Abstract—The estimation of IEEE 802.11 Wi-Fi access point (AP) densities is an important cornerstone in deriving accurate models for the deployment structure of opportunistic wireless networks. Such densities are usually derived through large-scale wardriving-like measurement campaigns with COTS devices. Due to shielding, limited receiver sensitivity, and sampling density constraints, in general only a subset of Wi-Fi APs can be observed. Furthermore, repeated measurement campaigns show that even if an AP has been observed in one visit to a study area, it may not be observed in subsequent visits, due to small-scale deviations in the measurement locations and unavoidable changes in the radio environment such as moving vehicles and pedestrians. This motivates our study of the application of capture-recapture models to establish more accurate estimates of the actual number of APs in a study area. We approach this problem by first developing a general system model and mathematical framework for AP observability. As we assume temporally constant population sizes but potential inhomogeneities in observation probabilities, we then assess the performance of two applicable population density estimators, namely the Lincoln-Petersen and jackknife estimators, through a simulation study. We demonstrate the practical significance of the proposed capture-recapture methodology by applying it to a data set from an extensive urban Wi-Fi measurement campaign that we have carried out in Cologne, Germany, quantifying the achievable gains and the estimators’ sensitivity to the measurement campaign design. We show that applying the capture-recapture techniques provides the practical advantage of yielding a similar accuracy in the estimation of Wi-Fi density even with significantly fewer measurement locations than surveyed in the full campaign. However, our results indicate that a high receiver sensitivity remains essential for such wardriving-like measurements, i.e. less sophisticated measurement setups such as smartphones will introduce high errors in the AP density estimation.

I. INTRODUCTION

An essential step in the evolution towards future wireless networks is the densification of the access network. In order to meet increased capacity demands, smaller and more densely distributed cells will be needed to bring the network closer to the terminal [1]. The development of algorithms, the quantification of achievable data rates, and the assessment of the prospects of such deployments will necessarily rely on accurate models for the location and number of infrastructure components in typical usage scenarios.

Current installations of Wi-Fi access points (APs) may be considered a good real-world example indicative of the structure of future opportunistic wireless networks, because their deployment is driven by similar market and technological forces as expected for future small-cell, heterogeneous cellular networks. However, there is little accurate knowledge on the detailed structure of such deployments. In our earlier work [2], [3] we have already studied how the geometry of such networks may be derived using data from wardriving-like measurement campaigns and localization methods for small-cell deployments. Our results rely, similar to other earlier works in this domain [4]–[6], on the assumption that each AP could be observed in at least one time instance and at least one measurement location. However, receiver sensitivity constraints of the measurement setup [7], shielding, temporal fluctuations in the radio environment, and physical accessibility constraints (due to street and building layouts) limit the observability of APs, particularly since they are mostly installed indoors. Consequently, the number of observed APs in a measurement campaign is in fact not static, but a complex random variable. Further, the number of individual APs seen in any given campaign can only establish a lower bound on the real number of installations. This paper therefore extends and refines our original research by estimating the number of APs that are actually present in a closed study area if AP observability is limited. Our proposal is to exploit information gathered through multiple revisits to the same study area to yield a better estimate of the actual number of APs.

Fig. 1. Heatmap of the number of observed APs at different measurement locations from a dense measurement campaign in Cologne, Germany. Red dots indicate one of the circa 1,400 measurement locations. The studied region is divided between a residential area in the West and a shopping area in the East. The exceptionally large number of APs observed in the North East likely originates from a hotel Wi-Fi installation.
In this paper we go beyond simple counting of the individual APs by applying methods and mathematical tools that have originally been developed for application to biology. Namely, we observe that the counting of individual APs in wardriving-like measurement campaigns is similar to the common problem in biology of estimating wildlife population sizes [8]. Propagation and shielding effects result in APs being only occasionally observable, and thus the visibility of individual APs changes between visits to the same survey area, i.e. there is an AP-dependent observation probability. Various mathematical tools for deriving total population sizes from multiple visits to the same study area have been developed in biology, which require capturing, tagging, releasing, and recapturing animals on different occasions; due to this methodology, they are often referred to as capture-recapture models. They have also been recently transferred to other scientific fields, e.g. in the estimation of programming errors in large software projects [9]. In this paper, we introduce the popular Lincoln-Petersen and jackknife estimators, and apply them to the problem of estimating Wi-Fi AP densities from measurement data. We have initially selected these estimators as they are tailored to scenarios with constant population sizes (which can be safely assumed over the time scale of a Wi-Fi measurement campaign) and potential inhomogeneities of observations probabilities (due to AP placement and local environment variability). In addition to testing the estimators against synthetic data from a proposed system model for AP observability, we also present our results from a large-scale measurement campaign we have carried out in the city centre of Cologne, Germany. We find that the proposed predictors enable a thinning of the measurement locations set, i.e. they allow a reduction of the surveying effort with reasonable loss in prediction accuracy. However, a high receiver sensitivity remains essential for the accurate estimation of total AP counts. The application of capture-recapture methods is thus beneficial for deriving robust models of the spatial structure of opportunistic wireless networks, since accurate estimates of node density are highly relevant for analyses on interference, coverage, and connectivity.

This paper is organized as follows. In Section II we discuss the constraints on AP observability in a realistic measurement campaign and derive a mathematical model for the observation probability based on extreme value theory. In Section III we introduce capture-recapture models as a means of estimating the number of APs in a study area. In Section IV we apply these models to a simulated scenario with a known number of APs and limited observability. In Section V we analyze the performance of the estimators for the Cologne data set. The paper is concluded in Section VI.

II. OBSERVABILITY OF WI-FI APs

The basis of our empirical study is data from a measurement campaign that we carried out in mid-2013 in the urban centre of the metropolitan city of Cologne, Germany. Using a custom bicycle setup [3] with an antenna mast and three COTS Wi-Fi adapters that connect into a laptop, we scanned for Wi-Fi APs on all 2.4 GHz and 5 GHz channels at 1,395 measurement locations (10 m inter-location distance) in an area of approximately 1 km² (Fig. 1). In order to maximize sensitivity, we used three Cyberbajt CB-V-LINESEKTOR-24017 directional antennas, each with a beamwidth of 120° and covering a distinct sector. The additional gain of 17 dBi allowed us to observe 7,373 individual APs, whereby we could infer from the overall signal strength distribution that most were deployed indoors. For each AP we recorded the maximum signal strength of its beacons as observed at the measurement location, which we determined using GPS.

Whether an AP is observable at all during such a wardriving measurement campaigns depends on a multitude of factors; due to wall shielding, the distance between the AP and the measurement location(s), fading, or polarization discrimination the received signal strength at the measuring Wi-Fi adapter may always remain below the receiver sensitivity of $\nu$ dBm. While the overall signal strength distribution is significantly more complex, we are solely interested in whether the maximum signal strength of an AP over all measurement locations and sectors exceeds this threshold. In the absence of additional information on the geometry or propagation characteristics in the scenario, its distribution is best approximated by a generalized extreme value (GEV) distribution [10]. This distribution is applicable for sets of random variables where each variable is the maximum observed value of an underlying random process. In our scenario, each AP generates an individual set of observed signal strength values, while the collection of respective maximum values of all APs establishes the set discussed in the following. The generalization comes from the fact that each individual AP signal strength distribution is a non-trivial value distribution. The complementary cumulative distribution function (CCDF) of the GEV distribution yields

![Fig. 2. Empirical probability density function (pdf) of the maximum observed signal strength for all APs. The red line shows a fitted generalized extreme value pdf function, whereas the blue line denotes an error-adjusted fit for which the region between -74 dBm and -70 dBm was linearly interpolated.](image-url)
an estimate for the probability of an AP being observed, i.e.
\[ Pr\{\text{AP observed}\} = 1 - \exp \left\{ - \left[ 1 + \frac{\nu - \mu}{\sigma} \right]^{-1/\xi} \right\}, \tag{1} \]
where \( \mu, \sigma, \) and \( \xi \) are the scenario and measurement setup-specific location, scale, and shape parameter of the distribution, respectively.

Fig. 2 shows the results of fitting our theoretical model of AP observation probabilities in (1) to the measurement data from our Cologne campaign. We have excluded data from those APs that were only observed within 50 m to the border of our study area in order to minimize edge effects. We found that the employed Wi-Fi adapters reported significantly more even than odd signal strength values, which leads us to conclude that the reporting accuracy for the particular COTS devices is limited to 2 dB steps. For postprocessing we therefore rounded the signal strength values to the closest even power value. The histogram plot of Fig. 2 furthermore exhibits an unexpectedly low relative number of samples at the range between -74 dBm and -70 dBm. Assuming this to be an unstable operation state of the Wi-Fi adapter, we have instead linearly interpolated the sample density to yield an error-adjusted fit.

However, despite these postprocessing steps, the numerical values of the fitting process do not significantly differ. \( \xi \) is estimated as -0.2, i.e. the empirical distribution resembles a reverse Weibull (type III) distribution. This is an interesting result as it indicates that the distribution is more strongly affected by the lower bound of the observed signal strength values than by the lower bound of the receiver sensitivity. The mode of the probability density function is at -66 dBm, which is close to the estimated location parameter value of \( \mu = -68 \) dBm, whereby the scale is approximately \( \sigma = 10 \) dB. We note that the shape of the distribution also matches intuition. While, in principle, there is a nearly infinite number of APs at larger distances that contribute to the lower tail of the distribution (although not being observable), the maximum transmit power of each AP is constrained by regulations. Thus, in a wardriving campaign it is impossible to observe APs beyond the maximum transmit power, i.e. the distribution is necessarily upper bounded.

III. APPLYING CAPTURE-RECAPTURE MODELS

Differences in propagation and slight variations in measurement locations will result in deviations in the sets of observed APs between different visits to the same study area. This is because the received signal strength of an AP will eventually remain below the receiver sensitivity, and thus render an AP occasionally unobservable. The fundamental idea of capture-recapture models is thus to derive the probability of observing an AP and use this metric for estimating the overall population size. If measurement locations are sufficiently close, multiple visits to the surveyed area thereby may also be emulated by splitting the measurement locations into non-overlapping sets. This is the technique we apply in our empirical study in Section V.

A basic assumption of simple capture-recapture models is that the probability of observing an AP over multiple revisits to the surveyed area is homogeneous over the population, i.e. that the probability of observing an AP is the same for all APs. Assuming that the same effort, i.e. the same number, location distribution, and duration of measurements, is used by the experimenter in the initial capturing process and any recapturing round, the ratio of initially captured devices compared to the estimated total number of devices \( \hat{N}_{LP} \) is equivalent to the ratio of the devices captured both times to the overall number of devices captured in the second round of the capturing. This so-called Lincoln-Petersen estimator [8] is the first population size predictor we consider; it is defined as
\[ \frac{n_2}{\hat{N}_{LP}} = \frac{M}{n_1} \iff \hat{N}_{LP} = \frac{n_1 \times n_2}{M}, \tag{2} \]
where \( n_1 \) is the number of APs initially identified, \( n_2 \) is number of APs found in the recapture, and \( M \) is the total number of distinct APs found.

While being computationally trivial to implement and very intuitive, the assumption of homogeneity of the AP population is a severe limitation of this estimation approach. To illustrate this, we show in Fig. 3 how the maximum signal strength of an AP over all measurement locations relates to the total number of measurement locations at which it was observed in our Cologne campaign. We see that for some high-power APs, which are most likely deployed either outdoors or close to windows facing the street, the (re-)capturing probability (for which the number of observation locations is a proxy) is significantly higher. If an equal capturing probability is assumed, this results in an underestimation of the overall AP population size, because only a single estimation of the observation probability is derived for all APs. The degree of inhomogeneity among the observability of APs (and the resulting estimation error) is specific to the scenario. For example, in the empirical data set used in this paper 50% of the APs were observed less than 5 times, and 75% of the APs were observed less than 10 times. We can thus assume the predominance of similarly deployed indoor APs, which may reasonably approximate the homogeneity condition required for the Lincoln-Petersen estimator.

When inhomogeneities become more severe, estimators that take different capturing probabilities into account can be employed. The most extensively used ones were developed by Quenouille and are known as jackknife estimators [11]. Through defining different estimation orders, these estimators can trade off inhomogeneity-induced bias with variance in the estimation error [12]. The \( n^{th} \)-order jackknife estimator is given by \( \hat{N}_{h} = M + \sum_{i=1}^{n} a_{n,i} f_i \), where the coefficients \( a_{n,i} \) are tabulated in [12], \( f_n \) is the number of APs seen in exactly \( n \) out of the \( t \) times the study area is surveyed, and \( M \) is the number of individual APs seen over all visits. We omit the derivation of the estimators for the sake of brevity, and refer the reader to the relevant literature, e.g. [11], [12]. Popular examples are the first order jackknife estimator,
\[ \hat{N}_{h} = M + \frac{t - 1}{t} f_1, \tag{3} \]
the second order jackknife estimator,
\[ \hat{N}_{2} = M + \frac{2t - 3}{t} f_{1} - \frac{(t - 2)^{2}}{t(t - 1)} f_{2}, \]  
and the third order jackknife estimator,
\[ \hat{N}_{3} = M + \frac{3t - 6}{t} f_{1} - \frac{3t^2 - 15t + 19}{t(t - 1)} f_{2} + \frac{(t - 3)^3}{t(t - 1)(t - 2)} f_{3}. \]

IV. Simulation Results

In order to evaluate the prediction accuracy of the different estimators introduced in Section III in the context of Wi-Fi AP density estimation, we have simulated signal strength distributions for a known population size of \( N = 1,000 \) APs. The maximum signal strength \( P_{\text{max},j} \) of each AP \( j \) is modelled by the empirical distribution function in Fig. 2. For each iteration \( i \) of the capturing process, we add a zero-mean Gaussian shadowing term \( \Xi_{i,j} \) to \( P_{\text{max},j} \). This term models attenuation which may originate from obstacles and small-scale offsets in the propagation path. Our empirical data set shows that the standard deviation of this term is approximately \( \sigma_{s} = 5.5 \text{ dB} \), thus we selected this value also for our simulation. An AP is considered “observed” in iteration \( i \) iff \( P_{\text{max},j} + \Xi_{i,j} \geq \nu \). We have repeated the simulation 100,000 times to acquire mean values and distributions of the different predictors.

The expected number of individual APs observed for a different number of iterations \( t \) can be determined analytically in this model as

\[ N_{\text{obs}}(t, \nu) = \frac{N}{\sigma \sigma_{s} \sqrt{2\pi}} \int_{-\infty}^{\infty} \left[ 1 + \xi \left( \frac{x - \mu}{\sigma} \right) \right]^{-1/\xi - 1} \times \exp \left\{ -1 + \xi \left( \frac{x - \mu}{\sigma} \right)^{-1/\xi} \right\} \times \left( 1 - \int_{-\infty}^{x} \exp \left\{ -\frac{t - y^2}{2\sigma_{s}^2} \right\} dy \right) dx. \]  

A proof is omitted here for space reasons, but follows straightforwardly from deriving the probability that the Gaussian shadowing term \( \Xi_{i,j} \) is smaller than the offset between receiver sensitivity and maximum received signal strength, conditioned on the distribution of the maximum signal strength in (1). Fig. 4 shows the probability density function (pdf) of the estimated number of APs as given by the different estimators for \( t = \{2, 3, 4\} \) observation rounds. The thick vertical lines...

Fig. 3. Maximum signal strength of observation vs. the number of measurement locations at which an AP was observed during Cologne measurement campaign.

Fig. 4. Probability density functions of the estimated number of APs for a simulation of 1,000 Wi-Fi APs for different decodability thresholds \( \nu \), number of captures \( t \), and estimation algorithms. Vertical lines show the mean of the number of individual APs observed.
indicate the mean number of APs observed for a given $t$, as
given by (6), cf. the real population size of 1,000 APs. For a
receiver sensitivity of $\nu = \mu - 70$ dBm, Fig. 4a shows that the
Lincoln-Petersen estimator yields the largest overall estimation
error with a mean value that is 21% smaller than the actual
number of APs. The first order jackknife estimator for the
same number of iterations, $t = 2$, performs slightly better with
an estimation error of only 18.5% on average. Additionally,
the jackknife estimation exhibits a smaller error spread, as is
apparent from the higher value of the mode. When the number
of iterations is increased, the jackknife estimators converge
towards the actual number of APs in the simulation. The main
difference here lies in the variance. The second order estimator
predicts a wider range of values relative to its mean compared
to the first order jackknife. However, even with this extended
spread the average error remains smaller than for the first order
estimator. We have conducted further experiments also with
higher order jackknife estimators not shown here, however,
we found no additional gains. Furthermore, in order for these
estimators to be applicable, the number of iterations $t$ must be
larger than the the order $n$ minus 1, which may be a practical
constraint in a measurement campaign.

Comparing Fig. 4a and Fig. 4b shows that when the decod-
ability threshold is raised, which may model a case when a
measurement campaign is carried out using less sophisticated
(i.e. higher receiver sensitivity) equipment, the number of
observed APs further decreases. Here, the real benefit of
additional visits to the study area comes into play, as we can
see for the case of $t = 4$ iterations. The second order jackknife
estimator yields an average error of only 27% compared to
the loss in observed APs of 41%. However, the estimation
spread becomes significantly larger, ranging between 630 and
802 APs.

V. EMPIRICAL RESULTS

In this section we apply the capture-recapture estimators
introduced in Section III to the data set from our extensive
Wi-Fi measurement campaign described in Section II. We note
that, since the real number of APs within the surveyed area
is by definition unknown, we cannot argue about the absolute
accuracy of the AP population size estimate. Instead, in this
section we study the effect on the estimators’ performance
when the sampling accuracy or effort are artificially decreased
by thinning of the data set. The results we present here thereby
give important insights into the requirements for real-world
Wi-Fi measurement campaigns, and demonstrate the benefits
of applying capture-recapture models to improve AP density
estimation.

The practical application of these models requires multiple
visits to the study area. However, if the measurement location
density is high, a reasonable technique for emulating multiple
visits is to split the measurement locations into $t$ equal-sized
and disjoint sets. Splitting needs to be done in a manner so as
to minimize inter-set distances, i.e. neighbouring measurement
locations should ideally be in different sets. We found that for
up to four sets the sampling density of our data set suffices so
that the difference between maximum signal strength values
for APs that are observed at locations in two sets is approxi-
mately Gaussian distributed.

A. Sensitivity of Estimators to Decodability Threshold

We iteratively removed APs from the sampling sets for
which the maximum signal strength value in the respective
set was below an artificial decodability threshold that we
set to be larger than the actual receiver sensitivity of our
measurement setup. This way, we emulate a loss of sampling
accuracy as would for example be observed when comparing
AP observations from our measurement setup to a hypothetical
setup using smartphones or less sophisticated antennas. Using
this reduced data set, we finally estimated the number of APs
in the surveyed area.

Fig. 5 shows the estimated total number of APs depend-
ing on the selected decodability threshold and estimation
algorithm. For comparison, we have also plotted the total
number of observed APs (black dots) to show the baseline
effect of using less sensitive measurement hardware on the
observability. The reduction in the estimators follows the same
slope for the different estimators, whereby jackknife estimators
predict highest AP counts, similar to the results from our
simulation study in Section IV. The Lincoln-Petersen estimator
is closest to the number of observed APs. We can conclude that
the sensitivity of the decodability threshold for the estimators
is high, i.e. the benefit in using the estimators to compensate
for losses in the decodability threshold is rather low.

However, our analysis shows that although overall the
population estimators do not sufficiently compensate for low
receiver sensitivity, there is at least a marginal benefit when
applying them compared to the traditional method of simply
counting observed APs, which is shown in Fig. 5 through the
black dotted line. To illustrate this, we define a relative loss

![Fig. 5. Estimated number of APs for the Cologne measurement campaign depending on the decodability threshold and applied estimator. In the unconstrained case without thinning of the data set, 7,372 APs are observed, i.e. a good estimate should exceed this lower bound on the actual number of APs.](image-url)
compensation metric as

$$ r(t, \nu) = \frac{N_{\text{est}}(t, -\infty) - N_{\text{est}}(t, \nu)}{N_{\text{obs}}(t, -\infty) - N_{\text{obs}}(t, \nu)} \times \frac{N_{\text{obs}}(t, -\infty)}{N_{\text{est}}(t, -\infty)}, \quad (7) $$

where \(N_{\text{est}}\) is the estimated number of APs for the respective estimation algorithm, with \(0 \leq r \leq \infty\). If \(r = 1\), the estimator shows the same decrease in the relative number of APs compared to unconstrained observability as the decrease in the observed APs under the same decodability threshold. This would be the case if, e.g., the estimator is a simple constant multiplier for the observed number of APs. When \(r < 1\), the estimator is capable of compensating for losses in the decodability threshold, because its relative reduction in the predicted number of APs is less than the loss in the number of observed APs for the same decodability threshold \(\nu\).

In Fig. 6 we show the performance of the estimators by applying the relative loss compensation metric in (7). We note that the effect of using the different estimators is most pronounced in the middle range of -75 to -55 dBm. For higher values of \(\nu\), all estimators converge towards 1, i.e. their performance is equal to a simple counting of the individual APs. The highest order jackknife estimator performs best, although we note that this estimator theoretically yields the highest total estimation error spread.

B. Sensitivity of Estimators to Number of Measurement Locations

For practical reason such as time or budgetary constraints, the feasible sampling density of a measurement campaign, defined as the number of visited measurement locations per square unit of the study area, may be limited. We have considered such a de-densification of Wi-Fi measurement locations by using only a subset of the measurement locations in the estimation process. We randomly selected a fraction of our measurement locations and conducted the estimation using only the data that had been acquired at these points. This process was repeated 100 times to remove any potential bias from the measurement location selection. The results of this estimation are compared for the first order jackknife estimator, which is theoretically the most robust estimator, and the (on average) most accurate third order jackknife estimator in the set of boxplots in Fig. 7.

Both estimators exhibit a logarithmic increase in the number of estimated APs, similar to the total number of observed APs which we show for reference in Fig. 7a. However, Fig. 7a shows that a simple counting of individual APs is very sensitive to the sampling density. With only 10% of the measurement locations, the number of observed APs drops to a median of 43.5%. The spread is rather large compared to the values for higher fractions of measurement locations, with a maximum value of 50% and a minimum value of 37%. Fig. 7a furthermore shows that for simple counting, the fraction of observed APs increases beyond 90% only if approximately 70% of the measurement locations are included in the estimation process. By contrast, Fig. 7b shows that the first-order jackknife estimator is superior: even with only 40% of the measurement locations included, the median ratio of estimated APs relative to the full data set estimation is 87.7%. Namely, these results indicate that applying capture-recapture estimators allows us to significantly reduce measurement campaign effort while maintaining high AP density estimation accuracy. As shown in Fig. 7c, the third-order jackknife estimator exhibits even better performance, achieving a similar median estimation value with only 30% of the measurement locations. In the extreme case of using only one-tenth of the measurement locations, the third-order jackknife estimator provides the best median performance with 65.5% of the original estimate. However, the relative spread in the estimated number of APs is largest, although it remains in all cases above the best case for the simple counting of individual APs. Our results in Fig. 7 thus show that the application of capture-recapture models outperforms simple counting statistics and can compensate for reduced sampling densities.

VI. CONCLUSIONS

In this paper we have proposed the application of capture-recapture based estimation methods for establishing the number of Wi-Fi APs in a closed study area if not all APs can be readily observed. To the best of our knowledge, this is the first time such a proposal has been made to improve the accuracy of measurement-derived density statistics for wireless opportunistic networks. The accurate derivation of such estimates is an important cornerstone of establishing models of the spatial distribution of opportunistic wireless networks. We have developed a mathematical framework for AP observability using extreme value theory, and applied it for a simulation study to assess the feasibility of such estimation methods.

Our simulation results show that Lincoln-Petersen and jackknife estimators, which are a sensible initial selection if population sizes are constant but partially inhomogeneous,
provide robust estimates of the number of APs. They allow the exploitation of data derived through visiting the same measurement area multiple times for improving estimation performance. In accordance with more theoretical works we found that although the order of the jackknife estimators increases mean performance, this comes at the cost of an increased error variance. However, the overall performance was always superior to the traditional approach of purely counting the number of observed Wi-Fi APs.

Using an extensive data set from a Wi-Fi measurement campaign in Cologne, Germany, we have tested the performance of the different estimators when either the sampling density (in terms of the total number of observation locations) is decreased or the decodability threshold (i.e., the signal strength value that must be exceeded for an AP to be visible) is increased. We found that the estimators do partially compensate for lower receiver performance, but that the overall loss in estimation accuracy remains. Nevertheless, a general improvement in estimation performance could be observed, which motivates the application of these estimators even in this case. Better results were found for the reduction in sampling density: even when only 10% of the measurement locations were taken into account, the estimated value from the highest-order jackknife estimator remained at 65.5%, whereby even with only 30% of the 1,395 measurement locations the estimator retained 90% of the original estimation value. This indicates the overall benefit and fitness of capture-recapture model for application to IEEE 802.11 Wi-Fi AP density estimation. In future work, we plan to assess the estimators’ performance also within sparser environments, e.g., sub-urban neighbourhoods, but anticipate similar gains due to the independence of our methodology from the overall AP density.

**REFERENCES**


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