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Supplementary Material - A systematic machine learning approach to assess biases in population data from mobile phone applications

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Traditional sources of population data, such as censuses and surveys, are costly, infrequent, and often unavailable in crisis-affected regions. Mobile phone application data (MPD) offer near-real-time, high-resolution insights into population distribution, but their utility is undermined by unequal access to digital technologies, creating biases that threaten representativeness. Despite recognition of these issues, no standard framework exists to address such biases, limiting the reliability of MPD for research and policy. We develop and implement a systematic, replicable framework to quantify and explain population coverage bias in aggregated mobile phone application data without requiring individual-level attributes. The approach combines an indicator of population coverage bias with explainable machine learning to identify contextual drivers of spatial variation in bias. Using four datasets for the United Kingdom benchmarked against the 2021 census, we show that MPD achieve higher population coverage than national surveys, but biases persist across sources and subnational areas. Population coverage bias is strongly associated with demographic, socioeconomic, and geographic features, often in complex nonlinear ways. Contrary to common assumptions, multi-application datasets do not necessarily reduce bias compared to single-app sources. Our findings establish a foundation for bias assessment standards in MPD, offering practical tools for researchers, statistical agencies, and policymakers.

1. Alternative data aggregation approaches for Facebook data

Facebook Population data was aggregated temporally by averaging daily population counts over a month and then spatially, by aggregating it into Local Authority Districts (LADs), ensuring alignment with official census data. To test the robustness of the population coverage bias indicator (Equation 3.2 in the main text) under data aggregation strategies, we compared results from this chosen approach with alternative ones. To this end, we examined the relationship between the LAD-level bias indicator obtained from Facebook data according to the chosen approach and from alternative aggregation approaches. We expect to find strong linear correlations if the bias indicator is robust to the aggregation approach. The robustness test is shown in Figure 1, where the x-axis shows the bias indicators under the chosen method, while the y-axis shows alternative aggregation approaches by: A) grouping into LADs, then averaging over a month; B) averaging over a week from March 2021, then grouping into LADs; C) grouping into LADs, then averaging over a week. For completeness we also compare bias indicators derived from Facebook under the chosen aggregation approach and bias indicators derived from other data sources: D) Twitter/X, E) Multi-app 1, F) Multi-app 2.

Strong linear relationships are observed between Facebook bias indicators across all aggregation approaches, with Pearson correlation coefficients of 1, confirming robustness to aggregation choices. In contrast, comparisons with other data sources show no such correlation, indicating that different LADs exhibit larger biases depending on the data source.

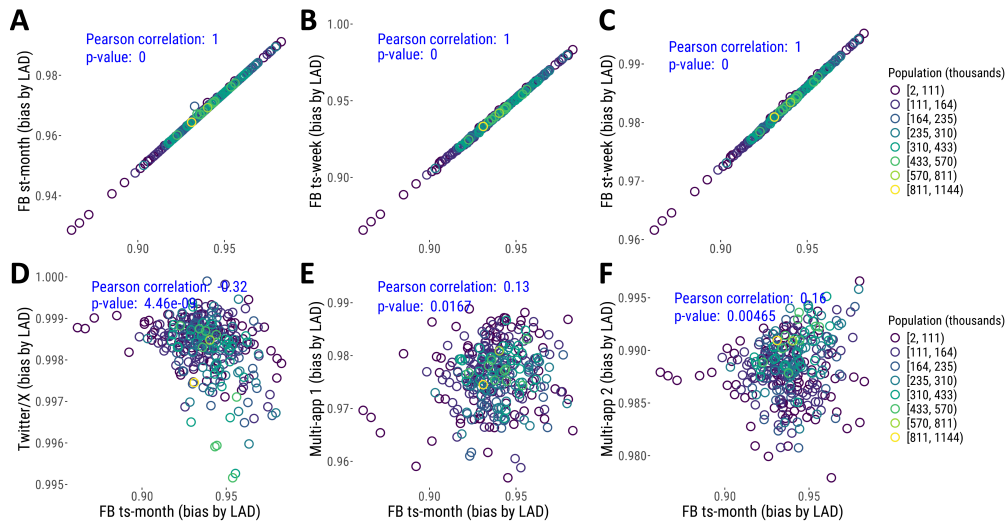


Figure 1. Robustness test of population coverage bias indicators derived from Facebook data, under alternative data aggregation approaches.

2. Testing for spatial autocorrelation in population coverage bias

We analysed the spatial distribution of the population coverage bias indicator across LADs. Figure 3 in the main text reports Moran's I values computed using queen contiguity neighbourhoods. For comparison, Table 2 presents Moran's I values and associated p-values obtained under alternative spatial weighting schemes.

	Queen neighbours	k-nearest neighbours	Distance band (optimal)	Distance band (user)
Twitter/X	0.019***	0.014**	0.009*	-5.289e-5 (n.s.)
Facebook				
tts-week	0.078*	0.103***	-0.104*	0.132***
tts-month	0.078*	0.101***	-0.103*	0.130***
stt-week	0.079*	0.103***	-0.104*	0.131***
stt-month	0.078*	0.101***	-0.104*	0.131***
Multi-app GPS 1	0.101***	0.009 (n.s.)	0.084***	0.078***
Multi-app GPS 2	0.467***	0.437***	0.295***	0.181***

***p<0.001, **p<0.01, *p<0.05, not significant (n.s.)

Figure 2. Moran's I coefficients and significance, computed according to four spatial weights schemes, 1) queen neighbourhood, 2) k-nearest neighbours, 3) optimal distance band, and 4) user-defined distance band.

Ethics. This research was conducted in accordance with the ethical standards of the University of Liverpool. All data used were anonymised and analysed at an aggregate level. No identifiable personal data were accessed or processed by the authors.

Data Accessibility. Please see data accessibility in the Data section. Code is openly available at <https://github.com/de-bias/bias-detection>.

Authors' Contributions. Both authors contributed equally.

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