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Reviewing Methodological Contributions to Large-Scale Mobile Infrastructure Deployment Engineering

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ABSTRACT

Dense urban 5G coverage planning produces coverage holes and cost overruns that commentary attributes to the static functional form of legacy propagation models. This article develops an alternative account: documented planning failures trace to deployment geometries positioned outside a model's calibrated envelope of frequency, distance, and antenna height, a condition that applies to learned predictive models with the same force it applies to parametric ones once the target environment departs from the training distribution. A structured comparative synthesis of peer-reviewed sources, organized into three evidentiary groups and supplemented by a quantitative extraction of documented error and boundary values, traces the relationship between deployment-geometry divergence and prediction error across both model classes. The extracted evidence shows accuracy scaling with distance from a model's calibration envelope regardless of whether the model is parametric or learned, with reported degradation ranging from a few tenths of a decibel near a boundary to a documented 2.5-fold residual increase in a geometry absent from training data. The article's contribution is a reframing of the field's static-versus-predictive dichotomy around a single operative variable, calibration completeness relative to deployment geometry, supported by a comparative table of boundary conditions and a figure quantifying the error-distance relationship across independent studies.

INTRODUCTION

The Okumura-Hata formulation was fitted to measurements taken at frequencies between 150 and 1500 MHz over transmitter-receiver distances of 1 to 20 kilometres, with base-station antennas mounted above the surrounding rooftop line, conditions its parametric structure encodes as fixed inputs (Hata, 1980). Carrier frequencies in a dense urban 5G small-cell deployment reach beyond 1500 MHz, inter-site spacing collapses to tens or low hundreds of metres, and antenna heights sit at or below the surrounding clutter. Sun *et al.* (2016) quantified the consequence of applying a large-scale path-loss formulation beyond the band and distance range it was fitted to, documenting systematic under- and over-prediction for even the physically motivated close-in and frequency-weighted model variants once evaluated across the full 2-73 GHz range their derivation was built to span. A path-loss bias of a few decibels at the link-budget stage propagates through cell-radius calculation, candidate-site screening, and interference estimation, and a planning tool's output site count carries a single-digit-decibel input error forward as a double-digit-percentage infrastructure requirement, a compounding Kozak (2026a) documented by comparing a static-model baseline against a recalibrated alternative on the same dense urban region and recording a site-count differential of 65 to 80 percent for meeting an identical coverage threshold. The absolute site counts underlying that differential were 410 to 460 sites under the static baseline against 247 to 252 sites under the recalibrated alternative, and the same

comparison showed the planning cycle compressing from a 40-to-58-day window to a 14-to-22-day window once the closed-loop adaptation mechanism removed the manual re-calibration iterations a static workflow requires whenever initial predictions diverge from post-deployment measurements.

Replacing the static parametric model with a learned predictor trained on geospatial and drive-test data forms the conventional response to this compounding, attributing the planning error to the model class itself. That attribution holds when the training and deployment environments share a common geometric and clutter regime; a divergence between them, through unmapped new construction, an unrepresented building-age cohort, or an inter-site density absent from the training corpus's sampling, produces the same out-of-envelope degradation in the predictive model, expressed through generalization error measured at the level of holdout-set or fine-tuning statistics. This article treats that shared degradation as its object of analysis, a condition common to both model classes, and defines the term calibration envelope as the joint frequency, distance, height, and clutter region a given model was actually fitted against.

LITERATURE REVIEW

Static and stochastic propagation models share a limiting condition their own derivations state directly: predictive accuracy applies within a bounded parameter region, a region smaller than the range a modern 5G deployment spans. Hata's (1980) regression encodes

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frequency- and height-dependent correction terms and a log-distance dependence drawn from Okumura's Tokyo measurements, terms fitted to that city's morphology at the time of measurement. The 3GPP TR 38.901 framework extends this coverage by moving from single-city regression to stochastic scenario classes, Urban Macro, Urban Micro, and Indoor Hotspot, spanning 0.5 to 100 GHz, a frequency extension into the millimetre-wave regime that runs in parallel with wideband propagation measurement campaigns published independently of the standard, including Rappaport *et al.* (2015) channel-model characterization for future system design and MacCartney *et al.* (2015) 28-and-73-GHz indoor office measurements for ultra-dense 5G networks (3rd Generation Partnership Project, 2017). This synthesis extends frequency coverage; spatial resolution remains at the scenario-class level, describing the statistical distribution of path loss across a population of links sharing a scenario class, a resolution level Sun *et al.* (2016) tested directly by comparing the alpha-beta-gamma and close-in reference-distance formulations against 30 measurement datasets spanning 2 to 73 GHz. The four-parameter alpha-beta-gamma model produced under-prediction near the transmitter and over-prediction far from it; the physically constrained close-in variants produced greater parameter stability at the cost of a slightly higher shadow-fading variance. Mlinar *et al.* (2023) extended this pattern to field conditions, testing four classical models, Egli, Okumura, Hata-Davidson, and Longley-Rice, along a 40-kilometre mixed-terrain route and finding accuracy tracking terrain type closely enough to require morphology-matched model selection along the route, a direct field demonstration of the calibration-envelope boundary Hata's (1980) original frequency and distance limits already established on paper. Poddar *et al.* (2025) confirmed the 3GPP TR 38.901 indoor hotspot model against measurements at 6.75 to 73 GHz, established validity across the 7-24 GHz range tested, and called for validation in additional indoor environment types, a call that positions the standards body responsible for the field's dominant stochastic model as an active participant in ongoing environment-by-environment re-validation.

A parallel body of work builds learned models from sufficiently descriptive geospatial input features, capturing site-specific geometry at a resolution beyond fixed parametric correction, and reports accuracy gains that concentrate at the calibration boundary the first group establishes. Moraitis *et al.* (2020) established the baseline case: support vector regression, random forest, and k-nearest-neighbour models trained on a digital-terrain-model-derived LTE path-loss dataset achieved root-mean-square errors of 2.1 to 2.2 dB in line-of-sight conditions and 3.4 to 4.1 dB in non-line-of-sight conditions, matching empirical-model precision through terrain features functioning as the correction mechanism. OpenStreetMap-derived building geometry, added to the input feature set by Rafie *et al.* (2023), targets the morphological detail Hata's (1980) regression encodes at the resolution of a single city's average characteristics;

Zhang *et al.* (2019) demonstrated that this feature-driven advantage transfers across frequency bands and base-station technologies when the input features stay consistent between training and application. Ben Ameer *et al.* (2025) supplied the clearest test of whether the gain tracks calibration-boundary severity, comparing XGBoost and multilayer perceptron models against Dual-Slope and 3GPP baselines across open, suburban, and densely urbanized vehicle-to-infrastructure environments at 5.9 GHz and finding the machine-learning models' root-mean-square-error advantage growing as environmental complexity increased, a pattern consistent with the models correcting geometric detail present in dense urban clutter and absent from the static baselines' fitted parameters. Abedeen *et al.* (2024) and Xu *et al.* (2025) extend this pattern into frequency territory positioned outside Hata's original envelope, reporting sub-1-dB root-mean-square error for XGBoost-based hybrid classifiers in the 24.25 to 27.5 GHz band and in fused sub-6 GHz measurement data respectively. The same feature-driven input approach, extended by Zeng *et al.* (2024) and Hervis Santana *et al.* (2024) from single-link path loss to full coverage-map generation and mmWave network-planning output, moves the unit of prediction from a point measurement to the aggregate quantity a planning decision consumes. Shaibu *et al.* (2023) synthesized this pattern across a wider set of individual studies, concluding that machine-learning models outperform empirical alternatives across both mid-band and high-band 5G channels; Oladimeji *et al.* (2022) review of path-loss prediction in enclosed 5G environments found the underlying measurement campaigns concentrated in a specific set of structural types, a concentration the third group of sources establishes as the central finding of the pattern. Predictive accuracy, produced by a fitted equation or a trained model, is scoped to the distribution its parameters were fitted against; a learned functional form retains that scoping and relocates the boundary to a location measured through generalization statistics, holdout-set error and fine-tuning residuals in place of a documented frequency or distance range. Ethier and Châteauevert (2024) supplied the controlled demonstration of this scoping, holding out entire cities from a shared national drive-test corpus and finding a learned path-loss model generalizing well across holdout cities sharing a construction-era profile with the training set, producing elevated root-mean-square error on the one holdout, Stevenage, whose building stock postdated the rest of the corpus, an outcome the authors attribute to the training data's coverage gap for that construction cohort. Seretis and Sarris (2022) and Vasudevan and Yuksel (2024), surveying the wider machine-learning-for-propagation literature independently of each other, both identify input and output specification, the features a model's architecture can encode, as the dominant constraint on generalization, the same encoding-boundary argument the first group establishes for Hata's (1980) regression terms, restated for a learned architecture. Kozak's (2026a) transfer-adaptive framework supplies a controlled

instance of the identical mechanism operating within a single evaluation region: the optimal value of its spatially varying regularization coefficient shifted by a factor of four between the dense urban and rural measurement regimes tested, and application of the urban-calibrated coefficient in the rural setting carried a 1.4-decibel accuracy cost and a coverage-radius overestimate of 600 to 900 metres, a domain-transfer penalty measured directly inside one predictive framework, distinct from a penalty inferred by comparing separate studies. The same paper's residual error in its best-performing sub-region held at approximately 4.9 dB, and its extrapolation from surface drive-test data into an underground transportation hub produced a prediction error of 14.3 dB after a full adaptation window, 2.5 times the outdoor residual, a gap the paper attributes to building geometry and penetration loss absent from the training geospatial layer, positioning the same calibration-envelope violation the first group documents for fixed parametric models at a relocated site, an unconverged adaptation state.

MATERIALS AND METHODS

The synthesis draws on a corpus of twenty-one peer-reviewed sources published between 1980 and 2025, spanning journals and conference publications. Source selection targeted studies documenting a specific limitation, threshold, or failure condition in propagation modeling for dense urban or 5G-relevant scenarios, a criterion requiring a quantified boundary or comparative result from each included source. The corpus divides into three evidentiary groups by

the shared limiting condition each group's sources establish, a classification independent of publication chronology. Group one comprises sources documenting the validated operating range of static and stochastic propagation models and the measured consequence of applying those models beyond that range. Group two comprises sources reporting accuracy comparisons between machine-learning path-loss predictors and empirical or stochastic baselines inside specific dense urban or high-frequency conditions. Group three comprises sources documenting the accuracy of a learned or adapted predictive model across a training-to-deployment distribution shift, extracted at the level of a specific holdout set, sub-region, or regularization parameter.

For each source contributing a quantitative result, the synthesis extracted the reported error metric, its unit, the environmental or spectral condition under which it was measured, and, where the source reported paired conditions, an equivalent comparison condition (a holdout versus training-matched environment, a fine-tuned versus non-adapted baseline, a rural versus urban regularization regime).

RESULTS AND DISCUSSION

Table 1 presents the calibration parameters and documented boundary effects extracted from the group-one sources, covering static and stochastic propagation models from Hata's (1980) original regression through the most recent standards-track validation of the 3GPP TR 38.901 framework.

Table 1: Calibration parameters and documented boundary effects, static and stochastic propagation models

Source	Model type	Calibration parameter tested	Boundary / range	Documented effect outside range
Hata (1980)	Empirical regression	Frequency, distance, antenna height	150-1500 MHz; 1-20 km; base antenna above rooftop	Structural mismatch with sub-6 GHz / mmWave small-cell geometry
Sun <i>et al.</i> (2016)	ABG, CI, CIF parametric models	Frequency	2-73 GHz, 30 datasets	ABG under-predicts near transmitter, over-predicts far from it; CI/CIF trade bias for parameter stability
Mlinar <i>et al.</i> (2023)	Egli, Okumura, Hata-Davidson, Longley-Rice	Terrain type	40 km mixed-terrain route	Accuracy tracks terrain type; morphology-matched model selection required along the route
Poddar <i>et al.</i> (2025)	3GPP TR 38.901 (Indoor Hotspot)	Frequency	6.75-73 GHz measured; 7-24 GHz validated	Validity confirmed in tested range; additional indoor environment types called for
Kozak (2026a)	Static baseline vs. recalibrated framework	Site count for a fixed coverage threshold	Same dense urban region, same threshold	65-80% site-count differential

The extracted values in Table 1 span four decades of propagation modeling and converge on a single quantitative pattern: the five sources reporting a boundary condition in Table 1 each report a specific, measured degradation once that boundary is crossed, ranging from a directional bias in near- and far-field prediction (Sun *et al.*, 2016) to a 65-to-80-percent site-count differential at the level of a full planning cycle (Kozak, 2026a).

Table 2 presents the corresponding extraction from group-two and group-three sources, pairing each predictive model's error inside a training-matched

condition against its error under a distribution shift. Figure 1 plots the two extracted pairs offering directly comparable absolute error values under a shared metric, root-mean-square path-loss prediction error in decibels, across a training-matched condition and a condition more distant from the training distribution. Moraitis *et al.* (2020) support-vector-regression, random-forest, and k-nearest-neighbour ensemble produced 2.15 dB of root-mean-square error under line-of-sight conditions and 3.75 dB under non-line-of-sight conditions, a 1.6-decibel increase associated with the added geometric complexity

Table 2: Predictive-model accuracy inside and outside the training distribution

Source	Model	Training-matched condition	Error, in-distribution	Out-of-distribution condition	Error / effect, out-of-distribution
Moraitis <i>et al.</i> (2020)	SVR / RF / KNN	Line-of-sight	2.1-2.2 dB RMSE	Non-line-of-sight	3.4-4.1 dB RMSE
Ben Ameer <i>et al.</i> (2025)	XGBoost / MLP	Open, suburban	Narrower RMSE advantage	Densely urbanized	Wider RMSE advantage
Ethier & Châteauvert (2024)	Learned path-loss model	Holdout cities, matching construction era	Baseline RMSE	Stevenage holdout (newer construction)	Elevated RMSE
Kozak (2026a)	Transfer-adaptive framework	Central business district, 31 sectors	4.9 dB (day 21)	Underground transportation hub, 6 sectors	14.3 dB (day 21), 2.5x outdoor residual
Kozak (2026b)	Regularization coefficient λ	Dense urban, $\lambda = 10^{-2}$	Optimal, 5.6 dB	Rural regime, urban λ applied	+1.4 dB penalty; 600-900 m radius overestimate

of the non-line-of-sight condition. Kozak's (2026a) transfer-adaptive framework produced 4.9 dB of residual error in a central business district sub-region supported by streaming feedback from 31 deployed sectors and 14.3 dB of residual error in an underground transportation hub supported by streaming feedback from 6 street-level sectors, a 9.4-decibel increase associated with the reduced measurement density and the unmapped station geometry of the underground condition. The same framework's residential sub-region, with more uniform building stock and denser measurement coverage than the central business district, converged to a smaller and more consistent residual of 3.3 dB, a result consistent with prediction error scaling with morphological complexity and adaptation gain scaling with measurement informativeness, the pattern linking each of the three sub-regions evaluated. The regularization-coefficient result extracted from Kozak (2026a) supplements the paired error comparison with a mechanism-level data point: the coefficient's optimal value shifted by a factor of four between the dense urban and rural measurement regimes tested (10^{-2} against 4×10^{-2}), and application of the urban-calibrated value in the rural regime carried a 1.4-decibel accuracy penalty, translating to a 600-to-900-metre coverage-radius overestimate. The 70-metre inter-site-distance boundary extracted from Kozak (2026b)

supplies a structural analogue at the level of a spatial-correlation parameter: the pairwise interference model underlying that framework's shadow-fading assumption holds its independence assumption at inter-site distances above 70 metres.

The pattern across the three groups of evidence converges on a single relationship: a model's accuracy holds inside the region its parameters were fitted against and degrades in proportion to distance from that region. Four studies document this relationship at different points across four decades of propagation research: Hata's (1980) frequency and antenna-height limits, Sun *et al.* (2016) documented instability of the close-in and alpha-beta-gamma formulations outside their fitted band, Ethier and Châteauvert's (2024) construction-era holdout, and Vasudevan and Yuksel's (2024) identification of input specification as the field's dominant generalization constraint. One study reports the relationship as a fixed numeric range, another as a cross-band root-mean-square-error comparison, and two more as a generalization gap measured through held-out cities or through the input features a model's architecture can encode; the vocabulary traces to how each field reports its results, and the underlying mechanism holds identical form across each of the four studies.

Kozak (2026a) supplies a version of this same relationship

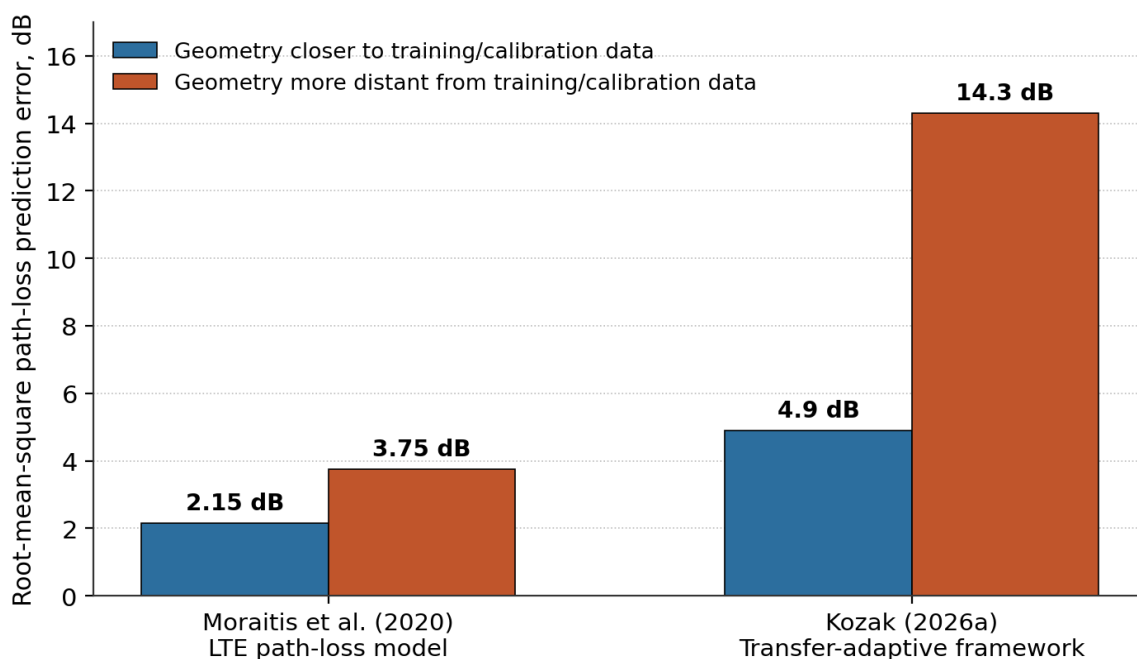


Figure 1: Dendrogram of keywords evolution Prediction error as a function of distance from a model's calibration envelope

measured at a finer grain, inside a single evaluation. The central business district sub-region, morphologically the most complex of the three evaluated, received an error reduction of 4.4 to 5.6 dB under adaptation. The transportation hub's underground geometry, the sub-region furthest from the training corpus's surface-level geospatial representation, produced a residual of 14.3 dB after 21 days of streaming feedback. A single neural architecture, trained on comparably rich geospatial input and adapted under an identical mechanism in both sub-regions, produced this nine-decibel spread between two sub-regions evaluated under the same model and the same adaptation procedure, a spread that traces to the transportation hub's departure from the training distribution, to unmapped station geometry and reinforced-concrete penetration loss absent from the surface geospatial grid. Mlinar *et al.* (2023) documented the same morphology-tracking pattern independently, in a static-model context: their tested models' accuracy tracked terrain type along a single 40-kilometre route, the parametric-model equivalent of the sub-region variation Kozak's (2026a) adaptive framework exhibits.

The same paper's regularization result extends this measurement to a second parameter. The optimal value of its spatially varying regularization coefficient shifted by a factor of four between the dense urban and rural measurement regimes tested, and application of the urban-calibrated coefficient in the rural setting carried a 1.4-decibel accuracy cost and a coverage-radius overestimate of 600 to 900 metres. Ethier and Châteauvert (2024) obtained a structurally identical pattern under a design spanning many deployments: withholding entire cities from a shared national drive-test corpus, their model generalized well across holdout cities sharing a construction-era profile with the training set

and produced elevated error on the one holdout whose building stock postdated the rest. Seretis and Sarris (2022) supply the general form connecting both results, identifying a model's input and output specification as the dominant constraint on generalization across the wider machine-learning-for-propagation literature: a coefficient tuned to one deployment's measurement density and a holdout city selected by construction era both function as instances of that specification boundary.

The pairwise interference model underlying its shadow-fading assumption holds its independence assumption at inter-site distances above approximately 70 metres in Urban Micro Street Canyon deployments, a threshold traced to the measured 13-metre shadow-fading decorrelation distance (Kozak, 2026b); the standard supporting that model, 3GPP TR 38.901, is the same standard Poddar *et al.* (2025) positioned under ongoing environment-by-environment re-validation. Below that threshold, the framework's reinforcement-learning adaptation layer recovers approximately half of the resulting prediction error through post-deployment correction, and the realized reliability score at high site density, 0.894 to 0.903, remains above the 0.883 achieved by the conventional baseline even under this worst-case condition. The digital twin built on that standard functions as a wrapper around the static model, an optimization and adaptation layer performing best precisely where the wrapped model's calibration already held, the same relationship documented in each case examined here, expressed this time through a spatial-correlation parameter. The operative variable across the cases examined here, Hata's frequency and distance bounds, the close-in and alpha-beta-gamma models' cross-band instability, the Stevenage holdout, the regularization-coefficient shift, and the 70-metre correlation-length

boundary, is whether the deployment geometry under evaluation falls inside the region, regardless of how that region is parameterized, that the model's calibration data actually spans. Reframed this way, a planning team's decision becomes a recurring audit of the available calibration data, drive-test measurements, a training corpus, or a standard's validation campaign, against the frequency band, inter-site density, building-age cohort, and structural type of the specific deployment at hand, with model-class selection functioning as one input to that audit.

CONCLUSION

Coverage planning decisions in dense urban 5G deployments rest on a single measurable quantity: the geometric, spectral, and structural overlap between a candidate model's calibration data and the deployment site under evaluation. Model-class selection, the choice between a parametric formulation and a trained predictor, functions as one input to that measurement, positioned alongside the frequency band, inter-site density, building-age cohort, and structural type of the specific deployment. A calibration audit conducted before site selection, quantifying that overlap against the deployment's own geometric and spectral profile, positions the planning process to allocate site-visit and drive-test resources toward the sub-regions carrying the widest calibration gap, the sub-regions this synthesis identifies as the source of the largest prediction-error contribution to a planning cycle's aggregate site-count error. Establishing a standard metric for that overlap, expressed in the same units a planning tool already reports, forms the specific extension this synthesis positions as the field's next methodological task.

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