Fixed Wireless Access: Coverage, Performance, and the Role of Cellular Infrastructure

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***Abstract*—Licensed Fixed Wireless Access (FWA) over cellular networks has become one of the fastest-growing broadband technologies in the U.S., with significant policy relevance through federal programs such as the Broadband Equity, Access, and Deployment (BEAD) program. Nevertheless, no large-scale empirical study has characterized its availability, performance, and relationship to the underlying co-located cellular network. In this work, we combine four years (2022-2025) of provider-reported availability data from the FCC's National Broadband Map, publicly-available Ookla Speedtest aggregated measurements, and individual Ookla measurements from eight U.S. cities to study FWA characteristics. We find that FWA coverage shows an overall increasing trend, and is primarily co-located in urban areas where wireline infrastructure is also available; when FWA exists as the sole connectivity option, it is predominantly in rural areas. In production networks across the eight U.S. cities, only 28% of individual FWA Speedtest measurements comply with the FCC's $\geq$100/20 Mbps and $\leq$100 ms broadband service threshold. Finally, we employ a fractional logit model to evaluate whether observable cellular context can predict FWA service compliance. We find that while co-located cellular features are statistically associated with FWA service compliance, they are not sufficiently predictive to substitute for direct FWA performance measurements.**

I. Introduction

Access to reliable, high-speed broadband is essential for full participation in economic, social, and civic life [1], [2]. Yet, millions of households in the United States (U.S.) lack high-quality broadband, particularly in rural areas and marginalized communities [3], [4]. To address these disparities, the U.S. federal government has launched several large-scale initiatives to support and incentivize providers to deploy broadband infrastructure in unserved and underserved areas. Accurately targeting these investments requires reliable data on broadband availability and quality. In the U.S., the Federal Communications Commission (FCC) publishes the National Broadband Map (NBM) [5], developed under the requirements of the Broadband DATA Act [6], to report broadband availability. The map is based on semiannual coverage submissions from internet service providers (ISPs), who report the technologies they offer and the maximum advertised speeds at each location they serve. However, since the NBM predominantly relies on this self-reported data from ISPs, it is prone to overstatements of coverage and performance, as confirmed by multiple studies [7]–[10]. Independent measurement platforms such as Ookla® Speedtest® [11] and Measurement Lab [12] are therefore essential for assessing real-world performance and validating ISP-reported coverage claims.

The NBM reports availability across multiple broadband technologies, including fixed wireline (fiber, cable, DSL), FWA, satellite, and mobile. Among these, FWA, which transmits broadband over radio links from nearby cellular base stations using unlicensed and/or licensed spectrum [13], is one of the fastest-growing in the U.S., and has become increasingly consequential given its eligibility under the $42.45 billion Broadband Equity, Access, and Deployment (BEAD) program.

In this study, we focus on licensed FWA,[1] which utilizes cellular spectrum to serve fixed locations. Since the rollout of 5G in the U.S. beginning in 2019 [14], FWA availability has expanded rapidly [15], [16]; today, major carriers report millions of FWA subscribers [17]. However, since FWA delivers broadband over cellular infrastructure, its performance tends to be variable due to radio conditions, congestion, shared cellular infrastructure, and other environmental factors [18]. In one study [19], addresses covered by terrestrial FWA accounted for the majority of challenge claims submitted to the FCC. Multiple studies have examined mobile broadband performance [20]–[24], and recent work has analyzed the interplay between U.S. broadband access technologies, including FWA, using performance trends from public datasets [25]. Yet, despite the technology's growing relevance, large-scale empirical characterizations of FWA performance in production networks, and its relationship to the performance of co-located cellular networks operating over shared infrastructure, remain understudied.

Within this context, the objective of our work is to analyze FWA coverage and performance in U.S. production networks. Specifically, we ask three research questions:

1) What are the longitudinal trends in FWA's U.S. coverage footprint and its associated performance?
2) What spatial and temporal factors drive variations in FWA performance?
3) What is the relationship between FWA and co-located cellular network performance?

To answer these questions, we present a large-scale empirical study of FWA coverage and performance in the U.S. To do so,

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[1]We refer to licensed FWA simply as FWA in the remainder of the paper.

we combine provider-reported availability from four years of NBM releases (December 2022 through December 2025) with Ookla Speedtest measurements from the same period. Ookla data consists of both publicly available quarterly aggregated data and proprietary, individual measurements from eight U.S. cities. The latter dataset was obtained through a Data Use Agreement (DUA) between our institution and Ookla.

Given FWA's reliance on cellular infrastructure, we are particularly interested in how FWA performance relates to that of co-located cellular networks. Hence, using the individual Ookla Speedtest measurements, we assess whether observable cellular characteristics are able to predict whether FWA performance will meet the FCC's broadband service threshold of $\geq$100/20 Mbps download/upload speed and $\leq$100 ms latency.

Our key findings are the following:

- U.S. FWA coverage shows an overall increasing trend and is primarily co-located with wireline networks. Locations where FWA is the sole fixed connectivity option are primarily rural.
- In 2025, over 45% of urban and 55% of rural FWA-covered BSLs report maximum advertised speeds below the 100/20 Mbps broadband service threshold. In production networks in the eight U.S. cities, only 28% of individual FWA Speedtest measurements in 2025 comply with the FCC's broadband service threshold.
- Ookla Speedtest consistently measured lower throughput over FWA than on cellular networks for the same carrier within the same geographic area in 2025. Cellular characteristics such as frequency band, signal strength (RSRP) and signal quality (RSRQ) are moderately correlated with FWA performance, but the magnitude varies across cities.
- Co-located cellular characteristics are statistically significant but insufficient predictors of FWA service compliance, with predictive relationships varying widely across cities and carriers. While shared infrastructure provides useful signal, cellular measurements do not reliably substitute for direct FWA performance assessment.

The remainder of this paper is organized as follows. Section II provides a brief background about licensed FWA and its characteristics. In Section III, we describe the datasets we utilize. Section IV presents our analysis of FWA coverage, production network performance, and its relationship with cellular networks. Section V examines the predictability of FWA service threshold compliance from observable cellular features. We review related literature in Section VI and conclude in Section VII.

II. Background

Licensed FWA delivers fixed broadband to a customer-premises equipment (CPE) over a cellular radio link, using the same licensed spectrum and base station infrastructure as the carrier's cellular network [13]. Modern FWA deployments operate across the spectrum bands used for 5G service, including sub-6 GHz, mid-band (C-band), and millimeter-wave (mmWave) frequencies, each with inherently different signal propagation characteristics that affect coverage, capacity, and performance [18]. Despite this shared infrastructure, FWA and cellular networks differ in several ways that impact end-user performance. FWA endpoints are stationary CPEs, rather than mobile devices, and are typically installed at fixed indoor or outdoor positions with directional, high-gain antennas oriented toward the serving cell [26]. As a result, FWA performance is not affected by handovers and other mobility-related signaling overheads that are characteristic of cellular networks [24]. Further, though FWA and mobile users typically share the same cells, spectrum, and scheduling resources, they may be governed by different Quality of Service (QoS) classes, scheduler priorities, or subscription policies.

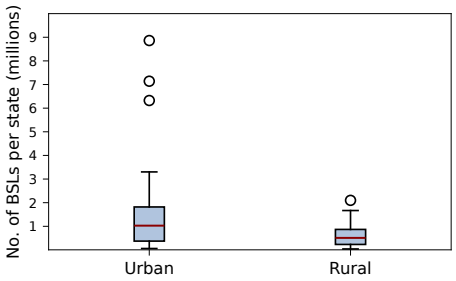


Fig. 1: Distribution of BSLs by state and area type.

In the U.S., FWA has become directly relevant in broadband infrastructure policy. Under the $42.45 billion BEAD program, FWA is eligible for deployment funding if it can reliably deliver at least 100/20 Mbps (download/upload) with round-trip latency no greater than 100 ms [27], [28]. This makes the empirical performance of FWA central to assessing both consumer broadband quality and federal investment decisions.

III. Datasets

In this section, we describe each of the datasets we utilize in our study and our strategy for integration.

A. *Broadband Serviceable Location Fabric*

The Broadband Serviceable Location Fabric (BSLF) [29] is a geospatial dataset that is updated semiannually. It was developed under the FCC's direction to identify all U.S. structures where fixed broadband is or could feasibly be deployed. Each location is represented as a (latitude, longitude) point with a unique identifier and is linked to census blocks and H3 hexagons (resolution eight) [30] for spatial analysis. For this study, we utilize 106.7 million broadband serviceable locations (BSLs), marked as residential and mixed-use, across the 50 states and the District of Columbia. Using the U.S. Census Bureau's urban-rural classification at the census block level [31], we observe that urban locations account for 72% of all BSLs, with state-level counts ranging from under 100k to nearly 10 million; rural locations account for the remaining 28%, as shown in Figure 1.

Limitations. Accuracy of the BSLF relies on the completeness and timeliness of input datasets. Lags in data updates, such as newly constructed buildings or recent infrastructure changes, can cause omissions or geolocation inaccuracies.

B. FCC National Broadband Map

The FCC's National Broadband Map (NBM) [5] presents provider-reported information on fixed and mobile broadband service in the U.S. It leverages BSLF data to obtain the set of locations where broadband service could be or is deployed, and primarily uses broadband availability and speed data submitted by internet service providers to report where different network technologies are deployed. Fixed broadband availability is reported at the granularity of individual locations. For each BSL, providers report one or more technology types (e.g., copper, cable, fiber, FWA) and a maximum advertised speed tier. Mobile network availability is mapped using H3 hexagonal cells at resolution nine ($\approx$0.1 km^2); providers report coverage by technology generation (3G, 4G LTE, 5G NR) and corresponding speed threshold. For our analysis, we use the yearly NBM snapshots for terrestrial fixed broadband availability from December 2022 through December 2025, to characterize the evolution of FWA availability. Our focus is on licensed FWA availability and performance, as this corresponds to FWA services that operate over dedicated licensed cellular spectrum.

Limitations. Provider-submitted data are known to overstate coverage footprints and advertised speeds, particularly in rural areas [7]–[9], [32], [33]. Independent audits and academic studies have repeatedly identified misclassified technologies and inflated speed tiers in both fixed and mobile datasets.

C. Ookla Speedtest Data

The Ookla® Speedtest platform allows users to assess the quality of their Internet connection through a web-based portal or a dedicated desktop or mobile application [11]. For each test, Ookla selects a geographically proximate measurement server with the lowest round-trip time (RTT) and dynamically scales parallel TCP connections to saturate the bottleneck link. While a single test captures an instantaneous snapshot of performance at a specific location and time, the aggregation of millions of measurements across diverse locations, times, and network conditions provides broad insight into performance trends for a given geographic area. We utilize two complementary Ookla datasets in this study.

Ookla Aggregated Data: Since January 2019, the Ookla Open Data Initiative has released an aggregated, quarterly (i.e., every three months) dataset of its global, crowdsourced Speedtest measurements [34]. Individual tests that include GPS-derived location information are aggregated into Web Mercator tiles [35] at zoom level sixteen ($\approx$610.8 m $\times$ 610.8 m at the equator); each tile is identified by a unique quadkey. For each tile and quarter, the dataset provides averages for fixed and mobile broadband, separately, reporting download speed, upload speed, round-trip latency, latency under load, the total number of tests, and the number of unique devices that submitted tests. For this study, we utilize quarterly aggregated U.S. fixed network Speedtest measurements from the same period as the NBM snapshots. During this period, the Speedtest dataset consists of roughly 60-75 million tests per year. This data spans 2.6-2.7 million unique tiles per year.

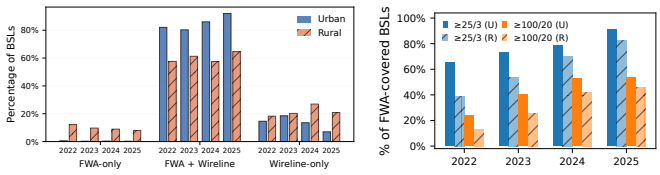
Ookla Individual Data: Through a Data Use Agreement (DUA), we obtained Ookla Speedtest Intelligence® data for eight major U.S. cities from January 2022 - December 2025.[2] In contrast to the publicly available aggregated data, this dataset contains granular, individual crowdsourced measurements and metadata, which includes per-test fixed and cellular provider identification, connection types, type of user equipment and chipset details, and physical-layer metrics (e.g., RSRP, RSRQ, and frequency band) for each measurement. Our analysis window includes roughly 14 million fixed tests, with 3.1-3.7 million tests per year, and 2 million mobile tests, consisting of 450-650k tests per year in the eight cities. For this study, we select two major U.S. cellular carriers that offer widespread FWA connectivity. This yields 3.5 million FWA measurements and 1.5 million cellular measurements. To account for measurement anomalies, we remove the top and bottom 1% of performance values across download speed, upload speed, and latency. 3.3 million FWA measurements and 1.4 million cellular measurements remain for analysis.

For an in-depth study, we focus on the 2025 data to characterize FWA performance under the current 5G cellular infrastructure landscape and use data from earlier years to study longitudinal trends. Each of the eight cities has a population between 400k and 700k and covers an area ranging from 90 to 350 mi^2. During our study period, median download speeds range from 75 to 300 Mbps, upload speeds from 10 to 55 Mbps, and latency from 15 to 30 ms across both datasets; we present their yearly medians in Table I of the Appendix.

FWA test identification. The fixed network measurements from the Ookla Individual Data report the ISP name for each test but do not include an explicit FWA flag. To reliably identify FWA tests, we apply three filters. First, we restrict our analysis to carriers that operate both a cellular and a co-located FWA service. Next, we retain tests whose connection-type metadata and ISP string indicate FWA service (e.g., "Wireless", "5G Home Internet"). A cellular carrier that offers FWA may also provide other wireline technologies (e.g., fiber, cable) at the same locations. For tests with unresolved classification from the previous filters that also have reliable location information, we retain those tests in resolution-8 H3 hexagons where the carrier reports licensed FWA availability and no other wireline technology. This removes ambiguous tests in dual-coverage areas. Together, these filters enable us to extract the most reliable set of FWA tests for our analysis.

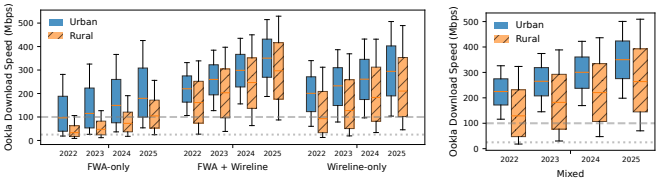
Limitations. Crowdsourced Speedtest measurements are inherently uncontrolled and may introduce sample and selection biases related to test timing, device capabilities, and subscription plans [36], [37]. Ookla Speedtests are user-initiated, and are hence subject to these biases. Prior studies have documented that users often run tests when experiencing

[2]The dataset can be obtained through a data use agreement. Due to our DUA, we are unable to disclose carrier names and city names.



(a) FWA coverage (b) FWA speed thresholds

Fig. 2: Evolution of reported U.S. FWA coverage and its advertised maximum speed thresholds.



(a) Single technology coverage (b) Mixed coverage

Fig. 3: Measured download speeds for areas with different reported FWA coverage footprints.

service issues or after equipment changes, and that higher-tier subscribers and tech-savvy individuals may be over-represented. Although these biases complicate characterizing every individual tile, our use of longitudinal aggregated data mitigates transient effects and captures a wide array of user scenarios, enabling meaningful analysis of trends in broadband performance.

D. *Dataset Integration*

Combining provider-reported coverage data with crowd-sourced performance and census datasets provides a view of broadband connectivity that no single dataset can offer on its own. However, these multiple datasets follow different temporal and spatial resolutions. For a robust analysis, we first map the location identifier of each BSL in the BSLF dataset to the NBM data to obtain the complete view of provider-reported fixed broadband availability. Employing geospatial methods, we compute spatial indices at the quadkey tile and H3 hexagon resolutions for each BSL, and perform spatial joins to associate provider-reported coverage with measured performance. We note that merging across differing spatial resolutions can blur fine-scale variations. We account for these caveats when interpreting our findings.

IV. Role of FWA in Broadband Connectivity

Our study is motivated by three research questions: how have FWA coverage and performance evolved, what are FWA's spatial and temporal characteristics in production networks, and what relationship does FWA share with co-located cellular network performance? To answer these questions, we first characterize how FWA coverage and advertised speeds in the U.S. have evolved during our analysis period using provider-reported data from the NBM. Then, we analyze how FWA performs in-the-wild, studying its performance trends, broadband service compliance, and spatial and temporal variability. Finally, we explore the relationship between FWA and co-located cellular network performance.

Question 1: What are the longitudinal trends in FWA's U.S. coverage footprint and its associated performance?

To answer this question, we utilize two datasets: provider-reported coverage data from the NBM joined with BSLF data and rural/urban area types, and the Ookla Aggregated data.

FWA coverage evolution and composition. We begin by examining how FWA coverage has evolved from 2022 to 2025, disaggregated by area type and technology overlap. The terrestrial broadband landscape can be subdivided into three categories: FWA + Wireline, where both FWA and wireline technologies are present; FWA-only, and Wireline-only, where FWA and wireline are the sole reported access technologies, respectively. Using these categories, we explore how broadband coverage and performance differ based on available access technologies.

Figure 2a presents the percentage of urban and rural BSLs in each category. The figure shows that there is an overall increasing trend in the reported FWA presence across both FWA-only and FWA + Wireline categories in urban and rural areas (roughly 84.3 million BSLs in 2022 to 92.6 million BSLs in 2025). Growth is concentrated in urban areas where wireline broadband is already present: the share of urban BSLs with both FWA and wireline coverage shows an increase from 82% in 2022 to 92% in 2025, an increase of roughly 7.7 million BSLs. In rural areas, the increase is from 58% to 65%. FWA-only coverage is negligible in urban areas. Rural areas experienced a decrease in BSLs with FWA-only coverage, from ∼12% in 2022 to ∼8% in 2025. Rural areas consistently have a greater percentage of BSLs with FWA-only and Wireline-only coverage than urban BSLs, indicating greater dependence on single access technologies.

FWA advertised speed tier benchmarks. In 2024, the FCC increased its broadband speed benchmark from 25/3 Mbps (download/upload) to 100/20 Mbps [38]. With this context, we analyze the share of FWA-covered BSLs (across both FWA-only and FWA + Wireline categories) whose advertised FWA speeds meet these two key broadband thresholds, as shown in Figure 2b.[3] The share of FWA-covered BSLs that report meeting these thresholds increased from 2022 to 2025, with urban (U) BSLs outpacing rural (R) for both thresholds. From 2022 to 2025, the percentage of urban BSLs that met 25/3 Mbps increased from 65% to 90%, while in rural BSLs, the percentage increased from 40% to 83%. At 100/20 Mbps, urban BSLs showed an increase from 24% to 54% while rural BSLs increased from 13% to 45%. However, despite this progress, as of 2025, over 45% of urban and 55% of rural FWA-covered BSLs still fall below the 100/20 Mbps threshold based on advertised speeds alone.

Performance trends by coverage type. We now examine the relationship between advertised maximum speeds and real-

[3]Between 2022 and 2025, the maximum advertised speeds for wireline and FWA increased substantially (shown in Figure 11 of the Appendix).

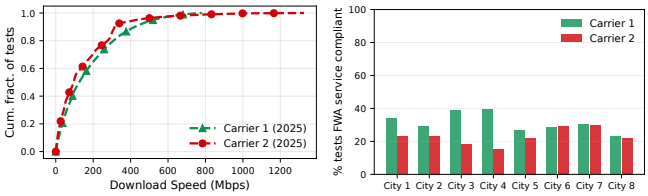
world Speedtest measurements, subdivided by the technology overlap type. We utilize the national level Ookla Aggregated Data for this analysis. However, we note that this aggregated data does not distinguish FWA from fixed wireline Speedtests within a tile.

Because the NBM reports availability at the individual BSL level while the Ookla aggregated data reports performance at the tile level, we apply the same three-way classification introduced earlier (FWA + Wireline, Wireline-only, FWA-only) at the tile level, categorizing each tile based on the technology mix reported across all its constituent BSLs:

- FWA + Wireline tiles, where *every* BSL within the tile reports coverage by both a wireline technology (e.g., cable, fiber, copper) and FWA
- Wireline-only tiles, where *every* BSL reports coverage exclusively by one or more wireline technologies and no FWA coverage
- FWA-only tiles, where *every* BSL lacks wireline availability and reports coverage solely by FWA

This approach allows us to isolate tiles where deployment strategies are consistent across all locations, reducing ambiguity caused by mixed footprints. It also enables comparisons of coverage patterns, performance distributions, and urban-rural variation across distinct infrastructure types. By evaluating these categories separately, we can assess how measured performance trends differ between areas where FWA is reported as the sole fixed access technology and areas where it is reported alongside wireline infrastructure. We restrict our analysis to tiles with at least five Speedtest measurements each year. This leaves roughly 1.4 million unique tiles per year (52-54% of total tiles). After excluding tiles with mixed-coverage footprints, roughly 25-30% of all Ookla tiles remain for the analysis each year.

Figure 3a presents the distribution of Ookla download speeds across the three tile categories, disaggregated by area type. All three categories show performance improvement over this period. FWA-only tiles exhibit the lowest absolute speeds but the highest relative growth: urban medians increase from ∼100 Mbps to 180 Mbps, while rural medians grow from ∼30 Mbps to 105 Mbps. Wireline-only tiles show steady improvement: urban and rural medians reach approximately 295 Mbps and 210 Mbps by 2025, respectively. FWA + Wireline tiles consistently deliver the highest measured speeds; urban medians reach 350 Mbps in 2025. Notably, in urban areas, FWA-only tiles show increasing but widely-varying performance, with only the upper percentile speeds reaching those of wireline-covered tiles by 2025. In rural areas, however, ∼50% of FWA-only tiles remain below the 100 Mbps broadband service threshold (shown as the dashed line), consistent with the advertised speed gaps identified earlier. We note that because FWA + Wireline tiles contain tests from both technologies, performance trends reflect their combined behavior, and observed improvements may stem from individual technology gains, shifts in test-taker composition, or evolving subscription tiers.



(a) FWA performance (b) FWA service compliance

Fig. 4: 2025 FWA download speeds and measurements meeting FWA service threshold (≥100/20 Mbps, ≤100ms).

Figure 3b shows the performance distribution of the remaining tiles, where BSLs report a mix of coverage types across the four years. The trends are consistent with that of the single technology tile categories across all years and area types, indicating that the subset in Figure 3a is representative of the broader Ookla speed distribution.

Having characterized FWA's evolving coverage footprint and its association with measured performance trends at a national level, we now leverage individual Speedtest measurements to explore the spatial and temporal characteristics driving FWA performance in production networks.

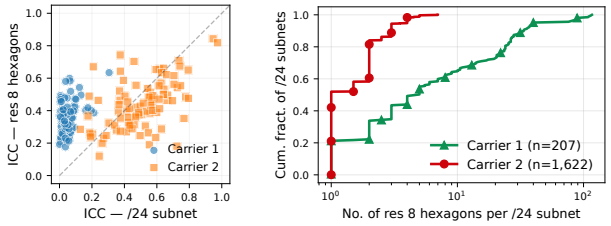
Question 2: What spatial and temporal factors drive variations in FWA performance within U.S. production networks?

To answer this question, we leverage the Ookla Individual Dataset, consisting of 3.3 million FWA measurements from eight cities, using the methodology described in Section III. Importantly, this dataset has carrier and device metadata that we leverage to disaggregate performance and characterize spatial and temporal properties. While we also analyze upload speed and latency, we focus our presented analysis on download speed because it is often a key determinant of user experience and typically demonstrates wider variation than upload speed; however, we confirm that the trends are consistent across all metrics. Broadly, the dataset indicates an upward trend in FWA adoption over our study period in all eight cities: Carrier 1 grows from ∼120k devices in 2022 to 165k in 2025; Carrier 2 grows from ∼35k to ∼60k.[4]

FWA performance. We begin by examining the distribution of FWA performance from individual Speedtests. Because performance steadily improves each year, we focus our analysis on the 2025 data, comprising 812k measurements. Figure 4a presents the cumulative distribution of FWA download speeds in 2025 by carrier. The distributions are similar, with median speeds of 100-125 Mbps, and 20% of tests exceeding 300 Mbps for both carriers. However, the lower tail is substantial: roughly 40-50% of tests for both carriers fall below 100 Mbps, the download speed broadband service threshold.

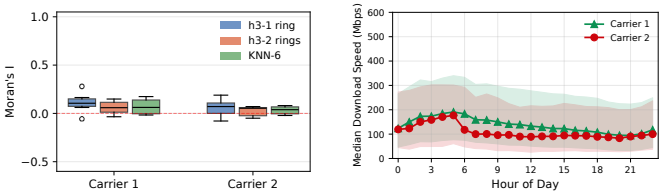
FWA service compliance. The BEAD program [27] includes FWA as an eligible technology for broadband deployment

[4]The Ookla individual dataset reports a unique device identifier for each test-taker, which we use as a proxy to track FWA adoption over time. For web-based tests, Ookla reports a session identifier, which serves as the closest proxy for a unique device unless the user clears their browser cache.



(a) Monthly ICC (b) FWA /24 subnets

Fig. 5: Spatial clustering of FWA download speeds and the spread of their subnets, by carrier.



(a) Moran's I (b) Impact of time of day

Fig. 6: Spatial and temporal influences on FWA speeds.

funding, subject to reliably offering at least 100/20 Mbps (download/upload) and at most 100 ms latency. We evaluate what fraction of FWA tests in our dataset meet this threshold, which we refer to as the FWA service compliance rate. Overall, we observe a 28% service compliance rate for individual FWA Speedtest measurements across all eight cities. Figure 4b presents the per-city overall service compliance rates. Both carriers demonstrate exceedingly low compliance: only 15% to 40% of Speedtest measurements meet the FWA service threshold in each city.

FWA performance variability. Because FWA operates over shared cellular infrastructure, its performance is inherently shaped by the same spatiotemporal factors that affect cellular networks, such as tower density, spectrum allocation, and user load. Industry reports have noted that FWA performance can degrade during peak hours due to congestion from co-located mobile users [39]. To understand to what extent these patterns manifest in our data, we examine the spatial and temporal dimensions on FWA performance.

Spatial analysis. For each test, Ookla reports the /24 IP subnet of the test-taker,[5] and whether the test location is IP-geolocated or GPS-geolocated. Of the 812k FWA tests in 2025, approximately 160k (roughly 20%) include GPS-derived location information. Because of the known inaccuracies in IP-geolocation, we focus on the GPS-derived subset, whose speed distributions closely match the full dataset, for our spatial analysis. Motivated by prior work that used /24 IP subnets as a unit of analysis for wireless ISP performance [40], we compare two candidate aggregation units: /24 IP subnets and H3 resolution 8[6] hexagons (hex8).

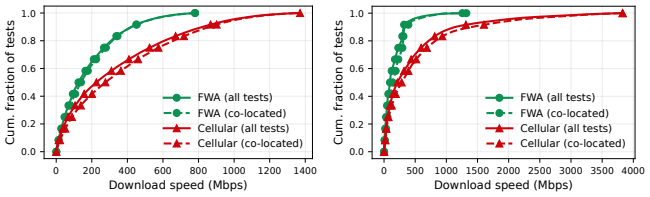
To quantify which aggregation unit produces more internally homogeneous performance groups, we compute the intraclass correlation coefficient (ICC), which measures the share of total variance in performance that is attributable to between-group differences versus within-group differences, for both units (we describe ICC in detail in the Appendix). We report the results for download speed. An ICC of 1 indicates all variation is between groups, while 0 indicates no group-level structure. We compute ICC separately for each city and month to account for IP churn [41]. Figure 5a presents the results. For Carrier 1, hex8 units consistently yield higher ICC (0.2-0.6) than /24 subnets, which rarely exceeds 0.1. This indicates that geographic proximity is a stronger grouping principle than network topology for this carrier. For Carrier 2, both units produce comparable ICC values, reflecting the carrier's use of geographically compact subnets, which we show in Figure 5b. We observe in Figure 5b that Carrier 1 subnets span a wide range, with roughly 40% covering more than 10 hexagons. This explains the low ICC observed for /24 grouping. Carrier 2 subnets are more compact, with over 80% spanning less than 5 hexagons. This results in comparable ICC values between /24 and hex8 units. Because hex8 grouping yields consistently high ICC for both carriers, we adopt it as the spatial aggregation unit for the remainder of our analysis.

Next, we examine whether FWA performance across these hex8 units exhibits spatial clustering. We compute Moran's I [42] on median hex8-level download speeds for each city-carrier combination, using the immediate H3 resolution 8 neighbor ring to define spatial weights; this retains over 90% of hexagons across all cities. Figure 6a presents the distribution of city-level Moran's I values. Across both carriers, I-values are mostly positive (-0.07-0.3), indicating that FWA performance is spatially clustered, although with varying levels across cities. To assess sensitivity to our choice of neighbors, we also compute Moran's I using 2-ring H3 neighbors and k-nearest-neighbor (KNN) spatial weights with the six nearest hexagons, and observe a similar pattern.

Temporal analysis. Cellular networks are known to experience performance degradation with higher network load. Here, we examine whether FWA exhibits similar patterns. Figure 6b presents the 2025 median hourly FWA download speeds; shaded regions indicate the interquartile range (P75-P25). Overnight hours (12 AM-6 AM) show the highest median speeds for both carriers, while daytime and evening periods show lower but relatively stable performance. A Kruskal-Wallis test across hourly bins confirms that the differences are statistically significant ($p < 0.001$) for both carriers, though the effect sizes are small: $\varepsilon^2 = 0.014$ for Carrier 1 and $\varepsilon^2 = 0.012$ for Carrier 2, indicating that time of day explains less than 2% of total performance variance.

[5]Ookla reports the IPv6 address only for few Speedtests. Hence we use IPv4 for this analysis.

[6]We use resolution 8 hexagons, as this aligns with the NBM coverage reporting for fixed broadband availability. It also works better than finer resolutions with the sparsity of crowdsourced data.



(a) Carrier 1 (b) Carrier 2

Fig. 7: Distribution of FWA and cellular performance for all tests vs co-located tests.

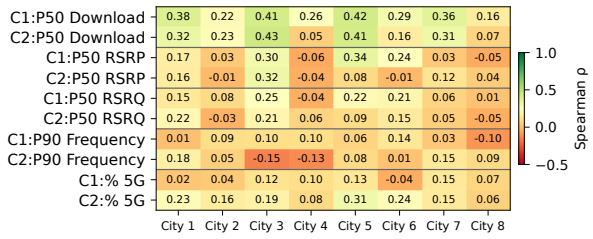


Fig. 8: Spearman correlation (ρ) heatmap between FWA and cellular features for co-located tests.

Question 3: What is the relationship between FWA and co-located cellular network performance?

To answer this question, we leverage the Ookla Individual Data, which contains 812k FWA and 264k cellular tests from 2025. Of these cellular tests, 215k are on 5G networks and 49k are on 4G. We begin by identifying FWA and cellular tests that are co-located using the GPS-geolocated tests at the hex8 spatial resolution (160k FWA and 177k cellular measurements, and 5000 unique carrier-hex8 groups). At this resolution, between 90% and 95% of FWA hexagons also contain at least one cellular test from the same carrier, confirming extensive geographic co-location. For this analysis, we use this subset of geographically co-located tests, comprising approximately 156k FWA and 159k cellular measurements, and 4700 unique carrier-hex8 groups. We note that because each Speedtest is independently initiated by a user, FWA and cellular tests are spatially co-located but not temporally paired.

We present the download speed distributions of all FWA and cellular tests, compared with those that are geographically co-located, in Figure 7. The distributions are nearly identical, confirming that this subset captures the underlying performance distribution. Interestingly, despite sharing the same underlying infrastructure, FWA speeds are lower than those of cellular networks for both carriers. This may be due to a variety of factors, such as different quality of service (QoS) policies, subscription tier limitations, and/or access point configurations between the two services.

We examine whether FWA and cellular performance are correlated within shared areas. For each hex8 where at least five FWA and five cellular tests are present (∼85% of co-located FWA and cellular tests, 2400 carrier-hex8 groups), we compute the medians of FWA download speed and cellular download speed in the same hexagon, per city and carrier. We then compute the Spearman rank correlation between the FWA and cellular median download speeds, and present the results in Figure 8 (rows 1 and 2 for Carrier 1 (C1) and Carrier 2 (C2), respectively). For both carriers, we observe moderate positive correlations across all cities. Carrier 1 shows correlations ranging from 0.16 to 0.42, while Carrier 2 shows slightly lower but positive correlations ranging from 0.05 to 0.43. The spread across cities is notable, with some city-carrier combinations showing correlations near zero and others exceeding 0.4, reflecting both carrier-level and city-level variability.

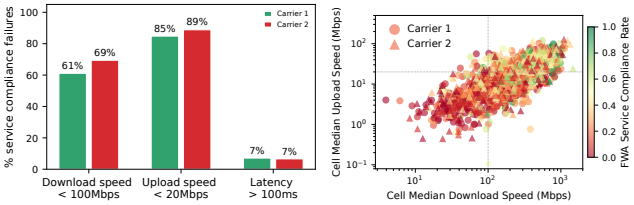
Cellular characteristics and FWA performance. Frequency band fundamentally determines the capacity of a cell, and radio parameters such as RSRP and RSRQ reflect signal conditions. Hence, we examine whether specific cellular network characteristics are associated with FWA performance in co-located hexagons. For each hexagon, we compute correlations between the 90^{th} percentile frequency (reflecting the upper range of cellular capability at that location), median RSRP, median RSRQ, and the share of 5G tests out of total cellular tests and the co-located FWA download speed. Figure 8 presents the city-level correlations by carrier in rows 3 through 10. The correlations with all three cellular characteristics are moderate to weak, with most city-level values close to zero. Further, there are widely varying patterns by carrier-city pairs. For instance, for Carrier 1, $P90$ frequency has weak, positive correlation (ρ=0.10) with FWA download speeds in City 3; however, Carrier 2 shows weak negative correlation for the same metric/city. We hypothesize that this could be due to differences in the infrastructure topology.

Key Takeaways: The Ookla Individual Data shows that overall FWA performance is similar between both carriers: median download speeds between 100 and 125 Mbps and higher tails extending to 1 Gbps. However, over 70% of the tests fail to meet the broadband service threshold, with this value varying widely across cities and carriers. FWA performance is higher during early morning hours and shows spatial clustering at the hex8 level. Despite sharing infrastructure with cellular networks, FWA delivers lower speeds, and the strength of association between cellular characteristics and FWA performance varies by city and carrier. Using these insights, we seek to explore whether co-located cellular features can collectively explain the reliability of FWA, using its service compliance.

V. FWA Reliability: The Role of Co-located Cellular Networks

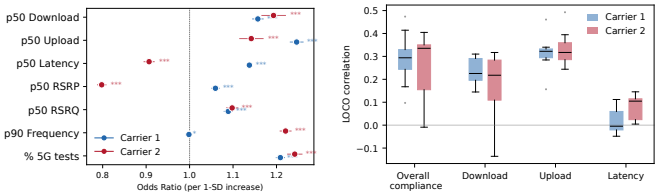
As we show in Question 2, FWA service compliance (ability of FWA to meet the broadband service threshold) varies widely. In this section, we model FWA service compliance rates as a function of observable co-located cellular context, using a fractional response model [43]. To do so, we utilize the hex8-level co-located FWA and cellular tests from Question 3.

Service compliance characteristics. The three components



(a) FWA service non-compliance (b) Effect of cellular speeds

Fig. 9: FWA service compliance failures and the impact of cellular speeds on FWA service compliance.



(a) Log odds ratio (b) LOCO-CV correlation

Fig. 10: Fractional logit model results for the prediction of FWA service compliance using co-located cellular context.

of the FWA service threshold tend to behave differently in cellular networks. Download speeds are typically higher and more variable than upload speeds, and are both shaped by carrier aggregation, channel bandwidth, and duplexing policies [23], [44]. Latency is primarily affected by distance to the server and network congestion. Since FWA shares cellular infrastructure, we examine whether these asymmetries also affect FWA service non-compliance. In Figure 9a, we present the share of all FWA Speedtests that fail to meet service compliance, disaggregated by individual component violations. Latency violations account for only 7% of failures overall, while upload speed is the dominant failure metric.

To investigate this further, we define, for each hex8, FWA service compliance rate as the fraction of FWA tests meeting the broadband service threshold. In Figure 9b, we present the hex8-level median cellular download versus upload speeds, colored by the FWA service compliance rate. Low cellular speeds correspond to low FWA service compliance, as expected, but at higher speeds, compliance becomes more variable. To systematically quantify these associations, we utilize a regression framework. Because our FWA and cellular tests are user-initiated and not temporally aligned, we aggregate them at the hex8 level, and model FWA service compliance rates as a function of aggregated cellular features at this level, ensuring a consistent spatial unit of analysis.

Fractional Logit Model. To model FWA service compliance rates as a function of observed cellular features, we employ a fractional logit model [43], widely used in econometrics for modeling proportion outcomes; we choose this model because FWA service compliance rate is a proportion bounded in [0, 1]. The model extends logistic regression to continuous dependent variables bounded between 0 and 1 by applying the logistic link function. Its coefficients yield interpretable odds ratios, allowing us to better quantify the marginal effect of each cellular feature on FWA service compliance. The model specifies:

$$E[y_i \mid \mathbf{x}_i] = \Lambda(\mathbf{x}_i\boldsymbol{\beta}) = \frac{\exp(\mathbf{x}_i\boldsymbol{\beta})}{1+\exp(\mathbf{x}_i\boldsymbol{\beta})} \tag{1}$$

where $y_i \in [0,1]$ is the FWA compliance rate in hexagon i, $\mathbf{x}_i$ is the vector of cellular features, and $\boldsymbol{\beta}$ is the vector of model coefficients estimated via quasi-maximum likelihood.

Data and preprocessing. To ensure sufficient compliance rate resolution, we only utilize hexagons with at least 10 FWA tests, while retaining the cellular minimum test requirement as five. This yields 131k FWA tests (∼85% of co-located tests, 1800 carrier-hex8 groups), indicating good test coverage across the eight cities. We reuse the aggregated same-carrier cellular features from Question 3: median download speed, upload speed, latency, RSRP, RSRQ, 90^{th} percentile frequency band, and share of 5G tests. All features are standardized, and show no severe multicollinearity (variance inflation factor (VIF) values below 3.5). Given carrier-specific FWA performance variation, we fit four fractional logit models for each carrier: one for the full service compliance threshold, and individual models for download, upload, and latency thresholds to account for varying failure rates. Due to city-level variations in FWA speeds, we use leave-one-city-out cross-validation (LOCO-CV): we train on seven cities and evaluate on the withheld city, repeating for all eight, to avoid spatial leakage. We report pseudo-R^2 (fraction of deviance explained relative to a null model), odds ratios (OR) per one standard deviation (SD) increase (multiplicative change in the odds of compliance), Pearson correlation between predicted and observed compliance rates, and mean absolute error (MAE).

Results. Figure 10a presents the odds ratios for the full FWA service compliance model. For Carrier 1, a one SD increase in cellular upload speed increases the odds of FWA compliance by 25%, making it the strongest predictor, followed by the share of 5G tests (21%) and download speed (16%). For Carrier 2, the share of 5G tests (24%) and 90^{th} percentile frequency (22%) dominate, while RSRP shows an inverse association (OR = 0.80^{***}[7]). This suggests that improved signal strength does not translate to higher FWA compliance for this carrier. While all features are significant ($p < 0.001$) for both carriers, their direction and magnitude of effects vary, reinforcing the observed carrier-level heterogeneity. Despite statistical significance, pseudo-R^2 values remain low (0.034 for Carrier 1, 0.053 for Carrier 2), indicating that the cellular features collectively account for only a small fraction of the variance in FWA compliance rates. This pattern is consistent for individual download and upload compliance rates, but latency lacks sufficient variance for meaningful prediction. We examine the distribution of LOCO residuals (actual -

[7]Asterisks denote statistical significance levels: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

predicted values) for both carriers and present the results for full FWA service compliance in Figure 12 of the Appendix. The residuals are mostly negative, indicating that our model overpredicts FWA compliance relative to the actual rates.

Figure 10b presents LOCO-CV correlations. For full FWA service compliance, pooled correlations are 0.30 and 0.24 for Carrier 1 and Carrier 2, respectively, with MAE values roughly 0.20 for both carriers. Upload compliance yields the strongest correlation (0.33, 0.27), download compliance shows moderate correlations (0.24, 0.22), while latency compliance is effectively unpredictable (< 0.15 for both carriers). City-level variation is substantial: for full service compliance, Carrier 1 ranges from 0.10 to 0.47, and Carrier 2 from -0.01 to 0.40. As a robustness check, we also fit non-linear models, gradient-boosted trees (XGBoost [45]) and Random Forest [46], and observe comparable results across all evaluation metrics for all four compliance models. This reinforces that the observable cellular context provides weak predictive signals for FWA service compliance. We present the MAE results for the full service compliance model in Figure 13 of the Appendix.

Takeaways. Our results confirm that co-located cellular characteristics are statistically significant predictors of FWA compliance. However, the low pseudo-R^2 values across both carriers and all thresholds indicate that the cellular features we observe account for only a small fraction of the total variance in FWA compliance rates. The moderate and varying LOCO-CV correlations indicate that the predictive relationship does not generalize across geographies. Additionally, feature importance differs between carriers, highlighting the role of carrier-specific deployment strategies and unobservable factors such as QoS policies and user subscription tiers. Together, these findings suggest that *co-located cellular features are statistically associated with FWA compliance but not sufficiently predictive to replace direct FWA performance measurements.*

Limitations. Our model uses aggregated, temporally non-aligned user-initiated Speedtests subject to sampling biases. Despite this, it identifies consistent patterns in associating cellular context and FWA service compliance. Availability of temporally paired FWA and cellular measurements would enable more precise estimation of the shared infrastructure relationship and could substantially improve predictive accuracy, informing infrastructure deployment decisions as FWA plays an increasingly central role in federal broadband programs.

VI. Related Work

Prior work has utilized crowdsourced speed test data to assess broadband performance and identify digital inequities. Platforms such as Ookla and NDT7 (M-Lab) have enabled researchers to benchmark regional performance [47]–[49] and explore sampling biases across demographic groups [37]. These efforts highlight the value of independently observed measurements in supplementing provider-reported data, while also emphasizing the need for contextualization and richer metadata [36], [50], [51]. Recent work [25] has combined provider-reported data with performance trends from crowdsourced datasets to analyze the interplay among U.S. broadband access technologies, including fixed wireless access.

Multiple prior measurement studies have analyzed cellular and FWA performance. In the cellular domain, [20], [21], [23], [24], [52]–[56] showed that mobile broadband performance and variability are shaped by spectrum, device capabilities, radio conditions, network load, mobility, deployment choices, and geographic and environmental context. While prior work has extensively characterized traditional wireless broadband on unlicensed spectrum, the 5G era has shifted focus to licensed cellular FWA delivered over shared cellular infrastructure. In this modern FWA context, early work analyzed antenna diversity techniques and mmWave architectures for 5G FWA, establishing it as a viable broadband alternative where fiber deployment is expensive [26], [57]. In terms of recent fixed wireless real-world measurements, [58] found that a rural standalone 5G FWA deployment can deliver sub-gigabit speeds under line-of-sight conditions, while [59] showed that mmWave FWA offers high peak speeds but is constrained by weather and line-of-sight requirements. These studies are predominantly simulation-based or are limited to localized deployments. A large-scale empirical characterization of FWA performance and its relationship to co-located cellular performance in-the-wild has previously been relatively underexplored.

VII. Conclusion

We have presented a large-scale empirical analysis of modern licensed FWA availability and performance in the U.S. While reported FWA coverage shows an overall increasing trend, our analysis reveals a stark digital divide: FWA speeds have increased significantly in both urban and rural areas, yet FWA Speedtests in rural regions consistently measure significantly lower speeds, with far fewer measurements meeting the broadband service threshold. Using a fractional logit model on individual performance measurements from eight U.S. cities, we showed that co-located cellular characteristics are statistically significant but insufficient predictors of FWA service compliance. Although cellular context provides some predictive signal, low pseudo-R^2 values and city and carrier-level variation indicate co-located cellular features are not sufficiently predictive to replace direct FWA performance measurements for service compliance assessment, and that unobservable factors, such as QoS policies and subscription tiers, potentially limit predictive power. Collectively, these findings reinforce the need for direct FWA performance measurement to better understand its operational landscape. As FWA plays an increasingly central role in U.S. federal broadband programs such as BEAD, this study opens avenues for future work on assessing shared network anomalies and on how a growing FWA subscriber base affects co-located cellular performance.

Acknowledgments. This work was funded by National Science Foundation Internet Measurement Research award #2220388. We also thank Ookla and the Ookla for Good program for sharing their data with us.

TABLE I: Median performance metrics from the Ookla aggregated and individual measurement datasets.

Metric	2022	2023	2024	2025
Ookla Aggregated Data (fixed networks)				
Download (Mbps)	163.84	205.14	242.76	289.86
Upload (Mbps)	19.02	22.99	34.51	55.43
Latency (ms)	16.00	16.00	15.00	14.00
Ookla Individual Data (fixed networks)				
Download (Mbps)	106.39	105.37	131.58	182.11
Upload (Mbps)	17.17	15.06	21.68	29.91
Latency (ms)	14.00	17.00	18.00	18.00
Ookla Individual Data (mobile networks)				
Download (Mbps)	73.95	88.19	129.01	157.85
Upload (Mbps)	11.59	11.29	12.91	13.77
Latency (ms)	30.00	29.00	28.00	26.00

APPENDIX

We use this appendix to present supplemental methodology and material that support our main analysis.

Ethics statement. Our study does not include human subjects research. Ookla's data sharing under the DUA is fully anonymized: full IP addresses are not disclosed, and GPS coordinates are truncated, ensuring that measurements cannot be associated with individual users or residences.

Intraclass Correlation Coefficient (ICC). To quantify which spatial unit produces more internally homogeneous performance groups, we compute the intraclass correlation coefficient (ICC) for FWA performance. ICC is defined as:

$$\text{ICC} = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_w^2} \tag{2}$$

where σ_b^2 is the between-group variance, capturing how much group means differ from the overall mean, and σ_w^2 is the within-group variance, capturing how much individual measurements vary around their group mean, estimated from a one-way random-effects ANOVA model [60]. A high ICC indicates that most variation occurs between groups, i.e., tests within the same group yield similar speeds, while different groups differ substantially.

A. *Ookla Speedtest Data*

Performance metrics: In Table I, we present the median of download and upload throughput and latency measurements for Ookla Aggregated and Ookla Individual datasets for our study period. Across both datasets, fixed networks comprise both wired and wireless Speedtest measurements.

B. *FWA performance characteristics*

Advertised speed distributions. Figure 11 presents the maximum advertised download speeds for wireline and FWA from 2022 to 2025, obtained from the National Broadband Map. Wireline median speeds double from approximately 1 Gbps to over 2 Gbps, with the 75^{th} percentile reaching 5 Gbps. FWA medians increase fourfold in urban areas (25 to 100 Mbps) and fivefold in rural (under 10 to 50 Mbps), but the gap with wireline remains substantial.

FWA Service compliance model residuals. Figure 12 presents the distribution of LOCO residuals (actual - predicted values) from the fractional logit model for full FWA service compliance for both carriers. We observe mostly negative residual values, indicating that our model more often overpredicts FWA compliance relative to the actual rates, with greater heterogeneity in Carrier 1 than Carrier 2.

FWA Service compliance model robustness. Figure 13 presents the distribution of LOCO-CV mean absolute errors (MAE) across cities for full FWA service compliance using three model types: fractional logit, gradient boosted tree, and random forest. All models yield comparable MAE results, confirming the weak predictive relationship between observable cellular features and FWA service compliance.

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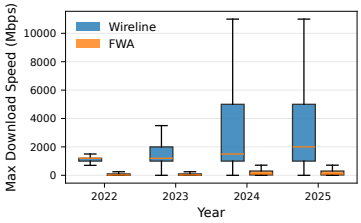
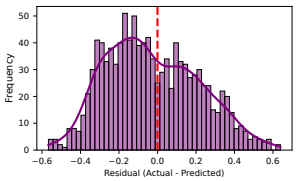
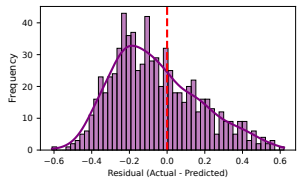


Fig. 11: FWA advertised speeds.



(a) Carrier 1



(b) Carrier 2

Fig. 12: LOCO residuals for FWA service compliance.

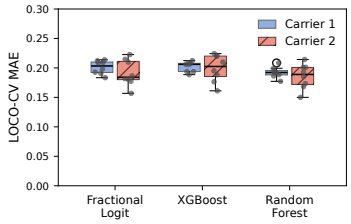


Fig. 13: LOCO-CV MAE.

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