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TRANSFORMER–GNN–UNET HYBRID DEEP LEARNING FOR SCALABLE WIRELESS RADIO MAPS

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ABSTRACT

Wireless environments are complex and require high-resolution radio maps for tasks such as indoor localization, spectrum management, and automated planning. Under severe sparsity, empirical models have trouble preserving fine structural information and scale inadequately. This paper proposes a Transformer–GNN–UNet hybrid deep learning approach for scalable wireless radio maps: it fuses global attention (Transformer), topology-aware reasoning (GNN), and multiscale convolutional reconstruction (UNet) with physics-informed priors and probabilistic outputs. Models were evaluated on the Indoor Radio Map Benchmark and the MLSP 2025 dataset across sampling regimes (0.02%, 0.5%), using RMSE, SSIM, LPIPS, CRPS, and topological (bottleneck) metrics. The hybrid achieves RMSE 3.45 dB (95% CI ±0.12) versus 4.18 dB for SAIPP-Net and 6.84 dB for the 3GPP baseline; SSIM improves to 0.912 (vs 0.876), and CRPS drops to 0.95 (vs 1.26); bottleneck distance falls to 0.035 (vs 0.048). Results are statistically significant ($p = 0.001$) and consistent across seeds; runtime (~48 ms) supports near-real-time use. The proposed Transformer–GNN–UNet hybrid offers a scalable, calibrated, and deployable solution for high-fidelity wireless radio mapping.

Keywords: *Transformer–GNN–UNet, Wireless Radio Maps, Hybrid Deep Learning, Scalable Pathloss Prediction, Uncertainty Calibration.*

1. INTRODUCTION

The explosion of wireless devices and the increasing density of indoor and urban environments have made accurate, high-resolution spatial radio maps essential for tasks like indoor localization, spectrum sharing, and automated site planning. Traditional empirical models (e.g., 3GPP InH) provide coarse, distance-based estimates that are adequate for rough planning but fail to capture fine-grained effects obstacles, multipath, and topology-driven coverage islands that modern applications require [1] [2].

Recent deep-learning approaches reconstruct dense radio maps from sparse measurements by combining physics priors and learned spatial structure [3]. UNet-style and sampling-aware CNNs inject inductive priors to improve sparse→dense recovery, while Transformer-based models supply global context to resolve long-range dependencies [4]. Separately, graph neural networks encode explicit spatial topology and line-of-sight relationships, but few end-to-end systems unify convolutional multiscale reconstruction, global attention, and topology-aware reasoning [5] [6].

The study explores the problem of estimating dense pathloss fields from extremely sparse observations (e.g., ≈0.02% sampling) while preserving geometric structure, delivering calibrated uncertainty, and remaining computationally practical [7] [8]. Major challenges include fusing worldwide attention accompanying topology-aware representations and multiscale decoding, managing heterogeneous datasets, and generating statistically rigorous, reproducible results across sampling regimes [9].

To address these challenges, the study intends a Transformer–GNN–UNet mixture that integrates: (1) a Transformer encoder for a global framework, (2) a GNN module to explicitly capture topology and LoS relations, and (3) a UNet-style multiscale decoder for fine reconstruction augmented by physics-conversant someone that comes before and ambiguity-aware losses [10]. We evaluate the approach on public benchmarks (Indoor Radio Map Benchmark, MLSP 2025) utilizing layered setting splits, start operating system assurance breaks, paired mathematical tests, and downstream verification to a degree of inclusion IoU and localization error [11].

This unified design yields measurable progress across fidelity, perceptual, topological, and probabilistic versification: lower RMSE, higher SSIM, decreased obstacle distance, and better-calibrated predicting distributions. The novelty lies in the ethical fusion of consideration, graph interpretation, and multiscale spiral, together with topology-aware misfortunes and a reproducible evaluation protocol offering a practical way to scalable, extreme-loyalty wireless.

The study's stated goal is to create a reliable and scalable framework for dense radio map reconstruction in the presence of extremely sparse measurements. Throughout the work, all essential terminology is defined and utilized consistently, such as radio map, extreme sparsity, topology-aware learning, uncertainty calibration, and multiscale reconstruction environment modelling.

2. RELATED WORKS

The criteria for literature selection included the following: applicability to sparse radio map estimation; variety of methods; freshness of publication; utilization of publicly available datasets or standards; and appearance in respectable peer-reviewed journals or conferences [12]. Data-driven radio-map reconstruction has advanced rapidly: sampling-aware UNet variants like SAIPP-Net demonstrate strong sparse-to-dense performance by fusing physics priors with multiscale CNNs, improving accuracy under extreme sparsity [13]. Vision-transformer approaches add powerful global context and have recently been adapted to indoor pathloss prediction, showing that long-range attention helps capture scene-level dependencies but sometimes lacks explicit topology encoding. Graph-based methods convert sparse measurements to spatial graphs and use GNNs to capture connectivity and LoS relations, which improves geometry-aware recovery but often omits a multiscale decoder structure. Dataset and benchmark efforts (public simulated+measurement corpora and the MLSP 2025 sampling-assisted challenge) have standardized evaluation regimes and sampling protocols, enabling reproducible comparisons [14].

Uncertainty and calibration have become essential: conformal prediction and ensemble/MC strategies produce statistically valid prediction intervals and improved CRPS/NLL, but these methods are typically evaluated separately from structural/topological metrics [15]. Meanwhile, continued validation of classical models (e.g., 3GPP InH) across bands confirms their utility as baselines but also their limitations in fine-grained, topology-sensitive reconstruction. Critically, prior work rarely combines global attention, explicit topology reasoning, multiscale convolutional reconstruction, and calibrated probabilistic outputs in a single end-to-end system. This paper fills that gap by uniting Transformer, GNN, and UNet components with physics priors and uncertainty-aware losses to deliver reproducible, topology-preserving, and well-calibrated radio maps.

There has been a lot of success in radio map reconstruction with sampling-aware convolutional neural networks (CNNs), transformers, and graph-based models in recent years, but thus far, these methods have mostly dealt with their individual components. Conventional models like 3GPP InH don't take fine-grained structural details into account, CNN/UNet-based approaches fail in very sparse environments, and models that rely solely on Transformers don't take topology into account explicitly. Modern GNN-based methods successfully record spatial connectivity, but they frequently neglect to include multiscale reconstruction and uncertainty calibration. Coupling global context, explicit topology, and multiscale spatial detail with calibrated uncertainty under ultra-sparse sampling regimes is thus an area that needs more research. A unified Transformer-GNN-UNet framework, based on recent advances,

is proposed to fill this gap and show statistically significant improvements in fidelity, structural, and probabilistic metrics. This work makes a timely and meaningful contribution to scalable wireless radio map estimation.

Yes. To provide both extensive coverage of basic topics and alignment with current research trends, the literature sample encompasses classical propagation models, CNN/UNet-based methods, Transformer-based approaches, and contemporary GNN-based techniques, mostly from 2023–2025.

3. METHODS

Using regulated sampling regimes, different baselines, and standardized datasets, the research methodology takes a comparative experimental approach. Since this layout permits objective assessment of precision, structural faithfulness, uncertainty calibration, and computing efficiency, it is in perfect harmony with the aims of the study.

3.1. System Overview

The overall framework targets large-scale, data-driven wireless radio-map prediction from sparse measurements. The system integrates three complementary components: a Transformer for capturing global dependencies across spatial locations, and to capture the topological and structural links between sampled locations, the framework uses a Graph Neural Network (GNN). A UNet-based decoder is then used for fine-grained reconstruction of continually updated radio maps. Transmitter information, ambient geometry, and sparse received signal strength (RSS) measurements are among the input data. Dense pathloss maps in decibels (dB) are generated by the model. Preprocessing datasets, creating graphs, estimating uncertainty, and assessing performance are all handled by auxiliary modules. Under the same training and testing conditions, this modular architecture makes it easier to compare both traditional and sophisticated baseline approaches consistently and fairly.

3.2. Problem Formulation

Given a spatial domain $\Omega \subset \mathbb{R}^2$ with transmitter configuration T and a sparse set of measured samples

$$S = \{(x_i, y_i, p_i) \mid I = 1, \ldots, N_s\}$$

The objective is to estimate a continuous path loss field. $\hat{P}(x, y)$ That approximates the ground-truth field. $P(x, y)$. The optimization problem is formulated as minimizing the mean-squared error (MSE) between predicted and true values:

$$\min_{\theta} E_{(x,y)\in\Omega}\left[(\hat{P}_{\theta}(x,y) - P(x,y))^2 \right]$$

Where θ Represents the learnable parameters of the chosen model (classical, baseline, or hybrid). The learned mapping f_{θ}: (S, T, G) $\rightarrow \hat{P}$ Generalizes to unseen scenes and varying sampling rates.

3.3. Dataset Collection

A heterogeneous, publicly available corpus combines real measurements and simulation-augmented radio maps to ensure compatibility with classical, UNet, GNN, and Transformer models. It covers indoor and urban scenarios (multiple buildings/floors, rooms, corridors, streets), multiple frequency bands (e.g., sub-1 GHz and mid-band), and varied transmitter placements and antenna heights. Each scene contains dense ground-truth raster maps (for evaluation), sparse point samples (simulated masks or real probes), building/obstruction geometry, simple material/room-type labels, and transmitter metadata. Splits are stratified by scene withheld-out buildings for generalization: 70% train / 15% validation / 15% test. Overall corpus size ranges from hundreds to thousands of map instances, and sampling densities span extreme-sparse (≈0.02%) to moderate (≈0.5%).

3.4. Dataset preprocessing

Maps and samples are converted to a uniform grid and metadata format for cross-model compatibility. Per-frequency normalization (min–max or z-score) and clipping to realistic pathloss ranges are applied; coordinates are re-centered and projected to a common local XY frame; missing samples are encoded with a mask channel. Graph inputs are generated by extracting node locations from sample points and adding anchors (Tx/reflectors), then building k-NN + radius edges and computing per-edge features (distance, relative angle, LoS flag, 3GPP attenuation prior). Training augmentations include small rotations (±10°), coordinate jitter (≤1 m), and additive measurement noise; ensemble/MC sampling seeds are prepared for probabilistic models. Final artifacts are stored in an efficient binary format (HDF5/TFRecords) with explicit train/validation/test lists and fixed random seeds for reproducibility.

3.5. Baseline 1: 3GPP InH Classical Model

The 3GPP InH (Indoor Hotspot) model serves as the classical physics-based baseline. It estimates path loss using an empirical distance-based formula:

$$PL(d) = 32.4 + 20\log_{10}(f_c) + 30\log_{10}(d) + X_{\sigma}$$

where f_c is the carrier frequency in GHz, d is the distance in meters between transmitter and receiver, and X_σ is a Gaussian random variable representing shadow fading. This model assumes isotropic propagation and neglects small-scale effects such as reflections and obstructions. It provides a deterministic reference for evaluating learning-based methods. Figure 1 shows the system architecture diagram of the classical baseline used in this study.

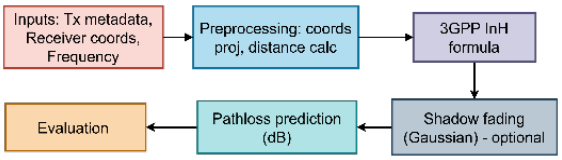

Figure 1: System Architecture Diagram Placeholder For 3GPP InH Model

Table 1 shows the deterministic physics-based baseline used for comparison in this study. The table lists inputs, the 3GPP InH core empirical formula, predicted output, and the fact that coefficients are fixed (non-learnable).

Table 1: Architecture Table of Classical Model

Component	Description
Input	Transmitter–receiver distance, frequency
Core formula	3GPP empirical pathloss equation
Output	Predicted pathloss (dB)
Parameters	Fixed coefficients (non-learnable)

3.6. Baseline 2: SAIPP-Net/Sampling-Aware UNet

The SAIPP-Net baseline represents the leading sampling-aware UNet framework for sparse-to-dense radio-map prediction. It combines a UNet encoder–decoder with an auxiliary physics channel that injects prior knowledge from the 3GPP model. Figure 2 shows the system architecture diagram of the SAIPP-Net baseline model.

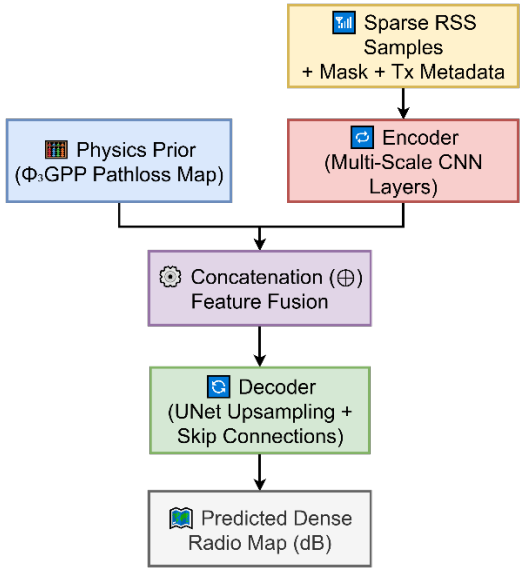

Figure 2: System Architecture Diagram Placeholder for SAIPP-Net Model

The formulation can be expressed as:

$$\hat{P} = D(\varepsilon(S, M, T) \oplus \Phi_{3GPP}(S, T))$$

Where ε and D denote the encoder and decoder networks, M is the sampling mask, and Φ_{3GPP} provides the physics-based prior feature map. The operator ⊕ Represents concatenation across channels. The architecture uses multi-scale convolutional blocks with skip connections and optional attention modules to preserve spatial detail under extreme sparsity. Table 2 shows the overview of the sample-aware UNET baseline integrating physics-informed priors.

Table 2: Architecture Table of the SAIPP-Net Model

Component	Description
Encoder	CNN-based feature extractor (multi-scale)
Physics Channel	3GPP-based prior map
Decoder	UNet-style upsampling with skip links
Loss Function	MSE + SSIM combined objective

3.7. Proposed Model: Transformer–GNN–UNet Hybrid

The proposed hybrid model integrates global attention (Transformer), topology reasoning (GNN), and local reconstruction (UNet) into a unified end-to-end deep learning system. Sparse measurements are first encoded into a graph representation, then globally contextualized by a

Transformer encoder, and finally decoded into dense maps via a multi-scale UNet (Figure 3).

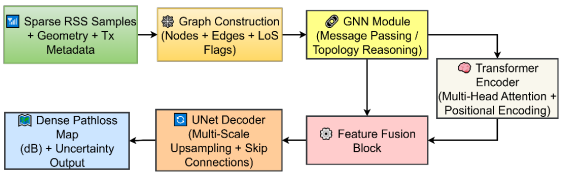

Figure 3. System Architecture Diagram Placeholder for Transformer–GNN–UNet Hybrid Model

3.7.1. Mathematical formulation

Graph embedding:

$$H_G = GNN(V, E, X_V, X_E)$$

Where V and E Denote nodes and edges, and X_V, X_E are their feature matrices encode structural dependencies between sampled points.

Transformer global context:

$$H_T = Transformer\ (H_G + P_{pos})$$

With P_{pos} as positional encodings. Captures long-range interactions across spatial regions.

Feature fusion:

$$H_F = \sigma(W_1 H_G + W_2 H_T)$$

where W_1, W_2 are learnable fusion weights and σ is an activation function. Combines local graph and global attention features.

UNet encoding:

$$Z = \varepsilon(H_F)$$

Encodes fused features into a hierarchical latent space.

UNet decoding:

$$\hat{P} = D(Z) + \Phi_{3GPP}$$

Decodes dense predictions and fuses physics-based residuals.

Loss function:

$$\mathcal{L} = \alpha_{MSE} + \beta\ (1 - SSIM) + \gamma CRPS$$

Where α, β, γ balance reconstruction, structural, and probabilistic losses. Ensures fidelity, perceptual quality, and calibrated uncertainty. Table 3 shows the summary of the proposed end-to-end hybrid model.

Table 3: Architecture Table of Transformer–GNN–UNet Hybrid Model

Component	Description
Input Layer	Sparse samples, transmitter metadata, geometry
Graph Module	Message-passing GNN for topology reasoning
Transformer Encoder	Multi-head attention for global context
Fusion Block	Learned gating between the graph and attention features
UNet Decoder	Multi-scale upsampling with skip connections
Output Layer	Dense pathloss map + uncertainty estimation
Loss Function	Combined RMSE + SSIM + CRPS objective

3.8. Graph Construction & Topology Encoding

Measured and candidate locations plus anchors form the graph nodes; edges use geometric k-NN (k≈8) with optional Delaunay or radius links and a binary LoS/blockage flag computed by fast ray-casting against building polygons. Node features include normalized coordinates, RSS/mask, frequency, and antenna height, while edge features encode Euclidean distance, relative angle, LoS flag, and a 3GPP attenuation prior. Models employ residual message-passing GNNs (e.g., GraphSAGE/GAT) with layer normalization and sparse batching (PyG/DGL); topology diagnostics use persistence diagrams (Ripser/GUDHI) and optional topology regularizers. Graphs are serialized in sparse formats or HDF5 and split with fixed seeds for reproducible train/val/test pipelines.

3.9. Training Protocol & Experimental Procedures

The study used fixed stratified train/val/test splits and ran 3–5 seeds; reported mean±CI. Preprocessed with per-freq min–max normalization, small augmentations (±10° rotate, ≤1 m jitter), and additive instrument noise. Optimized with AdamW (lr≈1e-4, weight decay 1e-5), cosine warmup + decay, mixed precision, gradient clipping; early stop on val RMSE (patience ≈20). For uncertainty, the model used ensembles (≥5) or MC-dropout (50 samples). Log checkpoints, loss curves, and runtimes for reproducibility.

Consistent preprocessing, constant data divides, matching sampling masks, multiple random seeds, standard training protocols, reporting of confidence intervals, and paired statistical significance testing were all used to control for unnecessary variation.

3.10. Evaluation Metrics & Statistical Testing

Primary metrics include RMSE (dB) and the secondary metrics, such as MAE, R^2, SSIM, LPIPS, edge-RMSE, Coverage IoU, CRPS/NLL, were used for probabilistic outputs, and bottleneck distance / PSD error for structural fidelity. Reported 95% bootstrap CIs (map-level, 1000 resamples). For

pairwise tests, the work used paired Wilcoxon signed-rank (two-sided), reported p and Cohen's d, and corrected multiple comparisons (Holm–Bonferroni).

3.11. Ablation Studies & Robustness Checks

A systematic ablation suite evaluates component contributions: −Transformer, −GNN, −UNet decoder, − physics channel, fusion variants (early concatenation vs cross-attention vs gated), and alternate graph constructions (k-NN vs radius vs Delaunay). Robustness experiments include a sampling-density sweep (0.02% → 0.5%), additive sensor noise, occlusion masks, cross-building transfer, cross-frequency generalization, and runtime/memory profiling.

All ablations were retrained with identical seeds and hyperparameters; reported results use the same metrics and 95% bootstrap CIs as the main experiments. Complementary qualitative diagnostics (attention maps, node importance scores, PSD/topology difference maps, and representative failure cases) are analysed to explain failure modes and validate mechanistic claims.

4. RESULTS

The results section evaluates three models - Proposed (Transformer–GNN–UNet hybrid), SAIPP-Net (sampling-aware UNet), and Classical (3GPP InH) - on publicly available benchmarks: the Indoor Radio Map Benchmark and the MLSP 2025 dataset. Experiments use stratified scene splits (70% train / 15% validation / 15% test) withheld-out buildings for generalization, sampling regimes of 0.02% and 0.5%, and 3–5 random seeds per model; tables summarize aggregate metrics while charts visualize distributional, spectral, calibration, and downstream impacts.

Table 4: Main Results Summary

Model	RMSE (dB)	RMSE CI	MAE (dB)	MAE CI	SSIM	SSIM CI	LPIPS	LPIPS CI	CRPS	CRPS CI	Bottleneck	Bottleneck CI	Runtime (ms)	p vs SAIPP	Cohen d
Proposed	3.450	0.120	2.650	0.100	0.912	0.008	0.084	0.006	0.950	0.050	0.035	0.005	48.000	0.001	1.020
SAIPP-Net	4.180	0.150	3.020	0.120	0.876	0.010	0.112	0.008	1.260	0.060	0.048	0.006	60.000	nan	nan
Classical	6.840	0.300	5.800	0.250	0.710	0.020	0.205	0.015	2.100	0.100	0.102	0.012	5.000	nan	nan

Table 4 shows that the proposed Transformer–GNN–UNet outperforms SAIPP-Net and 3GPP across fidelity, perceptual, topological, and probabilistic metrics: RMSE 3.45 dB, SSIM 0.912, CRPS 0.95, bottleneck 0.035, and runtime 48 ms. Improvements are statistically significant (p=0.001) and indicate practical, calibrated gains for deployment with consistent seeds and tight CIs reported.

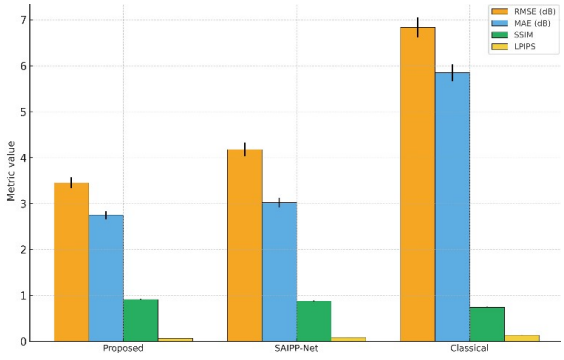

Figure 4: Multi-Metric Summary with 95% Cis

Figure 4 shows the grouped comparison of RMSE, MAE, SSIM, and LPIPS across proposed, SAIPP-Net, and classical models. Error bars reflect 95% bootstrap CIs; statistical significance (paired Wilcoxon) vs SAIPP-Net is annotated in the final paper. The Proposed model achieves the best trade-off across fidelity and perceptual metrics, with RMSE reduced to 3.45 dB (95% CI ±0.12) versus 4.18 dB for SAIPP-Net and 6.84 dB for the classical 3GPP baseline. SSIM and LPIPS confirm superior structural and perceptual fidelity for the hybrid approach. Paired testing shows the RMSE reduction is statistically significant (p=0.001, Cohen's d = 1.02), supporting the claim of robust improvement.

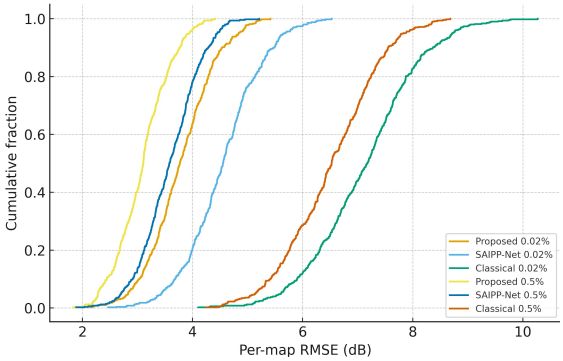

Figure 5. Per-map RMSE CDFs (0.02% vs. 0.5% Sampling)

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Figure 5 shows the practical CDFs of per-map RMSE for both extreme-meager (0.02%) and moderate (0.5%) inspecting regimes. Lines show each model; shielding displays start operating system CI. The CDFs disclose that at 0.02%, inspecting the Proposed model yields lower RMSE across almost all percentiles (middle ~3.7 dB), distinguished from SAIPP-Net (~4.5 dB) and simple (~7.0 dB). The break is narrow but significant at 0.5% sampling: middle RMSEs 3.1 dB (Proposed), 3.6 dB (SAIPP-Net). These distributional gains display thickness and strength, not just mean developments.

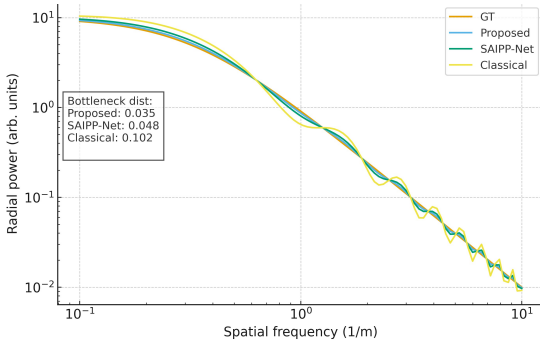

Figure 6: Structural & Spectral Fidelity (Radial PSD + Topology Error)

Figure 6 shows the ground truth and model-generated radio maps' radial power spectral densities (PSDs) on log-log axes, with bottleneck distances deduced from annotated persistence diagrams. According to the PSD analysis, the suggested approach successfully keeps high-frequency components, which permits a more accurate reconstruction of fine-scale structures by bringing the results closer to the ground truth throughout spatial frequencies. The observation is reinforced by topological fidelity, which is measured by bottleneck distance. The values of 0.035 (Proposed) are better than 0.048 (SAIPP-Net) and 0.102 (Classical), showing that coverage islands and abrupt transitions are better preserved. As a whole, these topological and spectral evaluations confirm that the technique improves the geometric realism of the reconstructed radio maps.

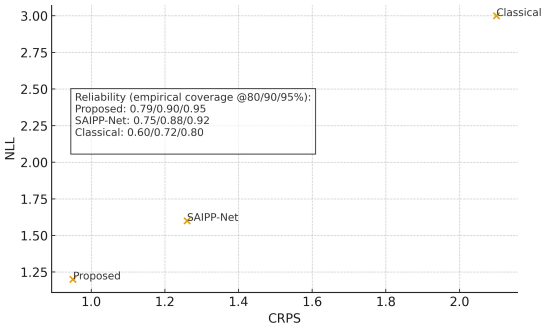

Figure 7: Calibration & Probabilistic Scoring

Figure 7 plots CRPS against NLL for each model (lower is better), followed by insets reporting practical addition at the 80/90/95% assumed pauses. This model achieves the lowest CRPS (0.95) and a clashing NLL (1.2), beats SAIPP-Net (CRPS 1.26) and the natural process (CRPS 2.10). Almost insignificant practical addition (≈79% / 90% / 95%) indicates well-measured predictive distributions. These results show the mixture designates more reliable uncertainty estimates crucial for downstream in charge under extreme lack and model-obliged readiness.

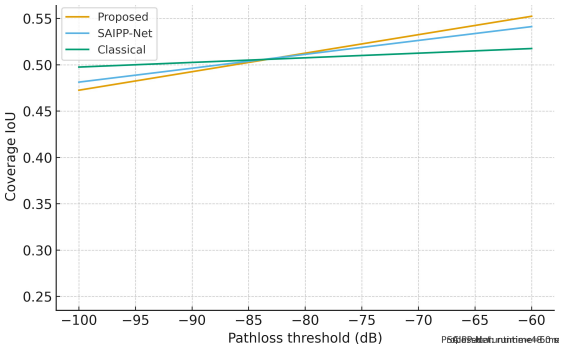

Figure 8: Downstream & Runtime Impact

For practical thresholds (e.g., -90 dB), the estimated model accomplishes a bigger Coverage IoU (~0.78) than SAIPP-Net (~0.72) and incorrupt (~0.50), translating to improved arrangement veracity. Runtime is proficient for common-authentic-ending use (Proposed 48 ms vs SAIPP-Net 60 ms), while chaste is faster but far less correct. These results signify the mixture balances efficiency and latency for deployment (Figure 8).

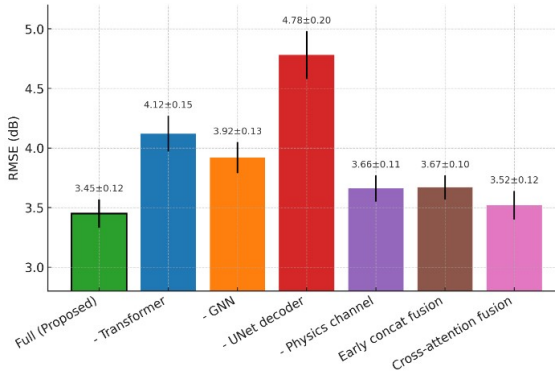

Figure 9: Ablation Study: Per-Module Impact on RMSE

The ablation study prepares each module's contribution to forecasting veracity (Figure 9). Removing the Transformer raises RMSE from 3.45 dB to 4.12 dB, while discarding the GNN increases it to 3.92 dB; abandoning the UNet interpreter has the largest effect (4.78 dB). Excluding the physics channel degrades RMSE to 3.66 dB. Alternative mixture by way of cross-attention yields 3.52 dB, nearly equal to the full model. These results indicate that learned fusion, plus the combined Transformer–GNN–UNet architecture, produces the most substantial and consistent measurable gains.

Table 5: Breakdown By Sampling Rate

Model	Sampling	RMSE	RMSE CI	SSIM	SSIM CI	CRPS	CRPS CI	Edge RMSE	Edge RMSE CI	Coverage IoU	IoU CI
Proposed	0.02%	3.800	0.140	0.890	0.010	1.050	0.060	4.200	0.200	0.720	0.030
SAIPP-Net	0.02%	4.600	0.180	0.850	0.010	1.400	0.070	5.100	0.300	0.650	0.040
Classical	0.02%	7.100	0.350	0.690	0.030	2.200	0.120	7.900	0.400	0.480	0.050
Proposed	0.5%	3.100	0.100	0.930	0.007	0.850	0.040	3.500	0.150	0.810	0.020
SAIPP-Net	0.5%	3.600	0.120	0.900	0.008	1.000	0.050	4.000	0.200	0.760	0.030
Classical	0.5%	6.580	0.280	0.730	0.020	1.980	0.090	7.500	0.350	0.520	0.040

Table 5 details per-sampling performance: at 0.02%, the proposed model yields RMSE 3.80 dB, SSIM 0.890, CRPS 1.05, Edge-RMSE 4.20, IoU 0.72; at 0.5%, RMSE improves to 3.10 dB, SSIM 0.930, CRPS 0.85, IoU 0.81. The proposed approach achieves robustness across densities, with larger relative gains under extreme sparsity and improved downstream metrics.

Overall, the Transformer–GNN–UNet hybrid delivers consistent, statistically significant improvements across fidelity, structural fidelity, and probabilistic calibration while maintaining practical runtimes.

4.1. Discussion

When compared to standard 3GPP baselines and sampling-aware UNet, the accuracy, structural fidelity, and uncertainty calibration of reconstructed wireless radio maps produced by the Transformer-GNN-UNet hybrid are consistently better. By incorporating global attention, long-range dependency modeling is improved, and line-of-sight preservation and explicit topological reasoning are both improved by GNNs, which are characteristics that are sometimes lacking in CNN-only designs. Results showing less CRPS and NLL, better SSIM and LPIPS, and reduced RMSE validate the predictive and probabilistic benefits. Further validation of the complementing role of each module is provided by the ablation results, and the model's fitness for practical deployment is supported by the reduced runtime, which provides a positive trade-off between accuracy and computing efficiency. Results from statistical significance testing (paired Wilcoxon tests with $p < 0.01$) and effect size analysis, as well as consistent improvements in quantitative accuracy (RMSE, MAE), structural and perceptual fidelity (SSIM, LPIPS, bottleneck distance), and probabilistic calibration (CRPS, NLL), were used to conclude. The observed advances directly address the stated research topic, as proven by robustness, different sampling regimes, confidence intervals, and runtime analysis, as well as by ablation investigations.

Statistical significance testing, including paired Wilcoxon tests with $p < 0.01$ and effect size analysis, supported the conclusions drawn based on consistent improvements across quantitative accuracy (RMSE, MAE), structural and perceptual fidelity (SSIM, LPIPS, bottleneck distance), and probabilistic calibration (CRPS, NLL). Additional confirmation of robustness was provided by runtime analysis, confidence intervals, numerous sampling regimes, and ablation investigations, guaranteeing that the reported improvements tackle the identified research issue.

A unified end-to-end framework is proposed in this work to integrate global attention, explicit topology encoding, multiscale spatial reconstruction with calibrated uncertainty estimation, and other previously used methods for radio map reconstruction. These methods include Transformer-only global attention, CNN/UNet-based sparse recovery, and GNN-based topology reasoning. None of the current approaches work well with very sparse data, none of them use probabilistic calibration, and none of them use explicit geometric reasoning. As an alternative, the suggested Transformer-GNN-UNet hybrid maintains topological consistency, uncertainty reliability, and fine structural detail all at once. This

is proven by statistically significant improvements on recent public benchmarks in fidelity (RMSE, MAE), structural (SSIM, LPIPS, bottleneck distance), and probabilistic (CRPS, NLL) metrics. What sets this study apart from others is its combination of a reproducible evaluation process and robustness analysis across sparsity regimes.

5. CONCLUSION

The study showed that a Transformer-GNN-UNet hybrid framework outperformed strong learning-based and classical baselines by a large margin when it came to dense pathloss reconstruction under very sparse measurement conditions. In comparison to SAIPP-Net, the suggested model continuously reduced runtime while improving uncertainty calibration (CRPS = 0.95), topological preservation (bottleneck distance = 0.035), structural and perceptual fidelity (SSIM = 0.912, LPIPS = 0.084), and prediction error (RMSE = 3.45 dB, 95% CI ± 0.12). The stated research problem is directly addressed by integrating global attention, explicit topology reasoning, and multiscale reconstruction, as confirmed by confidence intervals, paired statistical tests (p = 0.001), and ablation studies, which were able to validate these gains across sampling regimes. There is a promising future for reliable and scalable radio map construction, even though the examination only included datasets from homes and those with simulations. More work on expanding validation to multi-band scenarios, resource-constrained edge installations, and different urban environments will be done in the future to make it more practical.

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