Explainability of Predictive Uncertainty Models Under Drift in the Telecom Domain

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The Problem: When Models Meet the Real World

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Prediction

Accuracy drops as the test data distribution shifts away from training data

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Uncertainty

Model confidence becomes unreliable — it no longer reflects true prediction error

→

Explanations

XAI methods produce inconsistent, unreliable feature attributions under drift

Gap in the Literature ⚠

No existing framework jointly addresses how uncertainty, calibration quality, and XAI attributions co-evolve under controlled covariate drift in a regression setting, especially in real-world telecom environments

Our Unified Framework

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1
Dataset
IV2I+
AI4Mobile

2
Drift Injection
5%–50%
Covariate Drift

3
UQ Models
BNN (MC Dropout)
Deep Ensemble

4
Calibration
Isotonic Regression
+ ENCE Metric

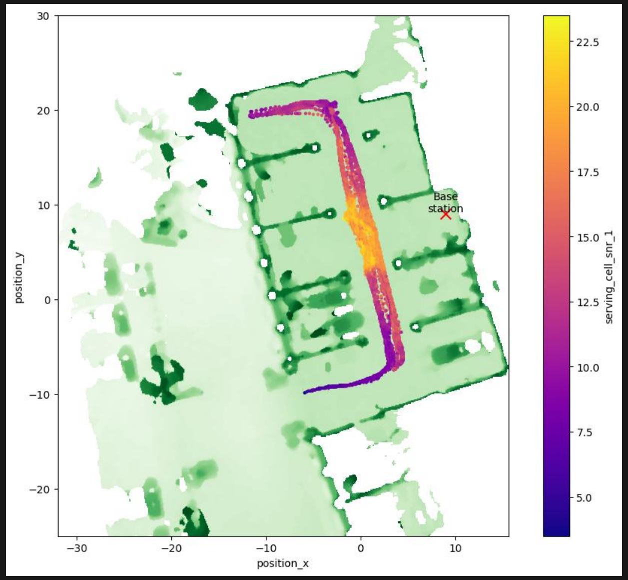
5
XAI Analysis
SHAP + LIME
on Uncertainty

Key Design Choices

- Drift injected into RSRP, RSRQ, RSSI, SNR only: controlled ground truth for validation
- XAI applied to predicted uncertainty (variance), not to point predictions
- Calibration quality assessed before AND after drift, using ENCE metric
- SHAP (global attribution) + LIME (local explanations) used together for cross-validation

Dataset & Model Architecture

AI4Mobile Dataset



Model 1 – Bayesian Neural Network

Architecture: MLP (10 → 128 → 64 → 32 → 1)
UQ Method: Monte Carlo Dropout (p=0.2, T forward passes)
Output: Predictive mean and variance (μ,σ^2)

Model 2 – Deep Ensemble

Architecture: 5 × MLP (10 → 128 → 64 → 32 → 1), different seeds
UQ Method: Variance across ensemble member predictions
Output: Predictive mean and variance (μ,σ^2)

- Both models share the same base architecture for a fair comparison between Bayesian and ensemble approaches to uncertainty quantification
- Calibration via isotonic regression is applied post-hoc, aligning predicted variance with observed squared errors

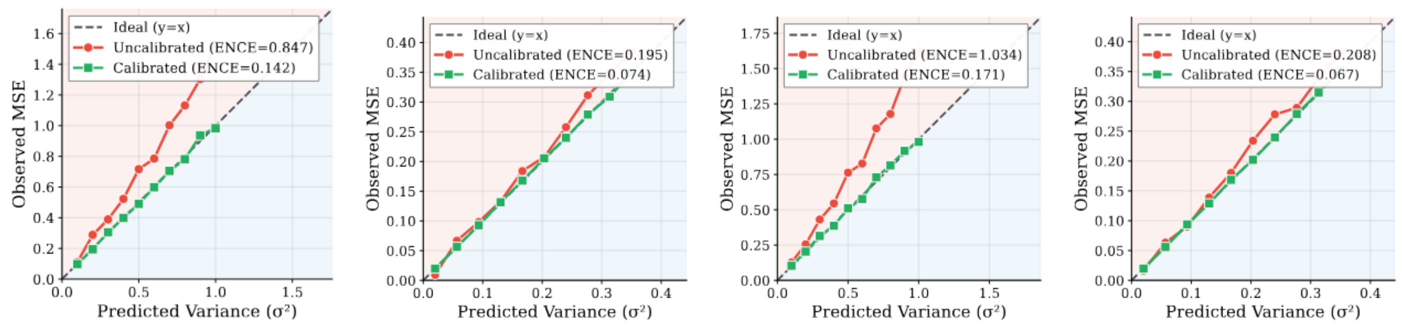
Results — Uncertainty & Calibration Under Drift

ENCE Values Across Drift Levels

Drift Level	BNN Uncalib.	BNN Calib.	Ens. Uncalib.	Ens. Calib.
0% (baseline)	0.847	0.142	0.195	0.074
10%	0.912	0.158	0.199	0.069
25%	1.034	0.171	0.193	0.070
50%	1.256	0.203	0.208	0.067

Key Observations

- **BNN —** Uncalibrated ENCE rises 0.847 → 1.256 (+48%), showing high sensitivity to drift
- **Deep Ensemble —** ENCE stays low and stable. More robust but less adaptive
- **Calibration always helps** — but degrades under drift



(a) BNN (0% drift) (b) Ensemble (0% drift) (c) BNN (25% drift) (d) Ensemble (25% drift)

Thank You!

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Problem	Method	Key Result
Dataset	**Drift Injection**	**UQ Models**
Drift breaks UQ + XAI jointly	BNN + Ensemble + SHAP + LIME	XAI on uncertainty = stable diagnostic

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