an upper-bound analytical approximation; in the simulation, cooperation is implemented via feature-level validation and fusion rather than a deterministic SINR increment.

Detection is implemented as a threshold-based sensing process combined with cooperative validation across neighboring RSUs. At each sensing epoch t , a detection is declared if at least k RSUs within the cooperation window observe an instantaneous SINR exceeding the detection threshold γ :

$$P_{\text{det}}(t) = \Pr \left\{ \sum_{i \in \mathcal{N}(t)} 1[\text{SINR}_i(t) \geq \gamma] \geq k \right\}. \quad (5)$$

This k-out-of-N decision rule follows a standard paradigm widely used in distributed detection and cooperative sensing systems. The detection threshold is fixed at $\gamma = -3$ dB as a pre-cooperation detection gate, while cooperative validation effectively increases the reliability of marginal detections. The selected threshold is used as a fixed pre-cooperation gate in the present simulation configuration. A comprehensive $P_d - P_{fa}$ trade-off analysis incorporating heterogeneous real-world ISM emitters remains a target for future work. Confirmed detections typically exhibit substantially higher effective SINR after spatial validation, with a mean observed value of approximately 10 dB.

Epoch-level verified detection coverage is empirically evaluated via Monte Carlo simulation as the fraction of one-second sensing epochs that satisfy the cooperative k-out-of-N validation criterion. This system-level coverage metric must not be interpreted as

a per-target Pd, a per-link detection probability, or false alarm performance (Pfa). This formulation captures the combined effects of propagation loss, terrain masking, altitude-dependent line-of-sight conditions, and spatially heterogeneous interference without relying on deterministic SINR accumulation or heuristic aggregation factors.

The simulation models a 600 s engagement with a temporal resolution of 1 s, with RSU-level sensing and cooperative validation performed at each time step. Twenty independent Monte Carlo runs are conducted, each representing an independent realization with randomized UAV trajectories, fading margins, and interference realizations, enabling estimation of mean values and confidence intervals. Each run uses a distinct but fixed random seed (from a predefined seed list) to ensure exact reproducibility.

Seven small fixed-wing UAVs are modeled, traveling at a constant speed of 50 m/s and operating at altitudes between 500 m and 1200 m. Their trajectories include longitudinal motion along the corridor with lateral offsets, representing coordinated incursions within the monitored area. A structured narrowband interferer is positioned at 130 km along the corridor, emitting 38 dBm EIRP in the 2.4 GHz and 5.8 GHz ISM bands to represent a high but plausible interference condition in civilian unlicensed spectrum, rather than an intentional jamming scenario.

The complete simulation loop integrates RSU initialization and synchronization, UAV motion, propagation, and SINR evaluation, cooperative validation, bearing estimation, and feature-level fusion. This configuration enables systematic evaluation of epoch-level verified detection coverage, bearing accuracy, and cooperative performance under calibrated propagation and interference conditions.

4. Results

This section evaluates the performance of the proposed cooperative V2X-based UAV detection framework under calibrated RF conditions and contrasts it with an intentionally uncalibrated baseline model. The analysis focuses on detection geometry, SINR behavior, bearing-estimation accuracy, and network-level cooperative performance. All numerical results for the calibrated configuration are obtained from twenty independent Monte Carlo runs, each simulating 600 s of activity by seven UAVs moving along a 200 km rural corridor instrumented with 80 roadside units (RSUs). RF conditions are calibrated using the IEEE DataPort dataset IQ Samples for V2X Communication System Combined with Narrow-Band Interference [12].

The sensing environment is shaped by terrain variations, RSU placement, UAV trajectories, and the presence of a narrowband interferer positioned at 130 km along the corridor. UAVs traverse the corridor with lateral offsets of up to ± 4 km, while RSUs are spaced at 2.5 km along the centerline. Figure 2 illustrates the terrain elevation, RSU locations, UAV trajectories, and interferer placement.

Terrain-induced masking modifies line-of-sight (LoS) visibility, altitude variations affect link geometry, and the interferer introduces spatially localized degradation of RF conditions along the route. These factors jointly shape the resulting SINR distributions and detection outcomes.

Figure 3 presents the SINR distribution across all RSU–UAV links in the calibrated configuration.

Across the twenty Monte Carlo runs, the mean SINR over all RSU–UAV links is -17.0 dB, with a 95% confidence interval of $[-17.1, -16.9]$ dB and a pooled standard deviation of 8.7 dB. The overall mean is dominated by non-detectable long-range links; in contrast, cooperatively validated detections exhibit substantially higher SINR (mean ≈ 10 dB, marked by the green dashed line in Figure 3). Detection decisions are therefore governed by the upper tail of the SINR distribution. Only a subset of links exceeds the -3 dB pre-

cooperation detection threshold defined in Section 3; confirmed detections concentrate in the upper tail of the SINR distribution after cooperative validation. The wide SINR spread reflects heterogeneous propagation conditions along the corridor, including terrain-dependent attenuation, altitude-dependent LoS effects, and spatially localized interference.

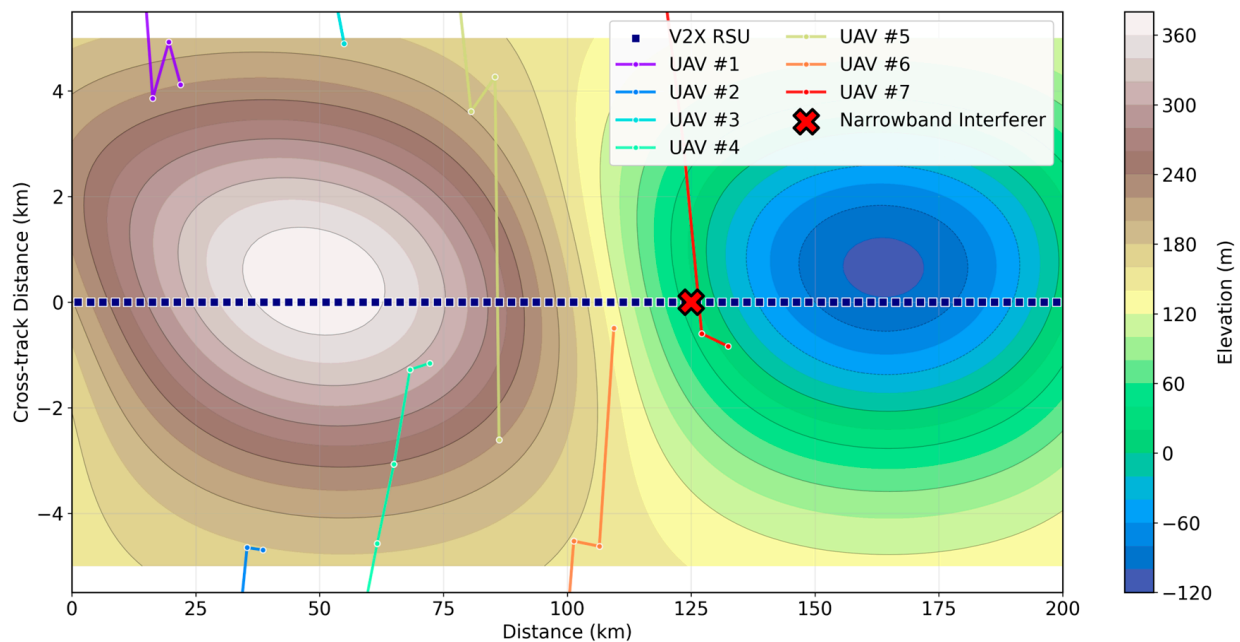


Figure 2. Topographic map of the 200 km corridor with RSU positions, UAV trajectories, and interferer location. RSUs are uniformly spaced at 2.5 km; seven fixed-wing UAVs operate at 500–1200 m altitude and 50 m/s; the narrowband interferer is placed at 130 km with 38 dBm EIRP.

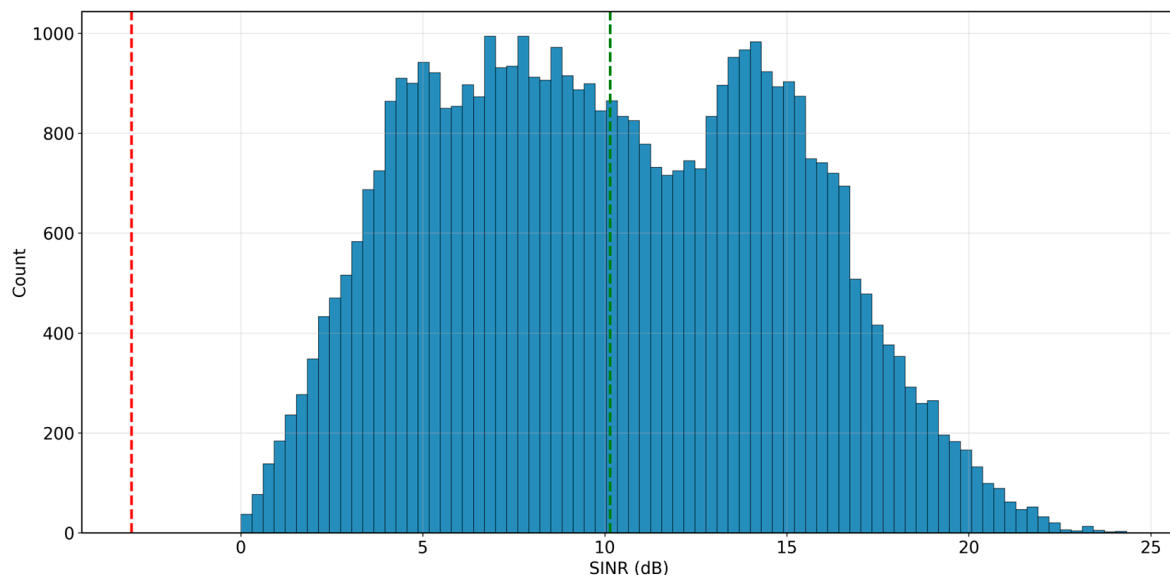


Figure 3. SINR distribution across all RSU–UAV links for the calibrated model. Results aggregated over 20 Monte Carlo runs with noise floor calibrated at -107 dBm and background interference at -103 dBm (IEEE DataPort V2X dataset). The red dashed line indicates the pre-cooperation detection threshold ($\gamma = -3$ dB). The green dashed line indicates the mean SINR of cooperatively validated detections (≈ 10 dB, observed; not a design parameter).

Figure 4 shows the detection geometry for the calibrated configuration. The left panel visualizes detection events in range–altitude space, color-coded by instantaneous

SINR, while the right panel shows the corresponding distribution of three-dimensional slant distances.

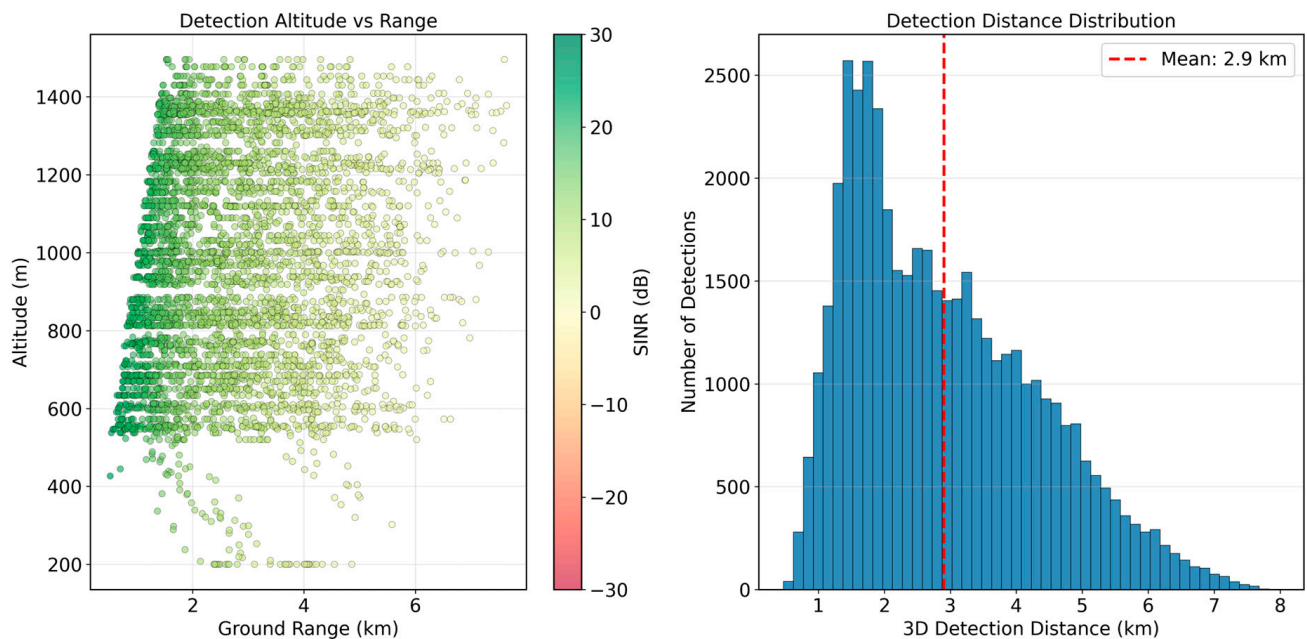


Figure 4. Detection altitude versus ground range (left) and 3D slant distance distribution (right) for the calibrated model. Results aggregated over 20 Monte Carlo runs (600 s each) under the calibrated configuration.

In the calibrated configuration, detections are concentrated within 1–6 km of the serving RSU, which is consistent with realistic coverage ranges in rural deployments. The mean 3D slant distance is 2.9 km (95% CI: [2.7, 3.1] km, SD: 0.8 km, variance: 0.64 km²). This near-field detection envelope reflects the calibrated noise and interference floors, terrain-dependent path loss, and the adopted pre-cooperation SINR threshold.

Figure 5 presents the uncalibrated configuration for comparison.

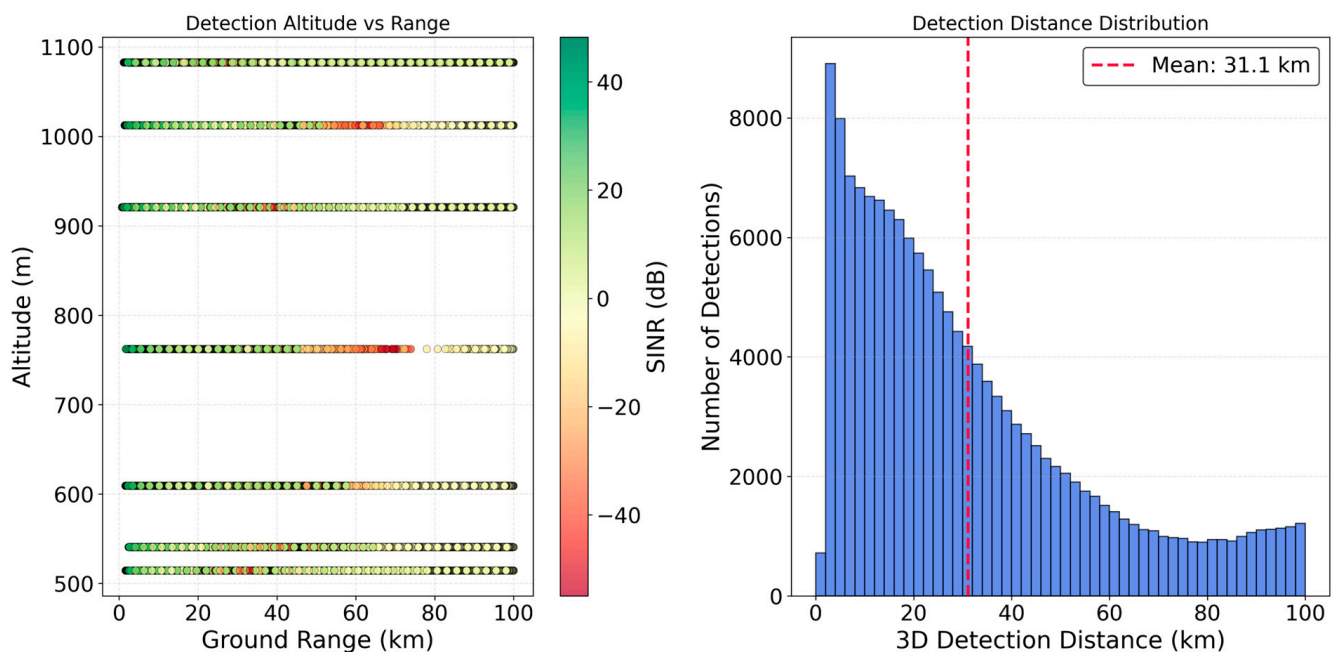


Figure 5. Detection geometry for the uncalibrated baseline, illustrating the effect of omitting RF calibration.

In the uncalibrated model, detection distances extend beyond physically plausible ranges for ISM-band passive sensing, reaching 80–90 km, with a mean 3D detection distance of 32.4 km. These far-field detections arise from uncalibrated propagation and noise assumptions. Discretized altitude modeling further introduces artificial horizontal banding, producing the bimodal structure visible in Figure 5. These artifacts are eliminated once realistic RF calibration is applied.

Figure 6 presents bearing estimation errors for the calibrated configuration, including the overall error distribution, and bearing error as a function of SINR.

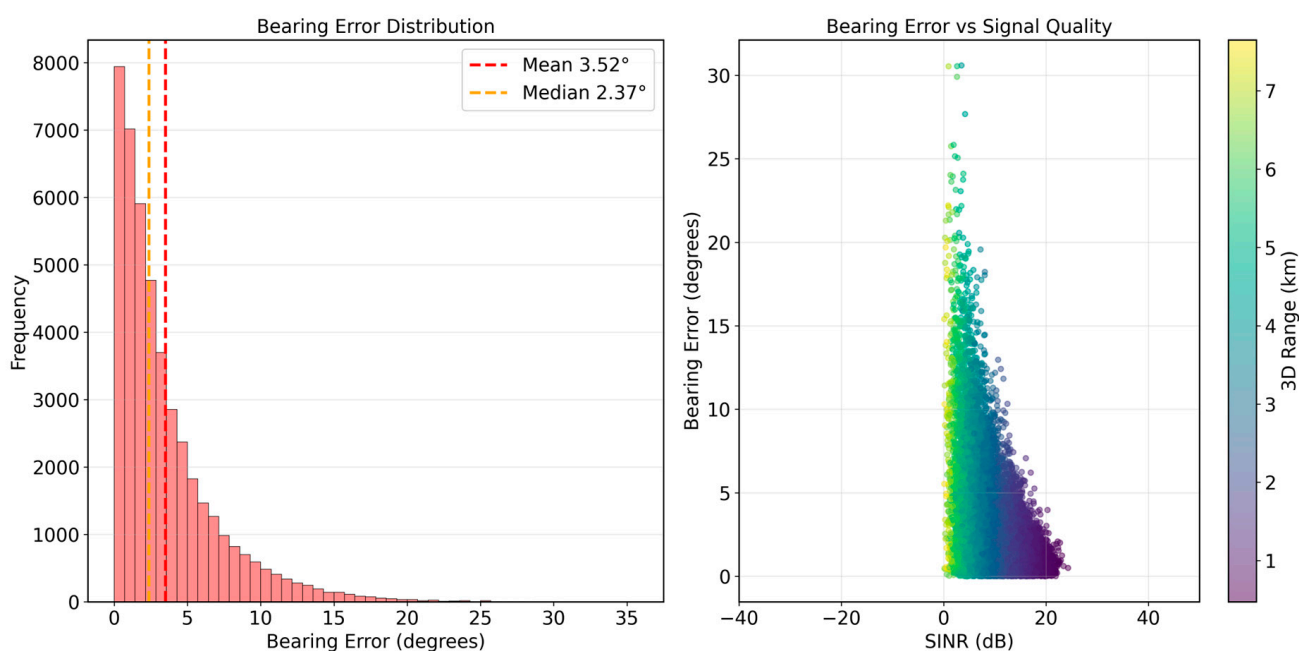


Figure 6. Bearing error distribution (left) and bearing error versus SINR (right) for the calibrated model. Results aggregated over 20 Monte Carlo runs (600 s each) under the calibrated configuration.

Most bearing estimates fall below 30°, with a mean error of 19.8° (95% CI: [19.8°, 19.9°], SD: 16.3°, variance: 264.5°²) and a median of approximately 15°. The difference between mean and median reflects a right-skewed error distribution, with occasional large errors occurring near the detection boundary and under low-SINR conditions. Higher-SINR links yield substantially tighter angular estimates, confirming the SINR dependence of bearing accuracy under calibrated RF conditions.

Figure 7 shows the corresponding bearing-error results for the uncalibrated configuration.

In the uncalibrated case, the error distribution exhibits a long tail extending beyond 100°, driven by unrealistically long-range detections. This comparison shows that optimistic detection ranges do not yield reliable angular information when realistic RF constraints are ignored.

Figure 8 evaluates the impact of cooperative processing. The left panel shows the analytical upper bound on cooperative SINR gain as a function of coalition size, while the right panel compares cooperative and single-RSU epoch-level verified detection coverage over the full observation interval.

Across the twenty Monte Carlo runs, cooperative processing achieves a mean epoch-level verified detection coverage of 54.72% (95% CI: [53.84%, 55.60%]), while single-RSU operation remains at 2.67%. Relative to the single-RSU baseline, this corresponds to an approximately 20× relative increase in epoch-level verified detection coverage, equivalent to an absolute gain of about 52 percentage points. This improvement reflects the

recovery of marginal detections through multi-node validation rather than deterministic SINR accumulation.

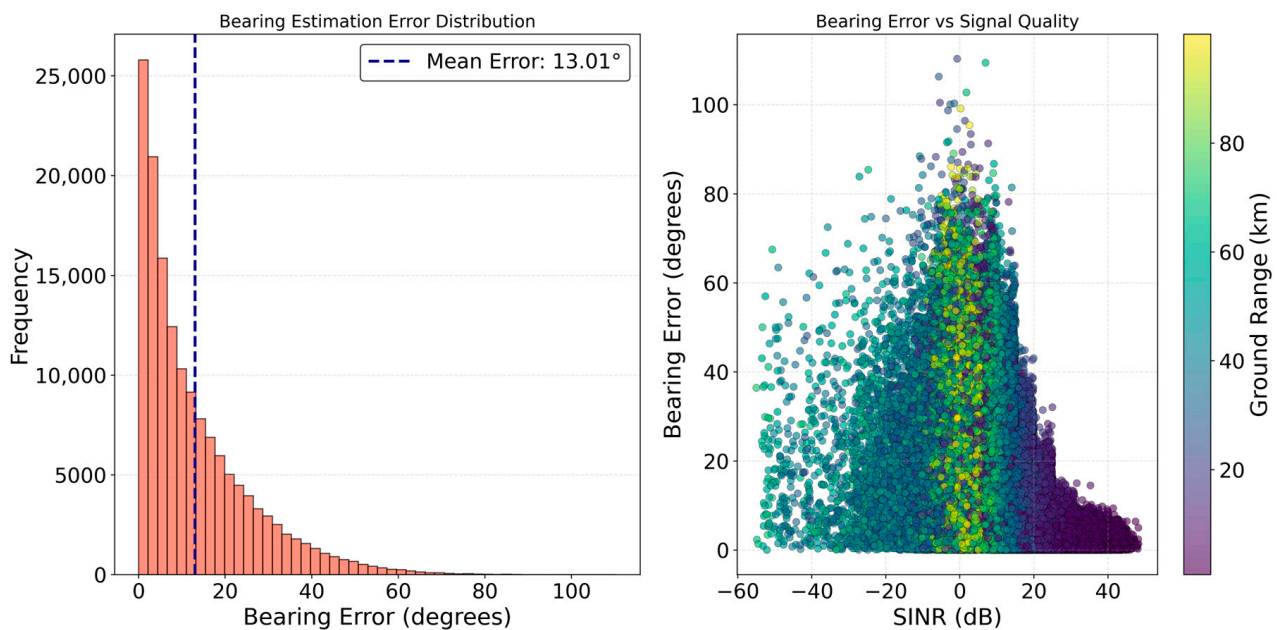


Figure 7. Bearing error distribution (left) and bearing error versus SINR (right) for the uncalibrated model. Results shown for the uncalibrated baseline model.

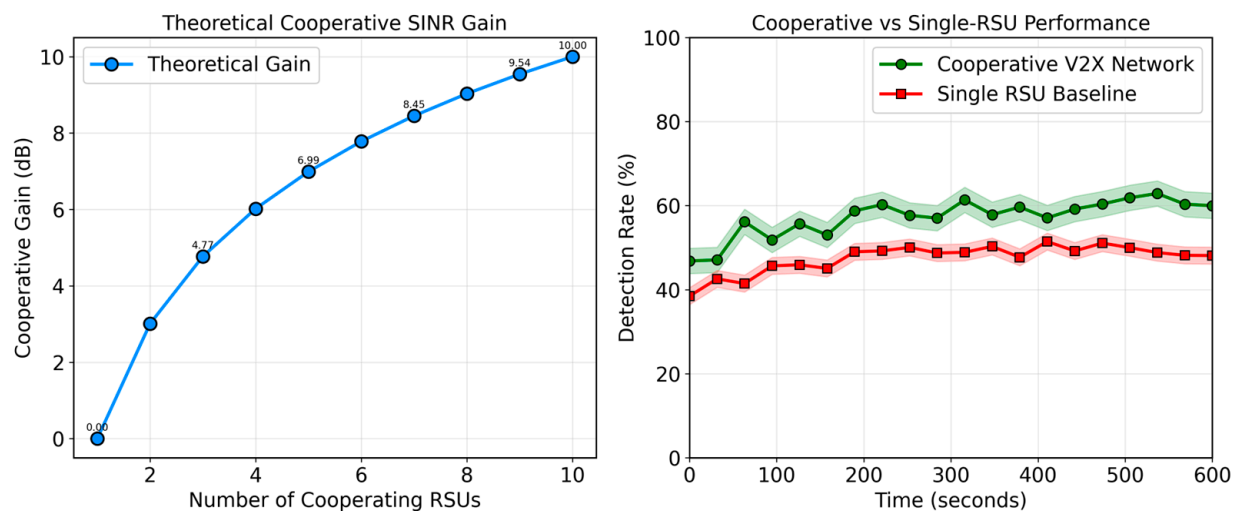


Figure 8. Theoretical upper bound on cooperative SINR gain versus the number of cooperating RSUs (left) and cooperative versus single-RSU epoch-level verified detection coverage for the calibrated model (right). Verified detection coverage is computed over 20 Monte Carlo runs, each simulating 600 one-second epochs with 7 UAVs and 80 RSUs.

Here, the epoch-level verified detection coverage is defined as the fraction of one-second sensing epochs, aggregated across all Monte Carlo runs, in which the cooperative k-out-of-N validation declares at least one confirmed detection event. The denominator is the total number of sensing epochs ($600\text{-time steps} \times 20\text{ runs}$), and the numerator counts epochs in which the validation criterion is satisfied. This metric reflects epoch-level system awareness over time, rather than a per-target P_d or a per-link detection probability. In particular, the metric does not capture whether every individual UAV is detected in a given epoch; an epoch is counted as detected if any one of the seven UAVs triggers a confirmed event.

Table 3 summarizes the key differences between the uncalibrated and calibrated configurations.

Table 3. Comparison of uncalibrated versus IEEE DataPort-calibrated performance.

Metric	Uncalibrated Model	Calibrated Model
Mean 3D detection distance	32.4 km	2.9 km (95% CI: [2.7, 3.1], SD: 0.8 km)
Detection-range envelope	Detections up to 80–90 km (non-physical artifact)	Detections concentrated within 1–6 km
Detection geometry	Bimodal pattern with far-field clusters	Compact near-field cloud with continuous altitude support
Mean bearing error	11.7°	19.8° (95% CI: [19.8°, 19.9], SD: 16.3°)
Mean SINR	Not calibrated	−17.0 dB (95% CI: [−17.1, −16.9], SD: 8.7 dB)
Cooperative epoch-level verified detection coverage	Not representative	54.72% (95% CI: [53.84%, 55.60])
Single-RSU epoch-level verified detection coverage	Not representative	2.67%
Cooperative gain	Not defined	≈20× relative gain (≈52 pp absolute)

The results show that RF calibration fundamentally alters the operating regime of the model. Calibration suppresses non-physical long-range detections and constrains the effective detection zone to a realistic near-field region around each RSU. Under these conditions, a trade-off emerges between epoch-level verified detection coverage and angular accuracy in interference-limited environments. Although calibrated bearing errors remain on the order of tens of degrees, cooperative processing yields statistically significant detection gains. The calibrated framework provides a deployment-relevant basis for evaluating cooperative V2X-based UAV detection under realistic RF conditions.

5. Discussion

This section interprets the calibrated simulation results and their implications for cooperative UAV detection using sparsely deployed V2X roadside units.

RF calibration places the system in a deployment-relevant operating regime. In contrast to the uncalibrated baseline, detections are confined to a few kilometers around each RSU. This behavior reflects measured noise floors, terrain masking, and realistic interference conditions. These results indicate that data-driven RF calibration is necessary for credible performance assessment in corridor-scale deployments.

Within this constrained regime, cooperative processing becomes the primary driver of detection performance. Spatial diversity across neighboring RSUs allows marginal emissions that remain sub-threshold at individual nodes to be validated collectively. This mechanism explains the improvement in epoch-level verified detection coverage relative to single-RSU operation. The observed gain exceeds that expected from independent single-node operation, highlighting the effectiveness of feature-level cooperation in sparse, linear topologies.

Bearing estimation reveals a clear trade-off between realism and performance. Angular errors increase compared with idealized propagation assumptions, particularly at low SINR and near the detection boundary. Despite this degradation, the achieved accuracy remains sufficient for sector-level awareness and track initiation. These results also show that extended detection ranges produced by uncalibrated models do not provide reliable angular information.

Several structural factors limit achievable performance relative to theoretical bounds. The 2.5 km RSU spacing reduces angular diversity for certain geometries, especially for trajectories aligned with the corridor axis. A parametric study over RSU spacing is outside the scope of this paper and is left for future work to quantify deployment trade-offs between

geometric diversity, neighbor availability for validation, and installation density. Terrain masking disproportionately affects low-altitude flight segments. In addition, spatially localized interference creates asymmetric RF conditions along the corridor. Together, these effects constrain both epoch-level verified detection coverage and bearing accuracy, even under cooperative operation.

From a deployment perspective, the evaluated configuration is compatible with supplementary RF-based UAV sensing using modest augmentation. The proposed approach is suited to early warning and sector-level situational awareness rather than precise localization. The current implementation focuses on detecting RF activity associated with UAV control links. The cooperative framework relies on time-stamped feature descriptors exchanged between RSUs; timing synchronization is therefore a practical consideration for deployment. Synchronization impairments are not modeled explicitly in the present simulation. Robust discrimination between UAV transmissions and other ISM-band emitters remains an open challenge.

This study does not report false alarm rate P_{fa} , precision/PPV, ROC/DET curves, or sensitivity to interference diversity in the 2.4/5.8 GHz ISM bands. The cooperative k-out-of-N rule is intended to reduce isolated local triggers by requiring cross-node descriptor agreement; however, correlated wide-area ISM activity (e.g., Wi-Fi, fixed wireless access, industrial telemetry) may still pass multi-node validation. Quantifying P_{fa} under realistic interference diversity requires dedicated interference corpora and/or field trials and is identified as a priority for future work.

This study is simulation-based and abstracts several real-world effects, including detailed multipath propagation, hardware impairments, and non-Gaussian interference. Scenario coverage is limited to fixed RSU spacing and representative interference conditions.

6. Conclusions

This work evaluated the feasibility of extending sparsely deployed V2X roadside units with passive RF sensing to support UAV detection in rural transportation corridors. Performance was assessed using a calibrated simulation environment based on measured V2X noise and interference characteristics under realistic propagation, terrain, and interference conditions. The evaluation is simulation-based and does not include field measurements or hardware prototyping.

The results show that cooperative validation across neighboring RSUs improves epoch-level verified detection coverage relative to single-RSU operation, including under interference-limited conditions. RF calibration constrains detections to physically realistic near-field ranges and produces SINR and bearing statistics consistent with corridor-scale propagation effects. Although bearing accuracy remains coarse, it is sufficient for early warning and track initiation rather than precise localization.

The evaluated approach relies on modest RSU augmentation, low-bandwidth inter-RSU feature exchange, and reliable timing synchronization. Primary V2X safety functions are preserved by confining sensing to unlicensed ISM bands and operating at the feature level. Phased trials on instrumented road segments would enable validation of detection reliability, false alarm behavior, and robustness under real RF and environmental conditions. Such trials are a necessary next step to confirm practical feasibility under realistic ISM-band emitter diversity and hardware impairments.

Several real-world effects remain outside the scope of the present study. These include detailed multipath propagation, hardware non-idealities, heterogeneous interference sources, and more complex UAV maneuvers. False alarm rate, precision, and ROC/DET characterization are not reported in this study; discrimination performance against real-world ISM-band emitter diversity remains uncharacterized. Operational readiness therefore

depends on future false alarm evaluation under ISM-band interference diversity. Addressing these factors through field experiments, expanded scenario coverage, and integration with complementary sensing modalities is necessary to assess operational performance.

In summary, cooperative V2X-based RF sensing provides a practical means to enhance airspace awareness along rural corridors where conventional surveillance coverage is limited. While it does not replace dedicated sensing systems, it provides a deployment-compatible capability that leverages existing transportation infrastructure.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full term
3GPP	Third Generation Partnership Project
ADS-B	Automatic Dependent Surveillance–Broadcast
C-V2X	Cellular Vehicle-to-Everything
CI	Confidence Interval
COM	Communication (subsystem/module)
CP	Cooperative Perception
DAB	Digital Audio Broadcasting
dB	Decibel
dBm	Decibel-milliwatt
DVB-T	Digital Video Broadcasting–Terrestrial
EIRP	Effective Isotropic Radiated Power
EO/IR	Electro-Optical/Infrared
ETSI	European Telecommunications Standards Institute
FSPL	Free-Space Path Loss
GHz	Gigahertz
GPS	Global Positioning System
IEEE	Institute of Electrical and Electronics Engineers
IQ	In-phase and Quadrature
ISAC	Integrated Sensing and Communication
ISM	Industrial, Scientific, and Medical
ITS	Intelligent Transportation Systems
ITS-G5	Intelligent Transport Systems at 5.9 GHz
LoS	Line-of-Sight
LTE	Long-Term Evolution
RF	Radiofrequency
RSU	Roadside Unit
SDR	Software-Defined Radio

SENS	Sensing (subsystem)
SINR	Signal-to-Interference-plus-Noise Ratio
sUAV	Small Unmanned Aerial Vehicle
TEN-T	Trans-European Transport Network
TMS	Transportation Management System
UAV	Unmanned Aerial Vehicle
UDP	User Datagram Protocol
V2X	Vehicle-to-Everything

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