Cellular Signal Coverage Mapping

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October 6, 2025

1. Abstract

This project presents a practical methodology for mapping and analyzing cellular network coverage in underrepresented regions. Signal measurements were collected across multiple locations and times, stored in a cloud database, and processed with custom Python scripts to generate detailed coverage maps. The maps reveal strong reception in central Ariel but highlight significant gaps along rural roads, illustrating the value of localized, empirical measurements. While limited by the scale of data collection and reliance on a small number of devices, the study demonstrates a replicable approach that can support both researchers and local authorities in assessing and improving mobile service quality.

Contents

2. Introduction

This chapter provides the background and rationale for the project, explaining the gap in existing coverage data for underrepresented regions and motivating the need for localized, empirical measurement campaigns.

2.1 Background

Mobile network coverage has become a fundamental element of modern life, enabling communication, access to essential services, and participation in the digital economy. Reliable connectivity is no longer a luxury, but a necessity. As mobile usage continues to grow, both users and service providers increasingly depend on accurate coverage data to assess service quality, identify connectivity issues, and plan infrastructure deployment.

To meet this need, several platforms, most notably OpenSignal[1] and CellMapper[2], offer crowdsourced coverage maps based on real-time signal measurements contributed by users worldwide. These platforms provide valuable insights and perform well in densely populated areas, where large volumes of user contributions ensure frequent updates and high spatial resolution. However, their effectiveness is uneven: in less populated regions, where fewer users contribute data, coverage maps are often incomplete, outdated, or misleading.

2.2 Motivation

In Israel, and particularly in semi-rural areas such as Ariel and the Shomron (Samaria) region, substantial gaps persist in publicly available coverage data. Weak or absent information makes it difficult for residents, researchers, and policymakers to evaluate service quality or plan infrastructure improvements.

This challenge is especially significant when considering emerging technologies such as autonomous vehicles and unmanned aerial systems (drones), which depend on continuous mobile connectivity for safe navigation and real-time data transmission. Inconsistent or weak coverage in rural regions can cause operational risks ranging from navigation failures to loss of mission control.

The limitations of existing platforms are evident in their output. Figure 1 shows OpenSignal's reported coverage for Ariel, which significantly underrepresents actual network availability. Figure 2 contrasts OpenSignal's estimated antenna positions (left) with verified locations from the official government dataset (right). The discrepancies between estimated and verified infrastructure highlight both the incompleteness of crowdsourced maps and the difficulties of accessing accurate, user-friendly antenna data in Israel.

Together, these observations motivate the need for targeted, empirical data collection to complement existing platforms. Accurate, localized coverage maps are essential not only for improving consumer experience but also for ensuring safety, accessibility, and infrastructure readiness in regions underserved by global mapping tools.

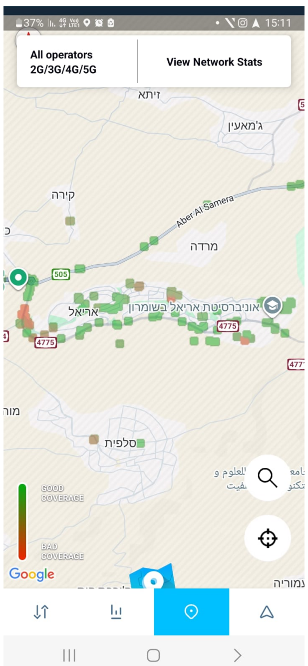

Figure 1. Reported coverage for Ariel in OpenSignal, showing sparse and incomplete representation of network availability.

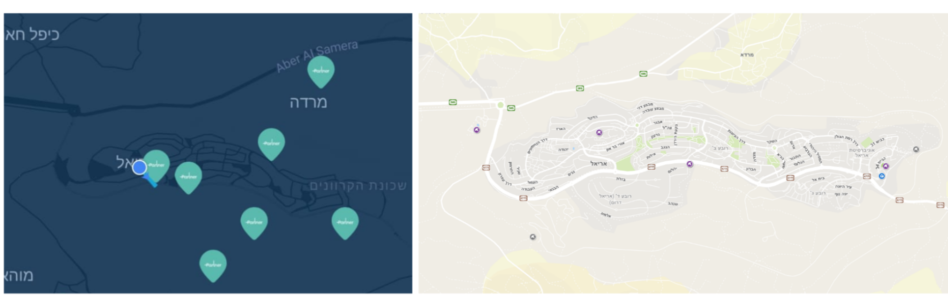

Figure 2. Antenna location data: OpenSignal's estimated placements (left) versus verified locations from the official government dataset (right).

2.3 Objectives

The primary objective of this project is to develop and apply a replicable methodology for generating accurate mobile coverage maps in underrepresented regions. Specifically, the project aims to:

- Collect reliable signal measurements using mobile devices and the G-MoN Pro application.
- Store and organize these measurements in a structured cloud database (Firebase) for reproducibility and further analysis.
- Generate high-resolution coverage maps through Python-based processing and interpolation techniques that combine measurement data with antenna information.
- Demonstrate comparisons across dimensions such as time of day, geographic region, and coverage type.
- Provide open-source tools and documentation that enable others to replicate, extend, and apply the methodology in additional contexts.

It is hypothesized that systematic field measurements, even when limited in scope, can yield coverage maps that are significantly more accurate and representative than existing crowdsourced platforms in semi-rural areas.

2.4 Related Challenge: Positioning Without GPS

Another challenge closely related to this study is the problem of inferring location without GPS. This topic has been extensively discussed in the literature [3, 4, 5]. While the present research focuses on estimating coverage quality based on known locations, the inverse problem aims to infer the user's position from measured signal strengths. This task, often referred to as *signal-based localization*, involves using radio measurements such as RSSI or RSRP to estimate geographic coordinates in the absence of satellite positioning data.

Although this study addresses the opposite direction, both problems share underlying signal-propagation characteristics and spatial modeling challenges. Understanding advances in signal-based localization may therefore help refine coverage estimation models and improve mapping accuracy.

3. Literature Review

This chapter reviews existing commercial platforms and academic research in cellular coverage mapping. It highlights their contributions, identifies common gaps and limitations, and clarifies how the current project builds upon and extends previous work.

3.1 Market Solutions for Network Coverage Mapping

Over the past decade, several commercial and open-source platforms have emerged to measure and visualize mobile network coverage. These solutions vary in methodology, ranging from crowdsourced user contributions to structured drive-test campaigns.

OpenSignal is among the most widely used platforms worldwide. Its mobile application collects parameters such as signal strength, data speed, latency, and service availability, which are then aggregated into interactive maps and benchmarking tools [1]. The strength of OpenSignal lies in its continuously updated, large-scale dataset, which makes it valuable for consumer-facing comparisons between providers. However, the platform does not provide technical details such as exact antenna locations or cell IDs, limiting its usefulness for engineering-level analysis.

CellMapper takes a more infrastructure-oriented approach. While the application runs, it records cell IDs, frequencies, GPS coordinates, and signal strength, enabling users to map both tower locations and associated coverage areas [2]. This makes it particularly valuable for engineers and researchers seeking insight into network topology. Still, the platform depends heavily on active contributors, and its maps often remain sparse or incomplete in less populated regions. There is no coverage map in their site of Ariel and the surrounding area.

Flycomm, an Israeli company, has developed an AI-powered solution for monitoring and optimizing 3G, 4G, and 5G coverage [6]. It combines crowdsourced data, dedicated drive tests, cloud-based processing, and real-time visualization. The platform's strengths include high accuracy, scalability, and full support for advanced mobile standards, making it suitable for both operators and research purposes. However, as a proprietary system, its methods and datasets are not fully open to public validation, they provide service only for customers.

3.2 Academic Approaches and Research

In parallel to commercial platforms, academic research has focused on combining empirical measurements with geospatial and computational analysis, aiming to achieve accurate and scalable coverage mapping.

Dharshini, Kumar, and Ramesh [7] proposed a low-cost methodology that uses mobile devices to collect signal strength data (RSSI), processed with open-source tools such as QGIS and Python. The resulting geographic heatmaps highlight weak coverage areas while remaining highly accessible for small-scale projects. However, data collection still requires manual effort and is limited to local scopes.

More advanced frameworks leverage simulation and 3D modeling. The Geo2SigMap system [8] integrates OpenStreetMap data, Blender models, and physical-layer simulation via Sionna to predict signal strength using a cascaded U-Net architecture. Similarly, Choi et al. [9] combined LiDAR-based 3D urban models with deep neural networks to generate detailed propagation maps in dense environments. Such models achieve strong predictive accuracy but rely heavily on computational resources and structured geospatial inputs.

Recent work has also explored fusing multiple data sources and AI-based approaches. Nguyen et al. [10] demonstrated multi-source signal data fusion using crowdsensed and GPS inputs, improving consistency in heterogeneous environments. Zhang et al. [11] and Ahmed and Kim [12] further advanced deep learning and hybrid modeling techniques to estimate coverage from environmental and propagation features, achieving reduced prediction errors compared to classical models.

Finally, several studies have addressed the challenge of estimating coverage in areas without direct measurements by incorporating antenna locations and interpolation algorithms [13]. While such methods provide continuity between sampled points, their accuracy depends strongly on data density and the availability of reliable infrastructure metadata.

Despite the progress demonstrated by these studies, challenges remain in translating advanced models and simulation-based methods into accessible, field-validated solutions. The diversity of data sources, geographic conditions, and modeling techniques highlights both the richness of the research landscape and the ongoing need for practical, reproducible approaches that can operate reliably in real-world environments.

3.3 Gaps and Limitations in Current Solutions

While recent commercial and academic efforts have significantly advanced coverage mapping, several challenges remain.

- **Uneven data availability:** Crowdsourced measurements are concentrated in urban centers, leaving rural and peripheral regions with limited or outdated coverage information [1, 2].
- **Restricted technical details:** Many platforms limit access to essential identifiers such as cell IDs, frequencies, or antenna metadata, which are valuable for engineering-level analysis.
- **Resource-intensive field testing:** Dedicated drive-test campaigns provide accurate results but involve high costs and logistical effort [6].
- **Model generalization and validation:** Machine-learning and hybrid models improve predictive accuracy [8, 11, 12] but often rely on simulated or localized datasets, limiting their transferability across environments.
- **Incomplete estimation of unmeasured areas:** Most systems show only direct measurements without extending coverage to unmeasured zones. Interpolation techniques exist [13] but are rarely integrated into public or open-access mapping tools.

These factors highlight the ongoing need for practical, transparent, and reproducible methods that bridge empirical data collection with scalable prediction, particularly in regions that lack consistent measurement coverage.

3.4 Relevance to the Current Project

The present project directly addresses several of the remaining challenges in current coverage mapping research. By collecting real-world measurements in underrepresented areas, it produces detailed and up-to-date maps that reflect actual on-ground conditions. The workflow integrates targeted field data collection with automated processing and visualization, providing results that are useful for both local users and technical stakeholders.

While inspired by the open-source and low-cost approach of Dharshini et al. [7], this project enhances accessibility by streamlining both data collection and visualization through Python scripts and a structured Firebase backend. Similarly, while drawing from the integration of field data and modeling in Geo2SigMap [8], it prioritizes practical deployment and transparency over computational complexity.

Recent studies have introduced advanced AI-based prediction methods [11, 12], yet most rely on simulated datasets rather than extensive real-world campaigns. In contrast, this project emphasizes empirical validation, combining raw measurements with antenna metadata and interpolation techniques [13] to estimate coverage in unmeasured areas. This produces continuous and realistic coverage maps, particularly valuable in regions with sparse measurement density.

Finally, the project contributes to reproducibility by releasing open-source code and a transparent methodology, enabling other researchers and practitioners to replicate or adapt the workflow for different locations and network conditions.

4. System Overview / Methodology

This chapter outlines the methodology, architecture, and tools used to design and implement the cellular coverage mapping system. Beyond documenting the technical process, an important aim of this work is knowledge sharing: by publishing the workflow and open-source code on GitHub, the project provides a practical blueprint that others can replicate, adapt to their own regions, or extend with new features.

4.1 General Approach

The project set out to map and analyze the quality of mobile network service in the target region. To achieve this, field measurements were conducted with the G-MoN Pro application [14], which captures real-time cellular and GPS parameters during drive tests. These measurements were processed, cleaned, and stored in a dedicated cloud backend, creating a structured and continuously updatable database. This database then served as the foundation for generating interactive coverage maps using inverse distance weighting (IDW) interpolation [13], and for conducting network performance analysis.

4.2 Tools and Technologies

The project integrates a set of tools that together form the pipeline for data collection, storage, processing, and visualization. Each tool fulfills a distinct role, ensuring that the system is both accurate and scalable, while producing outputs that are meaningful for technical analysis and accessible for broader stakeholders.

4.2.1 G-MoN Pro (Data Collection)

The G-MoN Pro mobile application[14] was the primary tool for collecting raw cellular and GPS data during drive tests (see Figure 3). It records a wide range of parameters in real time, including:

- **Network identification:** PLMN, network type (2G/3G/4G/5G), cell IDs, frequency bands.
- **Signal strength and quality:** RSSI, RSRP, RSRQ, SNR, CQI.

- **Geolocation:** GPS coordinates, speed, accuracy, Timing Advance.
- **Throughput and capacity:** Uplink/downlink throughput, bandwidth, carrier aggregation.
- **5G-specific metrics:** NR state, synchronization signal strength, SINR, channel state information.
- **Metadata:** Timestamps, roaming status, database lookup references.

These measurements enabled both quantitative analysis of network performance and visualization of coverage gaps, handover behavior, and operator differences. Notably, G-MoN Pro is capable of recording many of these radio and location parameters even without an active SIM card, as the device modem can still detect and log broadcasted cellular signals from nearby base stations.

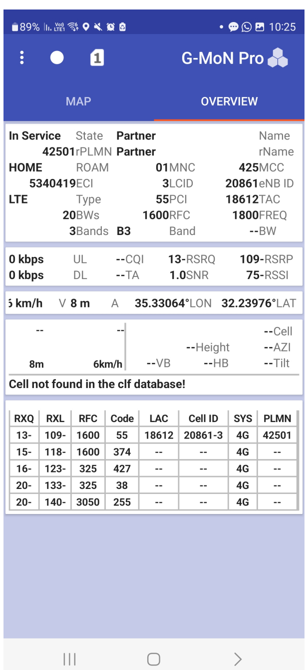

Figure 3. G-Mon Pro application data collection screen.

4.2.2 Firebase (Database and Cloud Backend)

The system uses Firebase[15] as its cloud-based backend, providing scalable data storage, real-time synchronization, and secure user management. Firebase served as the central repository where raw and processed data were stored and organized. The database was structured into four key collections:

1. *Users*
   User profiles and associated provider information, enabling secure access and filtering of contributions.

2. *Data*
   As shown in Figure 4, each measurement in the Firebase *Data* collection is stored as a structured document, identified by a unique *user_date_time* key and containing both signal parameters and GPS metadata.

3. *BaseStations*
   A reference collection of known cell towers (ID, coordinates, provider, frequency bands), allowing validation and comparison with measured data.

4. *Maps*
   Processed coverage maps, organized by region, operator, and time period.

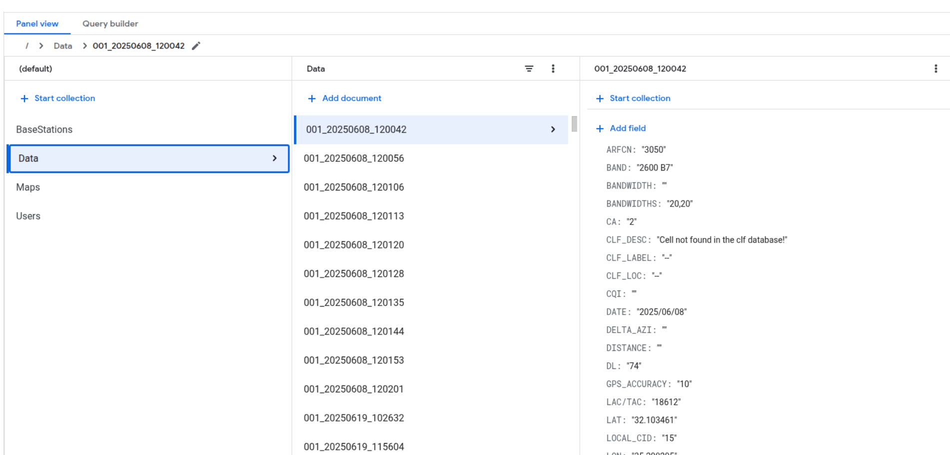

Figure 4. *Data* collection in the Firebase database. Each document represents a single measurement, indexed by a unique key (*user_date_time*) and containing signal parameters together with GPS coordinates.

4.2.3 Python (Data Processing and Analysis)

Python[16] served as the main programming environment for this project, supporting both data handling and coverage map generation. Since raw G-MoN Pro logs often contained unstructured or duplicate entries, Python scripts were essential for cleaning, preprocessing, and ensuring the consistency of the dataset.

Key processing tasks included:

- Parsing raw measurement logs into structured datasets.
- Extracting relevant rows from the Firebase database before generating specific coverage maps.
- Linking signal measurements with antenna location data to support spatial analysis.
- Generating KML layers for visualization in Google Earth.

In addition to preprocessing, Python was central to the creation of the coverage maps themselves. The code implemented an interpolation approach based on inverse distance weighting (IDW), a method that assigns greater influence to nearby measurements[13]. This technique made it possible to estimate signal strength in unmeasured areas, producing smooth, realistic coverage surfaces that combined raw field data with antenna locations.

Python was also used to automate data management tasks, including uploading new measurement files to Firebase, downloading filtered subsets for map generation, and exporting finalized maps back into the database for storage and retrieval.

The flexibility of Python enabled rapid iteration, testing of multiple visualization styles, and reliable integration of the measurement, storage, and mapping components. This ensured that outputs were accurate, reproducible, and well aligned with the project's analytical goals.

4.2.4 Google Earth / KML (Visualization)

For visualization, processed datasets were converted into KML files and displayed in Google Earth[17]. This stage transformed abstract measurements into intuitive geographic insights. Signal quality represented by gradient lines or shaded areas, with clear distinction between strong and weak coverage zones.

Through this visualization layer, raw cellular data was turned into actionable insights, allowing both technical specialists and decision-makers to understand and evaluate coverage in the studied region.

4.3 Workflow Diagram

The workflow of the system is illustrated in Figure 5. Data collection begins with GMon Pro, which records cellular measurements during a drive and exports them as a CSV file. The raw data is then uploaded to the Firebase database using a Python script, ensuring that it is stored securely and can be accessed for later processing. To generate maps, data is retrieved from the database according to selected parameters such as geographic area or time range. Using additional Python scripts, the relevant data is exported back into CSV format. Then the data is processed into a KML file, which can be visualized in Google Earth. The mapping scripts allow for flexible outputs, such as maps with or without cell tower locations, maps showing only sampled points, or broader coverage visualizations distinguishing between internet and call services. Finally, the generated maps are displayed in Google Earth for analysis and also stored back in the database for archiving and further use. In this way, the workflow connects raw field measurements with meaningful geographic visualizations, creating a complete and reproducible pipeline for cellular coverage mapping.

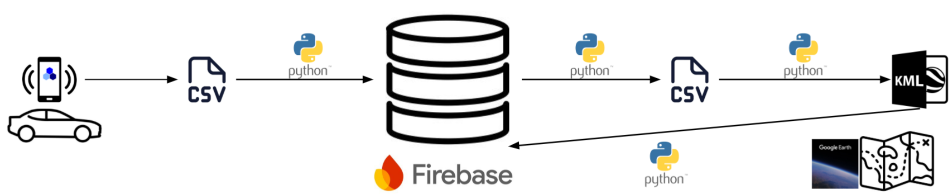

Figure 5. Workflow of the cellular coverage mapping system, from data collection with GMon Pro to storage in Firebase, processing with Python, and visualization in Google Earth.

4.4 Challenges in Data Collection

A major challenge in this project was obtaining reliable information on antenna locations and identifiers. Since no publicly accessible database provides complete and up-to-date details, this information had to be derived manually. The process required cross-referencing field measurements with available infrastructure data to identify cell towers and their corresponding identifiers. Complicating matters further, a single antenna can appear under multiple identifiers depending on factors such as reception angle and frequency band.

Although time-consuming, this effort greatly enhanced the value of the project by producing an organized and up-to-date dataset of antennas and signal measurements in the region. Beyond serving as the foundation for the present analysis, such a dataset can support future research, assist local councils in infrastructure planning, and potentially be integrated into national databases, ultimately improving the accessibility, accuracy, and efficiency of coverage information for the wider public.

4.5 Color Representation in Coverage Maps

Before moving on to the results section, it is important to clarify the meaning of the colors used in the coverage maps.

The color scale reflects the signal strength values measured or predicted at each location. Colors range from red, indicating weak signal, through yellow for moderate reception, to green for strong signal.

Technically, the values correspond to the received signal power (RSRP for LTE or RSCP/RSSI for other technologies), expressed in decibel-milliwatts (dBm). Higher (less negative) values such as –60 dBm indicate excellent reception and high data throughput potential, whereas lower values below –110 dBm represent poor or unreliable connectivity.

In the maps, green shades represent strong signals above –80 dBm, yellow tones correspond to moderate reception between –80 dBm and –100 dBm, and red shades indicate weak signals below –100 dBm. This color-based representation allows the map to visually communicate variations in network performance across the city, making it easy to identify both strong coverage areas and locations where service quality may degrade.

5. Results and Analysis

This chapter reports the results of the coverage mapping and provides analysis of key findings.

5.1 Coverage Maps of Ariel

The central outcome of this study is a detailed cellular coverage map of the city of Ariel, visualized through a color-coded representation of signal quality. The map highlights the locations of base stations as well as surrounding areas of strong and weak reception. Overall, coverage across most of the city is satisfactory, with several base stations providing overlapping service.

To ensure reliability, the dataset was filtered by provider, geographic boundaries, and measurement period, so that the map reflects the performance of a single operator under consistent conditions. After filtering, 5,391 measurements remained and were used to generate the coverage surface shown in Figure 6. The surface was created using inverse distance weighting (IDW) interpolation, which combines actual measurement points with known antenna locations. In this process, measurements closer to a given point have stronger influence, while antenna proximity is used to refine predictions. As a result, unmeasured areas are estimated realistically, with accuracy improving as measurement density increases.

This approach produces a high-resolution visualization that reveals both expected and less obvious patterns. In central Ariel, where data points are dense and multiple antennas overlap, the map shows stable and redundant coverage. At the city's edges, however, coverage rapidly shifts from strong to weak, often corresponding to line-of-sight obstructions or distance from the nearest tower. Importantly, the method also identifies "shadow zones" behind buildings or in complex terrain, which would be difficult to detect from measurements alone.

Figure 6. Predicted cellular coverage in Ariel for provider PHI, based on

5,391 filtered measurement points.

5.2 Comparing reception between times of day

Cellular reception in Ariel shows subtle variation between daytime and nighttime conditions. Figure 7 presents the coverage map generated from measurements collected between 07:00 and 21:00, while Figure 8 illustrates the corresponding map based on nighttime measurements (21:00–07:00). During the day, coverage remains generally strong, but more yellow and orange patches are visible, particularly at the city's periphery. At night, coverage appears slightly better, with broader and more continuous green areas indicating stable reception.

These differences suggest that time-of-day effects can influence perceived coverage quality. One possible explanation is reduced network load at night, which lowers interference and improves reception. Environmental conditions such as temperature inversions may also affect radio propagation, while the distribution of measurement routes may play a secondary role.

Daytime coverage was modeled using 4,207 measurements (Figure 7), while the nighttime map (Figure 8) is based on 1,925 measurements. Although the smaller nighttime dataset may lead to a somewhat coarser interpolation, the overall trends remain consistent. Both maps confirm that reception in Ariel is generally strong, with only modest variation between time periods.

Although the observed differences are relatively modest, this comparison illustrates the flexibility of the mapping framework. The same approach can be extended to a variety of scenarios: comparing different service providers, analyzing coverage across multiple years, or contrasting internet (data) performance with voice call connectivity. By filtering the Firebase database for the relevant subset of measurements, maps can be generated and compared under consistent conditions. This demonstrates that the project is not limited to producing a single coverage snapshot, but rather offers a scalable tool for systematic comparison across dimensions of time, operator, and service type.

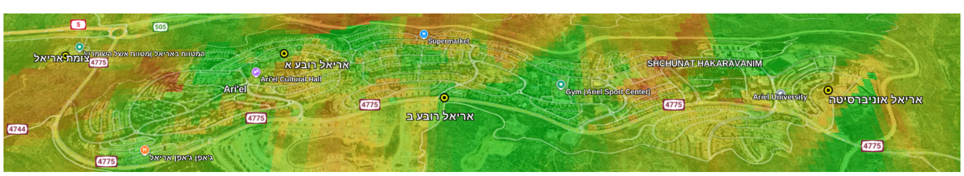

Figure 7. Predicted cellular coverage in Ariel during daytime hours (07:00–21:00), based on 4,207 filtered measurements. Coverage is generally strong,

though more yellow and orange patches appear at the city's periphery.

Figure 8. Predicted cellular coverage in Ariel during nighttime hours (21:00–07:00), based on 1,925 filtered measurements. Coverage appears slightly stronger, with broader green areas indicating more stable reception.

5.3 Road Segment Coverage

The coverage map along the road from Ariel to Elon Moreh demonstrates clear fluctuations in cellular service quality. As shown in Figure 9, certain segments maintain stable reception (indicated in green and yellow) with strong RSRP and SNR values, whereas other areas, particularly near sharp curves, valleys, and elevated terrain, exhibit rapid signal degradation (orange to red, and in some places blue). These fluctuations often result from topographic obstacles that block line-of-sight to the serving cell, forcing the device to switch to a weaker sector or a more distant antenna. In sections such as Figure 10, frequent handovers between neighboring cells are visible, marked by sudden changes in cell identifiers along the route, and reflected in abrupt shifts in color. A more prolonged weak-coverage area is highlighted in Figure 11, where topographic barriers consistently restrict signal strength for extended distances. While the figures are based on a single provider, additional measurements indicate that other networks display similar patterns in these areas, suggesting that the primary cause lies in the terrain rather than in provider-specific infrastructure.

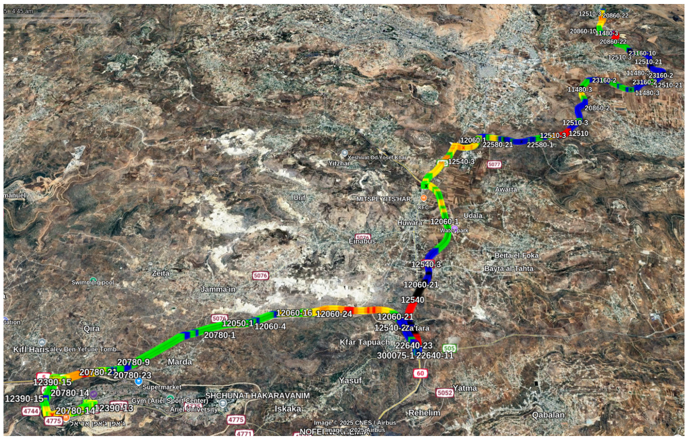

Figure 9. KML output from G-Mon Pro, illustrating alternating strong and weak coverage along a winding road segment, reflecting topographic influence.

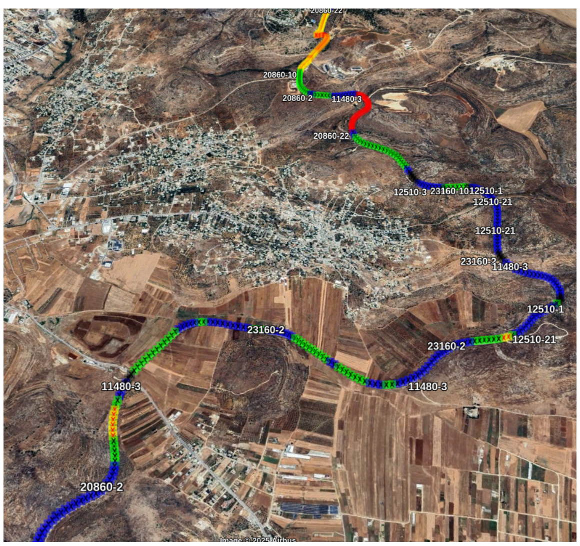

Figure 10. KML output from G-Mon Pro, showing frequent handovers between neighboring cells and rapid changes in signal quality.

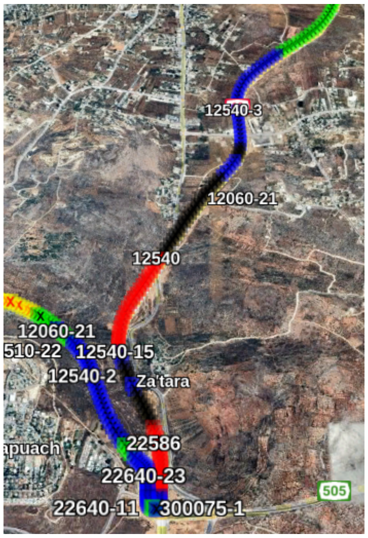

Figure 11. KML output from G-Mon Pro, highlighting persistent low coverage in a valley region, observed consistently across multiple providers.

5.4 Contribution of the Study

This study makes several contributions to both practice and research:

- **High-resolution coverage maps:** Produced detailed maps of the city of Ariel and surrounding roads, offering a resource for local authorities, service providers, and the public.
- **Replicable methodology:** Introduced a simple, adaptable workflow that can be applied in other regions and extended for future studies.
- **Open-source tools:** Released code that enables researchers and practitioners to extend the analysis, refine algorithms, and generate new comparisons.
- **Comparative potential:** Demonstrated that coverage maps can be compared across multiple dimensions—such as times of day, providers, years, or service types (data vs. voice)—to identify trends and contextualize service quality.
- **Updated antenna dataset (technical note):** Compiled an updated set of antenna locations in the region, which, while not the main focus, adds value by improving map accuracy and supporting future analysis.

The findings highlight two main conclusions:

- **Urban coverage:** Within Ariel, reception is generally sufficient, supported by overlapping antennas, though small pockets of weak service remain.
- **Rural gaps:** Along the road to Elon Moreh, large stretches of weak or absent connectivity persist, with potential consequences for accessibility and safety.

Overall, this analysis demonstrates the value of combining raw field measurements with geographic knowledge and interpolation techniques. The resulting maps provide a fine-grained, realistic picture of mobile coverage, while also illustrating the potential of community-driven, empirical data collection to complement and refine official coverage maps.

6. Limitations

This chapter discusses the limitations of the study and their implications for the validity and generalizability of the results.

6.1 Limited Data

Most measurements in this study were collected from a single provider (PHI), limiting the ability to compare operators systematically. While coverage patterns appeared broadly similar across other networks, a comprehensive multi-provider analysis was not possible. In addition, fewer measurements were available for nighttime hours, resulting in lower resolution for those maps. This imbalance may slightly influence the observed patterns, and future work should aim to collect more evenly distributed data across providers and time periods.

6.2 Accuracy and Dependence on Data Density

The accuracy of the generated maps depends heavily on measurement density. In central Ariel, where many points were collected, the maps closely reflect real-world conditions. In sparsely measured areas, however, the interpolation may underestimate coverage or exaggerate weak zones, as illustrated in Figure 12. Expanding data collection through additional fieldwork or crowdsourcing would improve the reliability of future maps.

Figure 12. Example of a coverage map generated from a sparse dataset. With too few measurement points, interpolation produces broad and less reliable zones of weak reception, which may not fully reflect real user experience.

6.3 Methodological Assumptions

The interpolation method (IDW) assumes that coverage changes smoothly with distance. While effective for producing a continuous map, this approach cannot fully capture sudden drops in reception caused by terrain, buildings, or network management. The maps should therefore be viewed as realistic approximations rather than exact reflections of user experience.

As a technical note, all data was collected on Android devices using the G-MoN Pro app; differences in hardware or software could introduce minor measurement bias. Additionally, the study focused on signal strength rather than user-facing metrics such as throughput or call quality.

7. Discussion and Implications

This chapter discusses the practical value of the findings and outlines directions for future research.

7.1 Usefulness for Municipalities and Researchers

The maps and methodology developed in this study have direct practical value for both municipalities and researchers. For local authorities, high-resolution coverage maps provide actionable insights into areas of weak reception that may affect accessibility, safety, and urban development planning. Municipal decision-makers can use such information when engaging with service providers or considering infrastructure investments, ensuring that underserved areas receive attention.

For researchers, the study demonstrates how empirical signal measurements, combined with interpolation techniques and open-source tools, can generate reliable and fine-grained coverage maps. The replicable framework allows future studies to extend the analysis to additional regions, test alternative interpolation methods, or integrate supplementary datasets. The implemented system is readily adaptable for importing measurement data from other regions, enabling the generation of diverse coverage maps with minimal configuration. This positions the project as a bridge between technical research and applied urban policy.

7.2 Future Research Directions

There are several ways to improve and expand this work:

- **Expanding geographic scope:** Extending data collection across additional regions of Israel and abroad, particularly rural and semi-urban areas, would provide a more representative national picture of mobile connectivity.
- **Crowdsourcing at scale:** Encouraging contributions from a larger pool of users could improve spatial and temporal coverage, while reducing route-specific bias. This aligns with the broader concept of participatory sensing, in which communities collectively contribute data to generate shared knowledge [18].
- **Automated analytics:** Incorporating advanced methods

such as machine learning could enable the detection of anomalies, prediction of coverage quality, and modeling of future infrastructure needs.

- **User-facing tools:** Developing a web-based or mobile interface would make it possible for end users to view and compare real-time coverage maps for their location and provider, fostering transparency and empowering consumers.
- **Localization research:** The collected signal data could also support studies on estimating device location from cellular measurements, contributing to the development of positioning methods that operate without GPS [3, 4, 5].

By combining these extensions, the system can evolve from a research prototype into a comprehensive, open, and continuously updated platform for evaluating mobile service quality in Israel and beyond.

8. Conclusion

This project demonstrates a practical and replicable methodology for mapping and analyzing mobile network coverage in underrepresented regions. Using G-MoN Pro for real-time signal measurement, Firebase for centralized data management, and automated visualization scripts, it was possible to generate detailed coverage maps of Ariel and the surrounding area. The results revealed both areas of strong, overlapping coverage and critical connectivity gaps, offering actionable insights for users, researchers, municipalities, and service providers.

Except for generating coverage maps, the study also contributed an open-source workflow that others can adapt and extend, as well as an updated antenna dataset that improves accuracy for future analyses. It further demonstrated how comparative analyses across providers, times, and service types can reveal patterns and contextualize service quality. These contributions highlight the broader research and practical value of empirical, community-driven data collection in refining and complementing official coverage maps.

Overall, the project illustrates the value of combining community-driven data collection with geographic modeling techniques to create realistic, fine-grained pictures of mobile coverage. Beyond its immediate findings in Ariel, the framework provides a foundation for broader studies in Israel and elsewhere, and points toward the potential of open, data-driven approaches to complement and refine official coverage maps.

9. Availability of Data and Code

The full implementation of this project, including source code and documentation, is openly available on GitHub at:
https://github.com/NetaCohen4/radio-map-generator. Researchers and practitioners are encouraged to access, use, and extend the code for their own mapping and analysis tasks.[19]

The dataset collected during this project is stored in a private Firebase database. Due to privacy considerations and storage limitations, the raw data cannot be shared publicly. However, processed and aggregated results are included in this paper, and additional details may be provided upon reasonable request to the author.

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