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Analysis of the Accuracy of Non-Survey-Grade GNSS Devices in Diverse Landscapes

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Abstract

This study evaluates the positioning performance of non-survey-grade GNSS devices (smartphones, sport watches, and IoT trackers) across open terrain, urban canyons, and forest environments. A spatio-temporal synchronization framework with decomposition into along-track and cross-track error components is applied using a post-processed geodetic reference. The results reveal pronounced generational differences among tracking devices, strong environment-dependent performance degradation, and fundamental physical limits of low-cost GNSS relevant to tactical and autonomous applications.

KEY WORDS: *GNSS accuracy, non-survey-grade devices, IoT trackers, positional deviation, landscape impact, spatial analysis, movement tracking.*

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1. Introduction

Positioning using Global Navigation Satellite Systems (GNSS) has become a standard capability not only in smartphones and sports electronics, but also in dedicated tracking devices. These low-cost (non-survey-grade) systems are widely deployed in professional applications, including those used by rescue services and security forces [1].

It is well established that GNSS performance degrades rapidly in challenging environments such as dense forests or urban built-up areas (commonly referred to as urban canyons), where signal obstruction and multipath effects are prevalent [2], [3]. Under such conditions, the limitations of small antennas and the smoothing algorithms implemented in commercial devices become evident.

The objective of this study is therefore not merely to confirm the decrease in positioning accuracy, but to quantify the extent of this degradation and, more importantly, to characterize the nature of the resulting errors. For operational planning and decision-making, it is particularly important to determine whether specific devices exhibit lateral deviations from the intended path (potentially resulting in false localization in adjacent streets), or whether inaccuracies are primarily caused by latency effects along the direction of movement.

This paper presents a methodology for the objective assessment of GNSS positional accuracy based on temporal synchronization and GIS analysis. The approach is applied across different landscape types and, through a case study, enables a comparison of the performance of different generations of tracking devices under dynamic conditions. In this study, positional accuracy is treated as a fundamental quantitative input, while positioning performance is used as an umbrella concept encompassing factors such as accuracy, stability, environmental sensitivity, and trajectory fidelity under dynamic conditions.

2. Methodology and Spatio-Temporal Data Processing

The research was conducted across diverse geographical environments, including open terrain, forested areas, and urban settings. The tested commercial devices were evaluated against a reference trajectory acquired using a Trimble Geo 7x GNSS receiver, operated as a differential mapping-grade reference. Due to frequent interruptions of real-time kinematic (RTK) corrections provided via the national CZEPOS reference network, caused by signal obstruction from buildings and vegetation, the reference data were subsequently refined through post-processing kinematic (PPK) techniques using archived CZEPOS correction data. This ensured the highest practically achievable accuracy of the reference trajectory, even under challenging conditions.

To further ensure data integrity, the Trimble reference trajectory was geometrically validated in ArcGIS Pro using a point-to-line proximity analysis (Near tool), with artifact points deviating more than 10 m from the digitized ground-truth path removed. Subsequently, prior to statistical evaluation, a rigorous kinematic filtering protocol was applied to the tested devices to exclude rare extreme multipath outliers associated with physically implausible velocity spikes. The filtering procedure was applied uniformly across all tested devices and did not affect the relative performance ranking but solely removed physically implausible observations. Data collection was performed under both walking and driving conditions in order to capture varying movement dynamics and levels of sky visibility.

The experimental campaign was divided into two distinct phases. In the first phase, a broad assessment of device categories (smartphones, smartwatches, and legacy tracking devices) was conducted to establish baseline performance characteristics across device categories. The second phase was designed to validate the initial findings and to enable a comparative evaluation of contemporary IoT tracking technologies, incorporating a new generation of hardware equipped with updated GNSS chipsets.

A total of 12 commercial and professional positioning devices were evaluated. Particular emphasis was placed on comparing legacy (Queclink GL300) and contemporary (Smartbox Mini) IoT trackers, alongside the Garmin Foretrex 601, which is commonly deployed in reconnaissance and field operations. Technical specifications are detailed in Table 1.

Table 1. Overview of tested GNSS devices.

Device Category and Model	GNSS Constellations and Chipset	Data Collection Method and Logging Interval
SMARTPHONES		
Samsung A54	Android (A-GPS, GPS, GLONASS, Galileo, BeiDou, QZSS)	GPS Logger, 1 s
iPhone SE 2022	iOS (A-GPS, GPS, GLONASS, Galileo, BeiDou, QZSS)	My Tracks, 1 s
Xiaomi Redmi 7	Android (A-GPS, GPS, GLONASS, Galileo, BeiDou, QZSS)	GPS Logger, 1 s
Huawei P20 Lite	Android (A-GPS, GPS, GLONASS, BeiDou)	GPS Logger, 1 s
SPORT WATCHES		
Polar M400	Polar OS (GPS)	System logging, 1 s
Suunto 9 Baro	Suunto OS (Multi-GNSS)	System logging, 1 s
Garmin Forerunner 35	Garmin OS (GPS)	System logging, 1 s
Garmin Venu 3S	Garmin OS (Multi-GNSS)	System logging, 1 s
TABLETS		
Lenovo Tab 3	Android (GPS)	GPS Logger, 1 s
IoT TRACKERS & OUTDOOR DEVICES		
Smartbox Mini	u-blox M10S (Multi-GNSS)	Internal memory and cloud storage, 10 s
Queclink GL300	u-blox All-In-One (GPS)	Internal memory and SMS transmission, 10 s
Garmin Foretrex 601	Garmin OS (Multi-GNSS)	System logging, 1 s

2.1 Temporal Synchronization and Deviation Decomposition

Given the dynamic nature of the measurements, a spatio-temporal synchronization approach implemented within a GIS environment (ArcGIS Pro) was employed. This method eliminates distortions associated with the use of static perpendicular point-to-line distance metrics applied to moving objects. During data pairing, differences in timekeeping systems had to be addressed: the tested devices recorded time in Coordinated Universal Time (UTC), whereas the reference receiver operated in GPS Time. Accurate synchronization therefore required compensation for the temporal offset introduced by leap seconds (currently 18 s).

Following temporal alignment, error vectors were generated and subsequently decomposed into two principal components:

- *Cross-track error:* the perpendicular spatial deviation from the reference trajectory, primarily reflecting signal reflection and multipath effects.
- *Along-track error:* the deviation along the trajectory axis, indicating temporal latency effects (hardware-induced delays) and/or the influence of smoothing algorithms.

To ensure a comprehensive evaluation of device performance across environments, descriptive statistical metrics were computed, including maximum error, mean, standard deviation, median, root mean square error (RMSE), and the 95th percentile. Overall performance stability was further quantified using a degradation index, defined as the ratio of median error values observed in challenging environments (forested and urban) relative to open terrain. Additionally, total recorded trajectory lengths were compared in order to identify devices that are artificially smooth or shorten trajectories due to aggressive filtering or low logging frequency.

2.2 Error Classification and Visual Interpretation

To map the overall severity of signal degradation, individual error vectors were first visualized in ArcGIS Pro using a five-level color scale based on their total magnitude: 0–2 m (green), 2–5 m (light green), 5–10 m (yellow), 10–25 m (orange), and over 25 m (red). The evaluation of total positional error provides a first-order indication of the overall reliability of positioning performance achieved by individual GNSS receivers and enables an initial comparison across device categories and environments. As illustrated by the demonstrative example in Figure 1, this general methodological approach is effective for visualizing the severity of signal degradation and for identifying obvious performance differences between tracking devices. Figure 1 therefore represents an illustrative case and should not be interpreted as a comprehensive or representative overview of all measurements.

However, total positional error alone is not sufficient for a detailed interpretation of positioning behavior, as identical error magnitudes may arise from fundamentally different underlying mechanisms. Therefore, to enable a more meaningful assessment of receiver behavior under dynamic conditions, the total positional error was decomposed into along-track and cross-track components. This decomposition forms the basis for the following classification defining three distinct behavioral states:

- *State 1 – Consistent Fixation (Absolute Accuracy):* Minimal total error (≤ 2 m) without observable latency or lateral displacement.
- *State 2 – Lateral Deviation (Spatial Displacement):* Significant total error driven predominantly by cross-track deviation (multipath effects), while latency remains negligible.
- *State 3 – Computational Latency:* Substantial total error dominated by along-track displacement, typically resulting from hardware limitations or low sampling frequency.

To visually distinguish between these behavioral states, device stability was further evaluated through scatter plots correlating along-track (Y-axis) and cross-track (X-axis) errors. The cross-track (X) axis was kept consistent across all scatter plots to enable direct comparison of lateral deviation, whereas the along-track (Y) axis was adapted in one case to accommodate substantially larger latency values while preserving interpretability. Based on this representation, four characteristic error distribution patterns were identified:

- *Core Cluster (dense concentration near the origin indicating high accuracy, Fig. 2A).*
- *Longitudinal Dispersion (vertical spread revealing massive latency and aggressive interpolation, Fig. 2B).*
- *Lateral Dispersion (horizontal excursions caused by environmental reflections, Fig. 2C).*
- *Complex Degradation (diffuse point cloud reflecting severe spatial and temporal tracking failure, Fig. 2D).*

Fig. 1. Visual comparison of trajectory recording during pedestrian movement in open terrain. Left: Legacy tracker (Queclink GL300) exhibiting massive along-track latency and corner-cutting. Right: New generation tracker (Smartbox Mini) demonstrating elimination of latency and sub-meter positional accuracy.

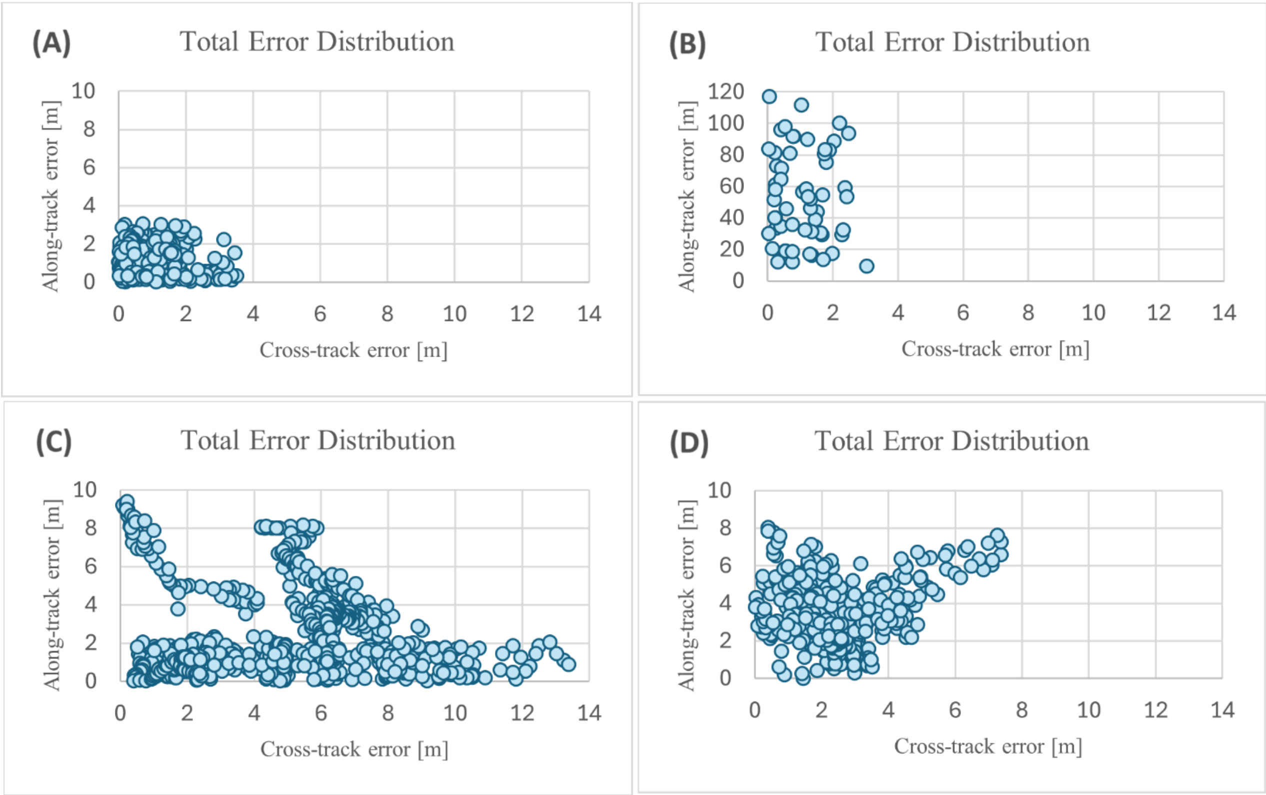

Fig. 2: Comparison of error distribution patterns for selected devices in open terrain. (A) Core Cluster (iPhone SE 2022), (B) Longitudinal Dispersion (Queclink GL300), (C) Lateral Dispersion (Polar M400), and (D) Complex Degradation (Suunto 9 Baro).

3. Results of Spatio-Temporal GNSS Error Analysis

This section presents the results of the spatio-temporal analysis of GNSS positioning accuracy across different environments and movement regimes. The evaluation is structured progressively, starting with open terrain measurements as a baseline reference, followed by environments characterized by signal reflection (urban canyons) and signal attenuation (forested areas). For each environment, total positional error is decomposed into cross-track and along-track components in order to distinguish between spatial displacement and temporal latency effects across device categories.

3.1 Open Terrain Performance and Error Decomposition (Baseline)

Measurements conducted in open terrain with an unobstructed sky view were used as a baseline to assess the maximum achievable performance of the tested hardware in the absence of signal obstruction from buildings or vegetation. The combined dataset from both experimental phases revealed fundamental performance differences across device categories. By decomposing total positional deviation into cross-track and along-track components, it was possible to distinguish whether observed errors originated from spatial inaccuracy or temporal latency.

Modern smartphones and tablets exhibited high levels of accuracy and stability. Under both walking and driving conditions, devices such as the iPhone SE (2022) and Samsung Galaxy A54 achieved median positional errors ranging from 1.8 m to 3.7 m. Error decomposition revealed a relatively balanced distribution between cross-track and along-track components (typically within the range of 40–60%). This proportionality indicates that GNSS chipsets in these devices provide near real-time positioning without significant algorithm-induced latency.

In contrast, the sports watch category demonstrated a pronounced sensitivity to movement dynamics. While acceptable performance was observed during pedestrian movement (e.g., the Garmin Venu 3S achieved a median error of 5.3 m), severe degradation occurred under vehicular conditions. The same device recorded an extreme maximum deviation of 294.8 m during driving. Decomposition analysis further revealed that approximately 80% of the total error was attributable to the along-track component. Detailed trajectory inspection showed that during even mild directional changes, the recorded path continued linearly due to inertial smoothing and only re-aligned with the actual trajectory after a delay of several seconds. This behavior indicates that smoothing algorithms optimized for low-speed movement are not capable of processing positional updates in real time under higher velocities. In contrast, the outdoor device Garmin Foretrex 601 maintained consistent performance irrespective of movement speed (1.3-4.8 m).

The most significant finding was the pronounced generational gap observed within the IoT tracker category. In the first experimental phase, legacy devices (represented by the Queclink GL300) exhibited critical performance degradation during vehicular movement, with average positional errors exceeding 50 m. Decomposition analysis demonstrated that cross-track deviation remained minimal (median values between 1.0 m and 2.6 m), whereas the along-track component accounted for approximately 95% of the total error. This indicates that satellite signal tracking was preserved, while substantial temporal latency was introduced due to outdated hardware and low sampling frequency (10 s). The resulting geometric distortion was directly proportional to movement speed; under pedestrian conditions, along-track error decreased to approximately 14-16 m, corresponding closely to the distance traversed during a single logging interval (see Fig. 1, left).

In contrast, the second experimental phase, incorporating a new generation of trackers (represented by the Smartbox Mini equipped with a u-blox M10S chipset), demonstrated a substantial performance improvement. Under open-terrain vehicular conditions, these devices achieved median errors in the range of 0.97 m to 1.24 m, thereby outperforming even high-end smartphones. Moreover, along-track latency was effectively minimized, contributing only 27-37% to the total positional error and remaining within sub-meter magnitude (see Fig. 1, right). These results indicate that contemporary IoT tracking hardware has largely mitigated the dynamic limitations characteristic of earlier device generations in unobstructed environments.

3.2 Signal Degradation in Urban Environments (Multipath Effect)

The transition from open terrain to dense urban environments (urban canyons) resulted in a substantial degradation of positioning accuracy across all device categories and was accompanied by a qualitative change in the dominant error mechanisms. In contrast to open terrain, where errors were primarily governed by movement dynamics and hardware latency, urban environments were dominated by multipath effects arising from signal reflections from surrounding building facades [4].

The analysis revealed a notable kinematic paradox: for certain devices, particularly legacy IoT trackers such as the Queclink GL300 and selected sports watches including the Garmin Venu 3S, positional accuracy during vehicular movement in urban environments was in some cases higher than in open terrain. For example, older-generation trackers exhibited a reduction in median error from values exceeding 50 m in open terrain to approximately 17–19 m in urban conditions. This apparent improvement was not attributable to enhanced signal quality, but rather to contextual kinematic effects, specifically reduced movement speeds and frequent stops in urban traffic, which effectively shortened the distance traveled within a single logging interval and thereby reduced along-track distortion.

In contrast, pedestrian positioning was severely affected by the multipath environment. While vehicles typically operate within the central portions of roadways with partial sky visibility, pedestrians are confined to sidewalks in close proximity to building facades, often leading to a substantial reduction or complete loss of line-of-sight to satellites. Under such conditions, positioning algorithms exhibited significant degradation. Even high-performing devices such as the iPhone SE (2022) showed an increase in median error to 16.0 m. A similar trend was observed for the Garmin Foretrex 601; while median errors of approximately 5 m were achieved under less constrained conditions, measurements in narrow urban corridors resulted in an increase to 17.0 m. Among the evaluated devices, the Samsung Galaxy A54 consistently maintained high performance, achieving median errors below 5 m, which is likely attributable to more advanced multipath mitigation strategies.

The impact of urban canyon effects was also evident in the performance of modern IoT tracking devices. Although the Smartbox Mini achieved near-smartphone accuracy during vehicular tests (approximately 2 m) (see Fig. 3, items 13-15), a substantial degradation was observed during pedestrian movement in narrow streets, with median errors ranging from 12.5 m to 35.1 m. Error decomposition provided a clear explanation for the observed spatial displacement of trajectories into adjacent building structures: reflected signals introduced systematic vector errors. The cross-track component increased significantly, resulting in lateral displacement of trajectories, while signal delay contributed to elevated along-track errors, accounting for approximately 70% of total positional deviation. These results indicate that although modern multi-GNSS chipsets effectively mitigate latency under open-sky conditions, the absence of direct satellite signal in dense urban environments remains a primary limiting factor.

3.3 Signal Degradation in Forest Environments (Biomass Absorption)

In contrast to urban environments, where signal reflection dominates, forested environments are primarily characterized by signal attenuation and absorption caused by biomass, including foliage, tree trunks, and moisture content. The results indicate that the degree of degradation is strongly influenced by canopy density and prevailing meteorological conditions, with a pronounced impact of moisture-related attenuation, particularly due to the high absorptive properties of water in the GNSS L-band. Similar effects of forest vegetation density on GNSS positioning accuracy, particularly related to signal attenuation and limited satellite visibility under dense canopy cover, have been reported in dedicated experimental studies focusing on forest environments [5].

This effect was clearly observed during vehicular measurements. When driving along forest roads, where a partial sky corridor is naturally present, relatively high positioning accuracy was maintained. Devices such as the Samsung Galaxy A54, iPhone SE (2022), and modern IoT trackers equipped with u-blox M10S chipsets achieved median errors in the range of approximately 2–4.5 m across both measurement phases. Furthermore, error decomposition revealed an approximately balanced distribution between cross-track and along-track components (close to a 50:50 ratio), indicating stable positioning under partial Line of Sight conditions.

A substantial degradation was observed during pedestrian movement beneath dense canopy cover, particularly under more demanding conditions encountered during the second measurement phase (characterized by increased vegetation density and elevated humidity following precipitation). Under these conditions, signal attenuation and the loss of direct satellite visibility resulted in a near-collapse of positioning performance for most devices. Median errors for consumer devices were substantial, with the Lenovo tablet reaching approximately 20 m and smartphones (iPhone SE 2022, Huawei P20 Lite) exceeding 23 m; concurrently, the Garmin Foretrex 601 exhibited a nearly threefold increase in median error (14.8 m) relative to its open-terrain performance. The only device demonstrating notable resilience under these conditions was the Samsung Galaxy A54, which maintained comparatively stable positioning accuracy.

Error decomposition revealed a distinct pattern characteristic of forest environments. Unlike urban settings, where cross-track errors dominate due to reflections, forest-induced errors were primarily associated with the along-track component, accounting for approximately 62-87% of total positional deviation. This behavior indicates that under severe signal attenuation, receivers do not produce large lateral displacements; instead, internal filtering mechanisms increasingly rely on prior positional estimates, resulting in significant temporal lag. Consequently, recorded trajectories systematically lag behind the true position of the moving object.

This limitation was also observed in modern IoT tracking devices such as the Smartbox Mini during pedestrian movement. Despite strong performance in open and urban environments, these devices exhibited substantial degradation under dense, moisture-rich canopy conditions, with median errors ranging from 20.6 m to 31.6 m and along-track components exceeding 77% of the total error. These findings demonstrate that while contemporary multi-GNSS technologies effectively address issues related to kinematic latency and partially mitigate multipath effects, fundamental physical constraints associated with signal attenuation and absorption in forested environments remain unresolved.

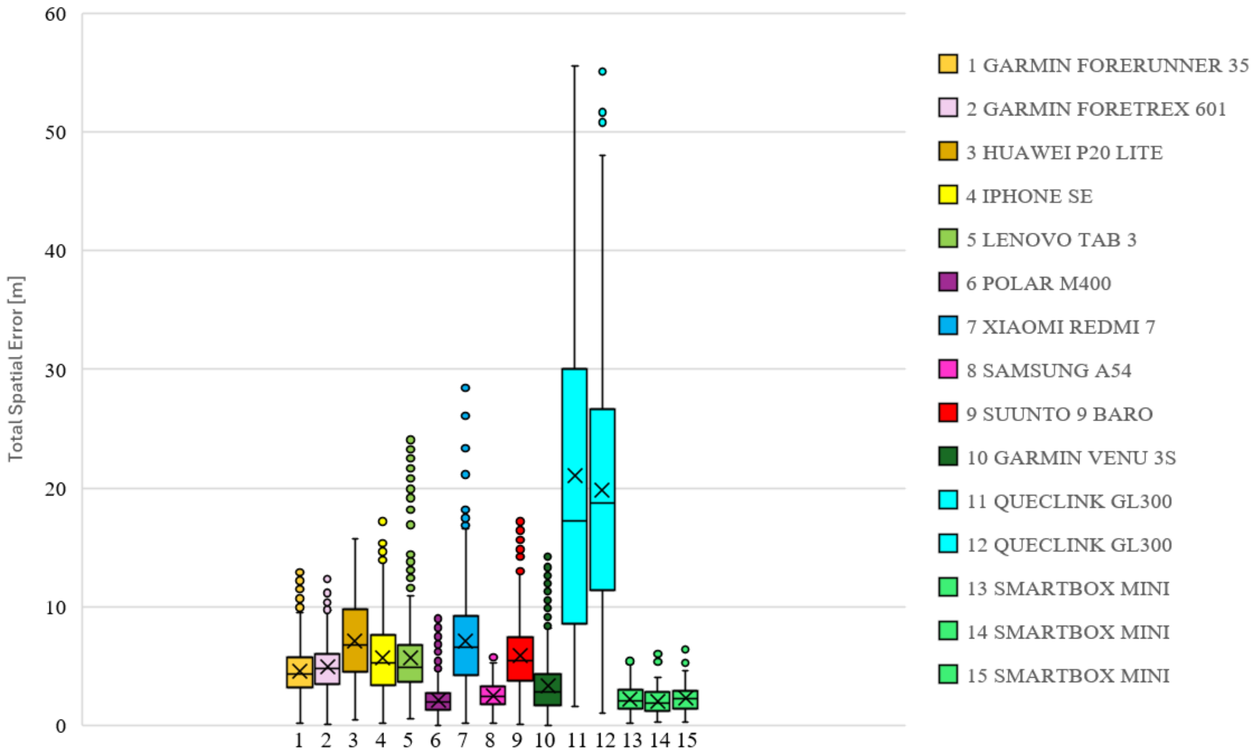

Fig. 3: Total spatial error in urban vehicular mode. Highlighting the generational leap from legacy trackers (11-12) to the new generation (13-15), compared to the stable Samsung A54 (8).

4. Statistical Analysis of Reliability, Measurement Consistency and Trajectory Deformation

The preceding sections focused on accuracy assessment with respect to environmental conditions and movement dynamics. However, a comprehensive evaluation of the tested devices also requires statistical indicators that extend beyond median error values and capture reliability, internal consistency, environmental sensitivity, and the geometric fidelity of recorded trajectories. For this reason, the present section evaluates Root Mean Square Error (RMSE), standard deviation (SD), the 95th percentile, the Accuracy Degradation Index (DI), and trajectory length deformation relative to the high-precision Trimble reference.

RMSE provides a stricter measure of reliability than median error because it emphasizes large deviations through quadratic weighting and is therefore particularly useful for detecting severe outlier behavior. The analysis revealed substantial differences in device performance depending on movement velocity and environmental conditions. Under vehicular conditions, devices equipped with modern GNSS chipsets demonstrated the best reliability. The new generation of IoT trackers achieved RMSE values between 1.4 m and 4.0 m across open terrain, urban areas, and forest roads, indicating that latency-related limitations observed in earlier generations have largely been mitigated. Comparable performance was observed for high-end smartphones, particularly the Samsung Galaxy A54, which maintained RMSE values below 3.6 m. In contrast, legacy IoT trackers exhibited substantial reliability limitations under vehicular conditions, primarily due to their low sampling frequency (10 s). In open terrain, RMSE values reached 60 m, while a reduction to approximately 24 m was observed in urban environments, most likely as a consequence of lower movement speeds and shorter effective displacement between logging intervals. Sports watches also showed marked limitations under vehicular conditions in open terrain; for example, the Garmin Venu 3S and Polar M400 exhibited RMSE values of 91.5 m and 31.9 m, respectively, indicating that their internal smoothing routines were not suited to high-speed dynamics. Among dedicated outdoor receivers, only the Garmin Foretrex 601 maintained comparatively consistent reliability across all tested environments, with RMSE values between 3.6 m and 6.1 m.

A marked shift was observed under pedestrian conditions. Reduced movement speeds led to a substantial decrease in RMSE for devices previously affected by latency. For example, the Garmin Venu 3S improved from 91.5 m during vehicular movement to values as low as 3.8 m in open terrain during pedestrian movement. Similarly, legacy trackers such as the Queclink GL300 achieved RMSE values of approximately 18.2–19.8 m in open terrain, confirming a strong dependence of error magnitude on movement velocity. At the same time, pedestrian measurements exposed increased susceptibility to multipath effects in urban environments. RMSE values increased to 16.8 m for the iPhone SE (2022) and 26.4 m for the Lenovo tablet 3, indicating reduced reliability due to signal reflections. The most severe degradation was observed during pedestrian movement in dense, moisture-rich forest environments. Under these conditions, RMSE increased substantially across all device categories. The strongest degradation was observed for the new generation of IoT trackers (Smartbox Mini), with RMSE values between 27.1 m and 39.5 m. Even modern chipsets were unable to maintain stable positioning under such conditions. Partial resilience was observed only for the Samsung Galaxy A54, which maintained RMSE values below 10 m. Overall, the RMSE analysis demonstrates that device reliability is highly context-dependent and varies markedly between movement modes and environmental conditions.

While RMSE primarily highlights extreme deviations, standard deviation and the 95th percentile provide a more complete view of measurement stability and operational error bounds. These metrics shift the focus from isolated outliers to the internal consistency of the recorded positioning vector and to the error range within which the majority of measurements can be expected to fall. During vehicular movement, the Samsung Galaxy A54 exhibited the most stable behavior across all environments, maintaining SD values between 1.0 m and 1.8 m even in demanding urban and forest settings. A notable result was also observed for the new generation of IoT trackers, which achieved SD values below 1.0 m in open terrain and remained within a range of 1.06–1.34 m even in forest conditions. This suggests that modern hardware can maintain a highly coherent trajectory provided that at least limited canopy openings preserve partial line of sight. In contrast, under pedestrian movement in dense and moisture-rich biomass, SD increased substantially across all devices, revealing a major limitation of the new trackers, whose SD values rose to 13.3–16.3 m. This indicates that the recorded trajectories were not only spatially shifted but also internally unstable. By comparison, the Xiaomi Redmi 7 and Huawei P20 Lite exhibited somewhat lower SD values (3.6–4.9 m), which may indicate the effect of stronger internal smoothing mechanisms under degraded signal conditions.

Movement velocity had a decisive effect on wearable devices. Under vehicular movement, most sports watches maintained acceptable internal stability, but the Garmin Venu 3S proved to be a clear outlier, with SD values reaching up to 84 m as its internal processing failed to keep pace with higher speeds. Under pedestrian movement, the category as a whole showed only moderate degradation. For devices such as the Garmin Forerunner 35, Polar M400, and Suunto 9 Baro, SD values remained relatively low, ranging from 1.3 to 3.9 m in open terrain, 3.7 to 7.6 m in forest environments, and 4.3 to 8.3 m in urban settings. This indicates that most wearable devices remain relatively stable across movement modes, although certain sport-oriented algorithms based on predictive estimation lose positional confidence at higher velocities and may produce pronounced geometric instability.

The 95th percentile further quantified the operational significance of these patterns. In open terrain during vehicular movement, smartphones and the new generation of IoT trackers achieved values below 4.5 m, indicating that 95% of measurements remained within this threshold and thus approached the practical limits of high-quality civilian GNSS positioning. In urban pedestrian measurements, however, the 95th percentile captured the real-world impact of multipath effects more clearly than median errors. Values increased to 29.1 m for the iPhone SE (2022) and 44.7 m for the Lenovo tablet 3, implying that even when median errors remain moderate, considerable positioning uncertainty must still be expected in operational use. In urban environments, such deviations frequently correspond to misplacement into adjacent streets or nearby buildings. The most critical values were recorded during pedestrian movement under dense forest canopy. For the new generation of IoT trackers, the 95th percentile ranged between 51.4 m and 64.5 m, clearly demonstrating that meter-level accuracy is not achievable for standard consumer devices under severe signal attenuation caused by dense, wet biomass. Even the Garmin Foretrex 601 reached a 95th percentile of 28.5 m under these conditions. A particularly notable comparison can be made between the Samsung Galaxy A54 and the Garmin Foretrex 601 in the forest environment: the Samsung device maintained a 95th percentile of 17.8 m, whereas the Foretrex reached 28.5 m. This supports the assumption that modern smartphones may benefit from supplementary positioning sources such as inertial sensing and network-assisted localization, which are typically unavailable in dedicated GNSS receivers.

Environmental sensitivity was further assessed using the Accuracy Degradation Index (DI), defined as the ratio between positional error in challenging environments and baseline error in open terrain. This metric must be interpreted with caution, because a low DI reflects consistency of error, not necessarily high accuracy. If a device already exhibits substantial baseline error, additional environmental obstacles may not significantly worsen its performance in relative terms. Urban environments were used to evaluate susceptibility to signal reflections from buildings. Devices such as the Lenovo tablet 3 and the iPhone SE (2022) showed pronounced degradation, with error increases by factors of 7.7 and 5.8, respectively, relative to open terrain. This behavior indicates strong sensitivity of standard antenna configurations to multipath interference. Conversely, legacy devices exhibited relatively low degradation indices, with error increases of approximately 1.7 or almost no relative change. This should not be interpreted as superior performance; rather, it reflects the fact that their baseline accuracy is already substantially compromised by sampling latency, so additional urban obstructions do not produce a strong relative effect. The Samsung Galaxy A54 again performed well, with a degradation index of approximately 0.9, indicating slight improvement relative to open terrain, probably due to auxiliary positioning sources such as Wi-Fi and cellular networks.

Forest environments revealed a different limitation structure, dominated by signal attenuation caused by wet foliage and tree trunks rather than by reflection. These conditions proved particularly demanding for the new generation of IoT devices. Although they performed very well in open terrain, their error margins increased substantially under biomass cover. The first model degraded by a factor of 9.8, while the second and third increased by factors of 5.9 and 5.1, respectively. Their excellent open-sky accuracy is therefore accompanied by a pronounced vulnerability to forest attenuation. In contrast, the Samsung Galaxy A54 maintained comparatively stable performance, with error increasing by a factor of only 2.7. This finding is consistent with the assumption that modern smartphones benefit from multi-sensor data fusion, which improves robustness in complex environments relative to dedicated single-purpose tracking devices.

The statistical deviations described above ultimately manifest in the geometric fidelity of recorded trajectories, expressed here as total trajectory length relative to the high-precision Trimble reference. The analysis of both measurement phases challenges the common assumption that poor signal conditions primarily cause trajectory inflation through positional noise. Instead, the dominant effect in obstructed environments is substantial trajectory shortening, caused by loss of positional fixes and subsequent linear interpolation between recorded points, effectively resulting in corner cutting. The most significant trajectory shortening was observed in legacy tracking units, which failed to maintain sufficient point density under challenging pedestrian conditions. In the first phase, these devices underestimated the total walking route length in urban environments by approximately 14%, omitting more than 1.1 km of the 8.1 km reference trajectory. The second phase showed that this limitation persists even in newer hardware: two of the new models underestimated the pedestrian forest trajectory by approximately 17%, recording 1.31 km instead of the 1.58 km reference. These results indicate that once optimal sky visibility is lost under dense biomass, even modern chipsets are unable to capture trajectory curvature with sufficient fidelity. Smartphones such as the iPhone SE (2022) and the Lenovo tablet 3 also exhibited trajectory shortening of approximately 8%, whereas the Samsung Galaxy A54 again demonstrated the lowest level of deformation among consumer devices, even under severe conditions.

Under higher vehicular velocities, device behavior differed substantially. Continuous and predictable movement along road networks was well suited to smartphone positioning algorithms, which achieved high path-length fidelity with deviations below 1%. In contrast, all tested tracking devices, including the Queclink GL300 and Smartbox Mini units, exhibited systematic trajectory shortening during vehicular movement across all environments. The Smartbox Mini models underestimated trajectory length by approximately 2% to 4.8%, while the Queclink GL300 models showed comparable shortening due primarily to their long logging intervals. At higher speeds, substantial distances are traversed between consecutive position fixes, resulting in linear interpolation of curved paths and consequent underestimation of route length. Although shortening was the dominant effect overall, certain devices exhibited the opposite behavior. For example, the Garmin Foretrex 601 overestimated trajectory length by 13.6% during low-speed movement in urban conditions. In environments affected by strong multipath interference, positional noise thus led to artificial trajectory elongation. A similar effect was observed for the Garmin Venu 3S during vehicular movement in forest conditions in Phase 1, where the recorded trajectory was extended by 6.5%, corresponding to an overestimation exceeding 1.5 km.

Figure 4 illustrates this contrast clearly in a forest vehicular trajectory, highlighting the pronounced overestimation produced by the Garmin Venu 3S as a consequence of positional noise, in contrast to the systematic shortening observed in legacy trackers.

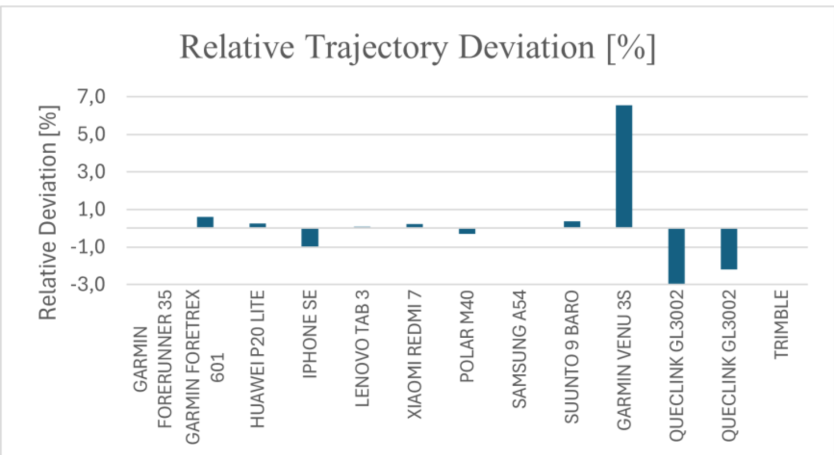

Figure 4: Vehicular trajectory deformation in a forest. Highlights massive overestimation by the Garmin Venu 3S (positional noise) versus systematic shortening by legacy trackers.

5. Generational Comparison of IoT Trackers and Implications for Tactical Field Deployment

This section presents a final comparison of the tested IoT trackers and evaluates their reliability for real-world deployment. The analysis focuses on differences between legacy receivers and a new generation of devices equipped with modern GNSS chipsets, with particular emphasis on their limitations in the context of tactical movement and military operations. Such operations frequently occur in environments characterized by degraded GNSS signal conditions (e.g., forest canopies and dense urban areas), thereby imposing substantial demands on tracking hardware.

5.1 Technological Advances and Environmental Limitations

Both generations of IoT trackers operated with an identical 10-second logging interval, which would traditionally imply comparable behavior during high-speed vehicular movement. However, despite exhibiting a similar geometric trajectory shortening ("corner-cutting") caused by the sampling interval, their positional behavior differed fundamentally, revealing a clear technological shift introduced by modern GNSS chipsets.

Legacy IoT trackers exhibited a consistent but substantial along-track error, often reaching several tens of meters, while cross-track deviation remained relatively low (approximately 2–3 m). This characteristic error pattern indicates pronounced computational latency: although position fixes are recorded at regular intervals, the internal position solution is calculated with delay, causing the reported coordinates to systematically lag behind the true position of the moving object. Consequently, recorded trajectories systematically trail the actual motion rather than exhibiting pronounced lateral offsets.

In contrast, the new generation of IoT trackers demonstrated a marked reduction in along-track error under open-terrain conditions. Despite maintaining the same 10-second logging interval, modern hardware is capable of near-instantaneous position computation, effectively eliminating latency-related displacement. As a result, although geometric simplification of curves remains unavoidable due to the sampling interval, the resulting trajectories are substantially more accurate along linear segments and better suited for both retrospective analysis and real-time monitoring.

When transitioning to challenging environments, particularly dense forest canopy and complex urban settings, a substantial change in performance characteristics was observed. During pedestrian movement under moisture-rich biomass and in urban corridors, the along-track error of the new-generation trackers increased significantly, in some cases approaching values observed for legacy devices. At the same time, cross-track error increased from minimal values to approximately 6 m. This behavior indicates that signal attenuation and multipath propagation introduce positional noise that cannot be fully mitigated by standalone GNSS chipsets, even when computational latency has been largely eliminated.

By comparison, legacy trackers maintained a relatively stable cross-track deviation (approximately 3–4 m) across these environments; however, their overall performance continued to be dominated by persistent along-track displacement. This apparent stability does not indicate superior performance but rather reflects the fact that baseline accuracy is already substantially compromised, rendering additional environmental degradation less visible in relative terms.

These observations confirm that modern GNSS chipsets represent a clear technological advancement through the elimination of computational latency, substantially improving performance in open and semi-open environments. Nevertheless, their reliability remains fundamentally constrained by environmental factors, particularly signal absorption and multipath interference, which become dominant during infantry movement in forested and dense urban terrain.

5.2 Tactical Utilization and Field Deployment Implications

Based on the obtained results, several key recommendations can be formulated regarding the deployment of localization systems in security and tactical applications.

The new generation of IoT trackers can be considered well suited for real-time vehicle tracking. Their ability to provide near-instantaneous positional updates (i.e., minimal latency) enables accurate monitoring of assets in open terrain. In contrast, legacy devices are not suitable for dynamic tracking applications.

Given the increasing prevalence of operations in urban environments, it is essential to account for multipath-induced positioning errors. The results indicate that even modern tracking devices exhibit increased along-track and cross-track errors under such conditions. From a command-and-control perspective, this implies that displayed positions may not fully correspond to the actual physical location of a unit. In practice, positional estimates may be displaced into adjacent streets or building structures, and this uncertainty must be explicitly incorporated into tactical decision-making processes.

Forest environments, particularly under wet canopy conditions, represent the most significant limitation for GNSS-based tracking. As demonstrated, the performance of IoT trackers degrades substantially in such conditions. When high-accuracy navigation is required in forested terrain, dedicated outdoor receivers such as the Garmin Foretrex 601 provide superior on-site positional stability. Their primary advantage lies in delivering reliable on-site navigation directly to the user. However, a key limitation of such devices is the absence of integrated communication capabilities, which prevents real-time positional transmission to command units.

Conversely, IoT tracking devices enable continuous remote transmission of positional information. Nevertheless, during infantry movement in dense forest enviroments, the transmitted positions may be significantly degraded, limiting their tactical reliability. Therefore, the reliability of modern IoT tracking systems for covert infantry operations in forested environments remains an open question and warrants further dedicated investigation.

6. Discussion and Conclusions

This study presented a comprehensive evaluation of the positional performance of various commercial GNSS devices, including smartphones, sports watches, and IoT trackers, with particular emphasis on their behavior under conditions relevant to tactical and security-oriented field deployment. The applied methodology enabled a detailed decomposition of positional error into along-track and cross-track components and linked statistical indicators of accuracy and stability with geometric deformation of recorded trajectories.

The results demonstrate that positioning performance is strongly context-dependent and driven by a combination of technological and environmental factors. While modern GNSS chipsets have largely eliminated computational latency that previously dominated the behavior of legacy tracking devices, their effectiveness remains fundamentally constrained by physical signal limitations. In open and semi-open environments, modern smartphones and new-generation IoT trackers exhibit high positional stability and reliable trajectory reconstruction. In contrast, dense urban structures and forest canopies introduce pronounced degradation through multipath propagation and signal attenuation, leading to positional deviations on the order of tens of meters and systematic deformation of recorded trajectories.

An important finding is that improvements in chipset technology primarily address algorithmic and processing-related limitations, whereas environmental effects represent a persistent and largely unavoidable constraint for standalone GNSS positioning. This distinction has direct operational implications, as apparent consistency of positioning data does not necessarily imply high accuracy under degraded signal conditions.

The proposed evaluation framework was developed and validated primarily to support the assessment of navigation and tracking solutions intended for a broad class of autonomous and semi-autonomous platforms. Such platforms are increasingly equipped with cost-effective GNSS receivers, where constraints in hardware complexity, energy consumption, and sensor availability preclude the use of professional-grade navigation systems. In this context, the presented methodology provides a structured means of quantifying performance limits and identifying operational envelopes under realistic movement dynamics and environmental conditions.

It is important to note that the scope of this study was limited to nominal GNSS operation. The intentional disruption of satellite navigation signals, including jamming and spoofing, was not considered within the applied methodology. Although signal interference represents a critical factor in contemporary military and security operations, its systematic investigation requires dedicated experimental setups and analytical approaches and lies outside the focus of the present work.

Overall, the results confirm that while modern low-cost GNSS-based devices can provide sufficient performance for selected applications and environments, their limitations must be explicitly acknowledged when deployed in complex terrain. The presented methodology offers a transferable and reproducible framework for evaluating such systems and may serve as a reference for future studies targeting navigation performance of autonomous or tactical platforms under realistic field conditions.

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