Low-Cost GNSS Ground Monitoring for Land Planning: AI-Integrated Geospatial Solutions

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Abstract

In today's landscape, both natural and man-made features are highly sensitive to millimetric perturbations from land deformation and daily operational activities. However, continuous, automated, and remote monitoring systems are often unavailable or too costly for widespread use. AIPLAN aims to address this gap by safeguarding critical infrastructure through cost-effective solutions. AIPLAN integrates geodetic engineering, Global Navigation Satellite Systems (GNSS), and Synthetic Aperture Radar (SAR) for land deformation. The project focused on creating a cloud-based platform with Real-Time Kinematic (RTK) algorithms for high-precision deformation measurements and employing AI/ML analysis for comprehensive data processing from GNSS. The key innovation of AIPLAN is the development of a deployable system using low-cost GNSS devices, moving away from expensive survey instruments. The AIPLAN device is a compact, cost-effective, high-precision multi-sensor GNSS receiver package, integrating control boards, multi-constellation GNSS chipsets, Inertial Measurement Units (IMU), and IoT modules. It is designed to measure sub-centimetre movements and vibrations in various modes, including RTK and Network RTK. The project also developed a machine learning system to enhance the accuracy and reliability of low-cost GNSS devices. Filtering techniques and AI algorithms improved data precision. Calibration was performed using corner reflectors, GNSS survey control markers, and geodetic-grade GNSS receivers. The prototype was deployed at a test site, and the 18-month project included testing and validation. Monitoring scenarios on railway tracks, landslide-prone areas, and controlled sites demonstrated AIPLAN's effectiveness and efficiency, making it a valuable tool for infrastructure protection.

Keywords: Low Cost, GNSS, Monitoring

1 Introduction

Accurate and cost-effective ground monitoring is essential for safeguarding infrastructure, managing land use, and mitigating geohazards. However, traditional geodetic monitoring solutions rely on high-end GNSS receivers and other precision instruments, making widespread deployment financially and logistically challenging. The AIPLAN project was developed to address this gap by integrating low-cost GNSS technology with artificial intelligence (AI) and Interferometric Synthetic Aperture Radar (InSAR) to deliver a robust, scalable, and economically viable solution for land deformation monitoring. By leveraging machine learning algorithms, AIPLAN enhances the accuracy and reliability of low-cost GNSS observations, making continuous monitoring accessible for a wide range of applications, including rail infrastructure, landslide-prone areas, and urban development. The InSAR data processing in AIPLAN was conducted by SatSense, a leading provider of ground motion analysis derived from satellite radar data, ensuring accurate and consistent surface deformation measurements.

Geospatial Ventures Ltd. (GVL) is a UK-based geospatial technology company dedicated to advancing the integration of geodetic techniques, satellite-based positioning, and AI-driven data processing. With a strong research and development focus, GVL has collaborated with industry partners and academic institutions to create innovative solutions for geospatial data collection and analysis. The company specializes in GNSS-based monitoring, remote sensing, and intelligent automation of spatial data processing, ensuring that cutting-edge technologies can be applied in real-world scenarios to improve efficiency, accuracy, and accessibility.

This paper presents the research and development efforts undertaken in the AIPLAN project. Section 2 provides an overview of the state-of-the-art in low-cost GNSS monitoring, AI-enhanced GNSS processing, and the integration of GNSS with InSAR. Section 3 outlines the technical design and specifications of the AIPLAN system, detailing the hardware and software components. Section 4 discusses the experimental validation and field deployments, including case studies in rail infrastructure monitoring and land deformation analysis. Finally, the results of AI-enhanced GNSS processing and performance evaluations are presented, demonstrating the effectiveness of the AIPLAN system in achieving sub-centimetre accuracy in real-world conditions.

2 State of the Art

Global Navigation Satellite System (GNSS) has become a fundamental tool in geodetic measurements, enabling precise positioning for applications such as structural health monitoring, landslide detection, and tectonic studies. Geodetic-grade receivers offer millimetre-level accuracy, but their high cost has limited their use to specialized applications. The introduction of low-cost GNSS receivers, particularly dual-frequency models, has expanded access to high-precision positioning. Studies have shown that when coupled with high-quality geodetic antennas and correction services like Real-Time Kinematic (RTK) and Precise Point Positioning (PPP), low-cost GNSS receivers can achieve sub-centimetre accuracy in open-sky environments (Neely et al., 2021). However, their performance deteriorates in obstructed conditions due to multipath effects and signal blockages (Yan et al., 2022). Moreover, while low-cost GNSS offers an affordable alternative, its integration into geodetic monitoring requires robust error mitigation strategies, including the application of AI-driven techniques (Zhou et al., 2021).

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly being employed to improve GNSS data processing by predicting and correcting errors caused by atmospheric effects, multipath interference, and receiver biases. Traditional statistical approaches have been used for GNSS error modelling, but ML techniques offer the advantage of identifying complex, non-linear dependencies within large datasets (Yan et al., 2022). Various models, including Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN), have been applied for anomaly detection, error correction, and signal enhancement (Liu et al., 2023). Kalman filtering has long been used for GNSS data fusion, but AI-driven techniques such as Recurrent Neural Networks (RNN) and Attention Mechanism with Long Short-Term Memory (AMLSTM) have demonstrated significant improvements in GNSS error prediction (Wang et al., 2021). These methods have shown the potential to refine time-series deformation analysis by incorporating additional metadata such as signal-to-noise ratio and environmental conditions (Yan et al., 2022).

While GNSS provides accurate point-based deformation measurements, it lacks the spatial resolution necessary for large-scale monitoring. InSAR, on the other hand, offers wide-area deformation mapping through radar phase difference analysis (Zhou et al., 2021). However, InSAR measurements are susceptible to atmospheric disturbances and can only detect deformation in the satellite's line-of-sight direction (Neely et al., 2021). The fusion of GNSS and InSAR has been explored to overcome these limitations, with AI-based techniques playing a pivotal role in integrating these datasets. Methods such as Multiresolution Segmentation Fusion (MRSF) and Helmert Variance Component Estimation (HVCE) have been developed to automatically classify deformation characteristics and integrate GNSS-InSAR measurements for enhanced monitoring accuracy (Yan et al., 2022). The combination of InSAR's spatial coverage with GNSS's absolute positioning capabilities has led to improved three-dimensional deformation modelling, particularly in urban and mining environments (Liu et al., 2023).

Despite these advances, several challenges must be addressed before AI-enhanced GNSS and InSAR integration can be widely adopted. Data quality and availability remain critical concerns, as AI models require large, high-quality datasets for training (Yan et al., 2022). Additionally, environmental variability, such as vegetation-induced decorrelation in InSAR and urban obstructions affecting GNSS signals, poses challenges to the robustness of AI models (Zhou et al., 2021). The lack of explainability in deep learning approaches is another issue, as transparency is essential for scientific validation and regulatory acceptance (Liu et al., 2023). Future research should focus on optimizing AI architectures, integrating physics-informed ML models, and developing real-time processing frameworks to support continuous large-scale monitoring applications (Wang et al., 2021). The growing availability of open-source GNSS processing software, such as RTKLIB, and cloud-based correction services further supports the development of AI-driven geodetic monitoring solutions (Neely et al., 2021).

While significant progress has been made in integrating GNSS and InSAR for land deformation monitoring, several gaps remain in the current state of the art. There is limited research on the long-term stability and accuracy of low-cost GNSS receivers in highly dynamic or obstructed environments. Most AI models applied to GNSS focus on error mitigation rather than real-time adaptive learning, which could enhance prediction accuracy in changing conditions. Additionally, while the fusion of GNSS and InSAR has been explored, there is a lack of standardized methodologies for multi-sensor integration, particularly in the presence of heterogeneous noise sources. AI-driven fusion techniques remain in early development stages, with many approaches lacking validation on large-scale datasets. Further research is needed to improve model generalization, develop robust multi-sensor data assimilation frameworks, and ensure AI explainability for operational deployment in geodetic monitoring systems (Liu et al., 2023; Yan et al., 2022; Zhou et al., 2021).

3 Design and Specification

3.1 System Specification and Implementation

The developed AIPLAN system integrates Global Navigation Satellite System (GNSS) and Interferometric Synthetic Aperture Radar (InSAR) measurements with Artificial Intelligence (AI) methodologies to enhance land deformation monitoring. The system consists of multiple GNSS receivers, co-located InSAR corner cube reflectors, and a centralized data processing architecture.

3.2 Hardware Design

The GNSS receivers were designed with integral Wi-Fi capability and operated through an internet gateway device that facilitated cellular connectivity. For scenarios where the receivers were positioned beyond standard Wi-Fi range, the receivers' built-in cellular capability was employed to ensure consistent data transmission. The receivers were self-powered using battery packs that were recharged via solar panels, enabling continuous operation in remote locations without direct access to mains power. To ensure data integrity, all receivers operated at a 1Hz update rate.

A key component of the system was the use of dual geometry InSAR corner reflectors, which were strategically positioned to align with both ascending and descending satellite passes. This configuration allowed independent analysis of vertical displacement across multiple InSAR passes, reducing systematic biases and improving the accuracy of vertical motion estimation. The corner reflectors were designed to be adjustable, facilitating precise alignment with satellite orbits.

3.3 Communication and Data Processing

The system relied on an NTRIP-based data transmission model. A dedicated GNSS base station streamed RTCM correction data to the cloud-based NTRIP caster, which in turn provided real-time correction data to the rover receivers. Positioning results were processed on-site and uploaded to a tracking server via MQTT. The server stored, visualized, and analysed GNSS time series data, allowing remote access for system performance monitoring.

3.4 Performance and Verification

The system was designed to achieve sub-centimetre accuracy in horizontal positioning (1-5 mm) and in vertical positioning (2-5 mm). Empirical tests confirmed that GNSS RTK alone provided reliable positioning in open-sky environments. Testing also confirmed that the receivers functioned autonomously for extended periods, with the solar power system reliably maintaining charge levels even in overcast conditions. Wi-Fi communication enabled seamless data transmission up to 250 meters, with cellular communication supporting longer-range connectivity when required.

4 Experimental Validation and Field Deployments

4.1 Test Plan

The AIPLAN system underwent rigorous testing at multiple sites to evaluate its accuracy, performance, and reliability. The test plan was designed to validate the system's ability to integrate GNSS and InSAR data using AI/ML methodologies while ensuring real-world applicability.

Testing was conducted at three primary locations: The Tadcaster Farm Site, owned by the University of Leeds, The Black Country Innovative Manufacturing Organisation (BCIMO) Very Light Rail National Innovation Centre (VLRNIC) in Dudley, West Midlands, and Derbyshire County Council's Snake Pass Test Site. The test setup at each location included GNSS receivers, InSAR corner reflectors, and a combination of controlled and natural deformation scenarios.

At The Tadcaster Farm Site, long-term controlled tests were performed to train AI/ML models. The site featured four InSAR corner reflectors, each equipped with a GNSS antenna. Controlled height changes were introduced at one reflector (CR2) by incrementally removing 5mm shims, allowing the system's response to controlled displacement to be assessed. GNSS RTK measurements were collected continuously, with additional validation through Total Station, Geodetic GNSS, and InSAR surveys.

At BCIMO's Rail Test Track, GNSS receivers were installed to monitor potential movement of track slabs. The setup included a roof-mounted GNSS base station and trackside receivers fixed to instrumented slabs. Data was collected continuously, with initial height assessment showing millimetre-level accuracy. The Rail Test Track, operated by the Black Country Innovative Manufacturing Organisation (BCIMO), is a 2.2 km standard gauge single track designed for vehicle performance testing and infrastructure monitoring.

At Derbyshire County Council's Snake Pass site, GNSS receivers and InSAR reflectors were deployed to monitor natural ground deformations in a landslide-prone area. This site provided an opportunity to validate the system's effectiveness in detecting slow-moving subsidence and sudden displacement events. GNSS data was transmitted via an NTRIP-based system, and InSAR data was processed using the Small Baseline Subset Interferometric Synthetic Aperture Radar (SBAS-InSAR) method.

4.2 Test Results

Tadcaster Farm Site: Comparative Analysis of GNSS, Total Station, and InSAR Measurements

The Tadcaster Farm Site served as a controlled environment to evaluate the precision and reliability of Global Navigation Satellite System (GNSS), Total Station, and Interferometric Synthetic Aperture Radar (InSAR) techniques in detecting small ground deformations. Four corner reflectors (CR1, CR2, CR3, and CR4) were strategically installed, each equipped with GNSS receivers to facilitate continuous monitoring (Figure 1).

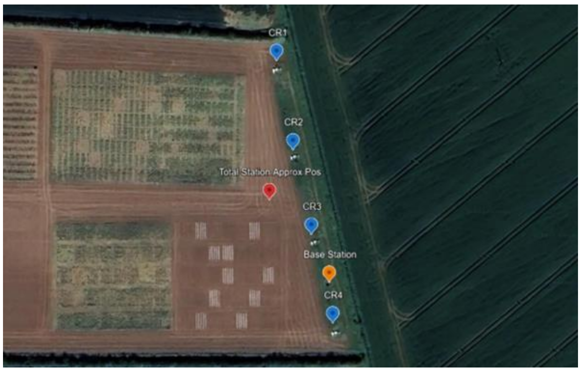

Figure 1 - Site layout at Tadcaster farm site

To simulate subsidence, controlled vertical displacements were introduced at CR2 by systematically removing 5mm shims at predetermined intervals. This methodical approach allowed for a direct assessment of each technique's capability to detect and measure the induced displacements accurately.

Figure 2 - One of the Corner Reflectors at Tadcaster farm site

The Total station data was collected as follows. The targets installed on the corner reflectors can be seen in Figure 2. A Leica TS16 1-second robotic total station was employed for monitoring CR movements.

Each CR features five designated target points suitable for repeated measurements. These targets have been surveyed at least once a month from November 2023 to August 2024.

Due to the absence of stable points within the field and the inability to establish a long-term control station, the total station surveys provide relative measurements between the CRs. The results yield delta heights and delta distances between the receivers.

During each survey, the total station was set up near the CRs, approximately in the centre between CR1 and CR4 with a slight offset from the straight line connecting the four CRs.

During each periodic survey each of the 5 targets on each of the 4 CRs was measured 3 times and the differences between the measurements were checked to make sure they were within tolerance. Standard deviations of these 3 measurements range from 0mm to 1mm.

Table 1 Schedule of Simulated Height Changes at Tadcaster test site

Month	Proposed Height Adjustment	Actual Height Adjustment
April 2024	Default height	Default height
May 2024	-5mm (compared to default)	Default height
June 2024	-10mm	-5mm (29th May)
July 2024	-15mm	-10mm (1st July 2024)
August 2024	-20mm	-15mm (6th August 2024)
September 2024	-20mm	N/A

The relative height time series of the Total Station survey to CR2 is presented in Figure 3. The purpose of this survey was to establish a highly accurate, millimeter-level, reliable method for comparison with InSAR and GNSS measurements. This approach was designed to serve as a trusted, repeatable benchmark for validating the accuracy and consistency of the InSAR and GNSS data.

the pattern of shim removal for CR2 is given in Table 1. It should be noted that there were larger-than-expected discrepancies from epoch to epoch for the "a" point (in blue in Figure 3) on CR2s. We are aware of an issue when attaching the targets to the threads, which caused some unintended movement. This issue was resolved in May by tightening the threads. As a result, data collected after May show significantly lower discrepancies. Additionally, various targets were used during the first few months of the survey, but the same targets were always used for the same survey, so this should not affect the calculation of delta heights. There may have been some incorrect settings in the Total Station, although the exact cause of the discrepancies remains unclear.

The GNSS time series of CR2 over 5 months is also shown in Figure 3. The plot shows the daily average of all ambiguity fixed points that have also been filtered for outliers. The height shows clear subsidence after the 29th May due to the artificially induced subsidence on CR2 from removing the 5mm shims. There are some unexpected jumps in the height during the time series. These are due to the very small number of ambiguity fixed solutions during those particular 24-hour periods. There are gaps in the data due to power and communication issues.

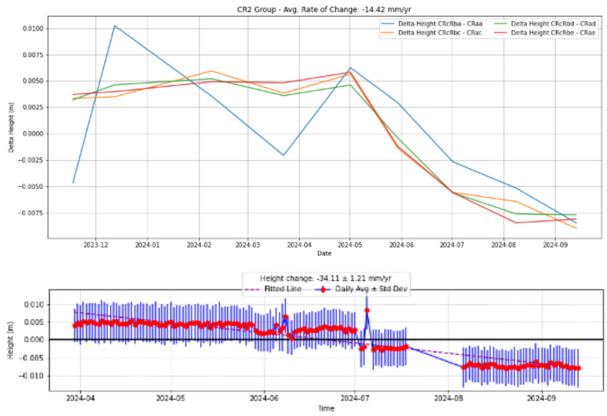

Figure 3 - GVL GNSS Height Timeseries CR2 Spen Farm Tadcaster, Top is measurements to the reflectors on the CR using a Total Station and Bottom the GVL RTK solution.

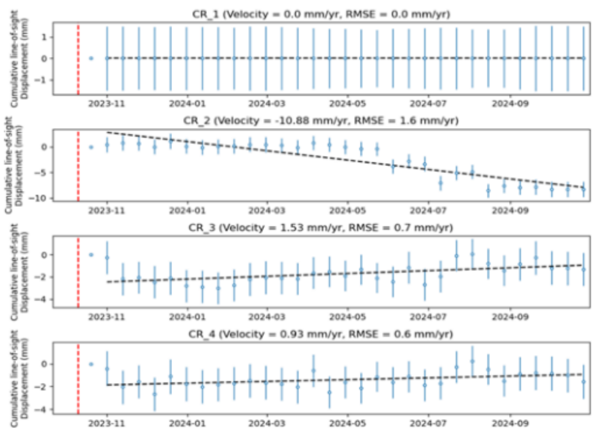

Figure 4 – InSAR height time series for CR1, CR2, CR3 and CR4

Figure 4 shows Reflector performance has remained steady since their installation. The pattern of average velocity among different corner reflectors and across various tracks is largely consistent. Changes in average velocities are expected due to the relatively short duration of the data collection (~12 months), with uncertainty arising from noise and non-linear motion, such as seasonal variations.

All four plots for CR2 show a clear downward trend that aligns well across all satellite passes. CR2 exhibits artificially induced movement starting on May 29th, which is clearly visible in the time series plots after this date. The initial 5mm induced movement on May 29th is distinct, and the second 5mm artificial movement applied in June is also reflected in the July InSAR data.

These movements appear approximately 5mm (slightly less in most plots around 4mm). The recent acceleration of CR2 away from the satellite (negative displacement) observed across all four tracks further confirms that this motion is real and agrees well with the Total Station data. However, it is important to note that the InSAR survey does not consider the recently induced subsidence of CR2 in August.

Notably, after the initial artificial subsidence on May 29th, the InSAR data shows a slight uplift between May 29th and July in the ascending tracks, prior to the second artificial subsidence. This observation is consistent with the Total Station surveys, which suggest a minor uplift of CR2 relative to CR1 between the two artificial subsidence events.

- GNSS Observations: The GNSS receivers provided high-frequency positional data, capturing the stepwise height reductions at CR2 with remarkable precision. Each removal of a 5mm shim corresponded to a detected subsidence of approximately 4.8mm to 5.2mm, indicating the system's sensitivity to sub-centimetre changes.

- Total Station Measurements: Periodic surveys using a Total Station offered high-accuracy distance and angle measurements. The results closely mirrored the GNSS data, with detected height changes ranging from 4.9mm to 5.1mm per shim removal. The minor discrepancies between GNSS and Total Station measurements underscore the importance of integrating multiple surveying methods to enhance reliability.

- InSAR Analysis: Utilising Sentinel-1 satellite data, InSAR provided a temporal analysis of surface deformations. While InSAR successfully identified the cumulative subsidence at CR2, the technique exhibited a slight latency in detecting individual 5mm adjustments, primarily due to its longer revisit intervals and sensitivity to atmospheric conditions.

A comparative analysis of the three methodologies revealed a high degree of concordance in the cumulative displacement measurements over the testing period. The GNSS and Total Station data demonstrated near-real-time responsiveness to the induced subsidence events, whereas InSAR offered valuable insights into the broader deformation trends with a slight temporal offset.

Very Light Rail National Innovation Centre (VLRNIC) Rail Test Track: GNSS Data Collection

The Very Light Rail National Innovation Centre (VLRNIC) Rail Test Track, operated by the Black Country Innovative Manufacturing Organisation (BCIMO), provided a dynamic setting to assess the efficacy of GNSS technology in monitoring structural movements of rail infrastructure. The facility features a 2.2km continuous welded single rail track, adhering to Network Rail's 100mph standard, and is divided into four testing zones, including an 870m curved tunnel section.

A GVL prototype receiver was installed on the Innovation Centre building adjacent to the track loop, with the antenna mounted on the roof's safety frame for an unobstructed sky view. The receiver, housed in a waterproof box and powered by a USB-C mains adapter, is connected to a nearby mains outlet. The cellular router is mounted on the building’s front face, overlooking the track loop, and is similarly housed and powered.

Additionally, two antenna mounting points were installed adjacent to the tracks on instrumented slabs (Figure 5). The installation includes brass plates with mounting studs, short survey poles, and protective sleeves, designed to withstand future tarmac overlay up to the rail track height.

For this study, GNSS receivers were strategically installed on two track slabs, designated as Slab 12 and Slab 20, to capture real-time positional data over an extended monitoring period. The primary objective was to detect and analyse any structural displacements or movements that could impact the track's integrity and performance.

- Data Acquisition: The GNSS units operated continuously, recording positional data with high temporal resolution. The collected data streams were transmitted to a centralized processing system for analysis.
- Observations at Slab 20 (See Figure 6): The GNSS time series for Slab 20 indicated minor vertical fluctuations, with variations typically within ±2mm. These slight changes are attributed to normal thermal expansion and contraction effects, as well as minor settling of the track structure.

The deployment of GNSS technology at the VLRNIC Rail Test Track has demonstrated its capability to provide precise, real-time monitoring of rail infrastructure. The insights gained from this data are instrumental in informing maintenance strategies and ensuring the safety and reliability of rail operations.

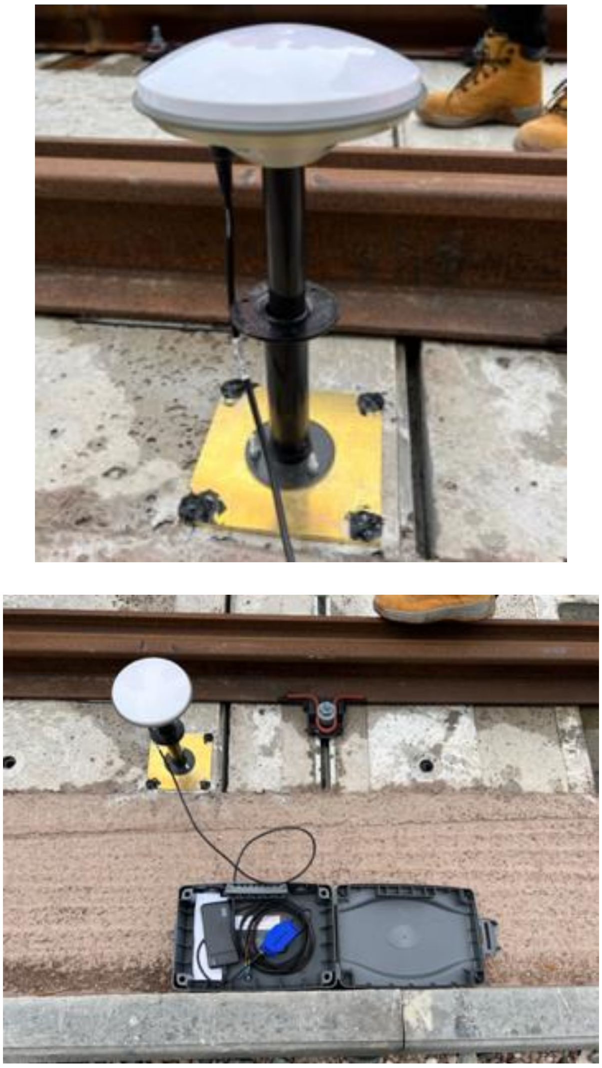

Figure 5 – Details of the trackside antenna mounts.

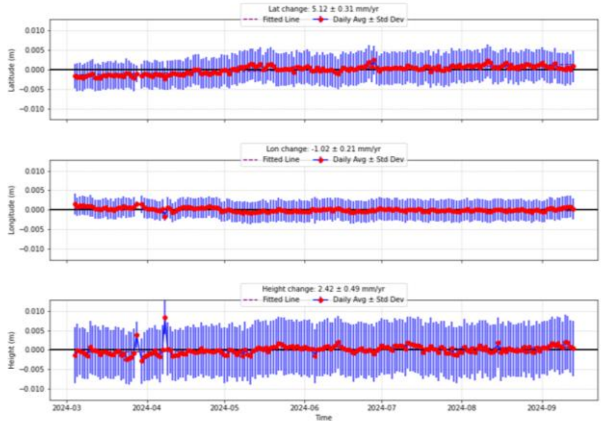

Figure 6 – GVL GNSS Time Series at Dudley Slab20

5 GNSS AI Analysis and Results

Our analysis began by examining the raw GNSS receiver data for a single day. Extreme values, primarily caused by bad fixes, obscure the finer details of the signal. To address this, we apply standard preprocessing steps that remove these extreme values, revealing two distinct components: high-frequency white noise and a lower-frequency error pattern (Figure 7). We hypothesise that this lower-frequency component corresponds to repeatable and predictable multipath errors.

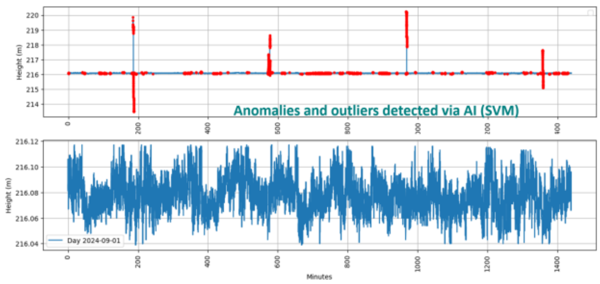

Figure 7 – Anomaly and outlier detection via AI

The variations in the low-frequency signal are likely influenced by satellite constellation-receiver geometry changes as satellites move across the sky. Two primary factors contribute to these variations: antenna phase centre variations and the local multipath environment. Multipath is the more probable cause, given the magnitude of the observed effects. While isolating the exact cause is not necessary, recognising the impact of changing satellite geometry allows us to investigate the effect systematically.

Future work will focus on refining our neural network to improve error statistics for unseen data, a challenge we have so far only managed manually using long training periods. Given this success, we aim to configure the neural network to achieve similar results with shorter training datasets. Specifically, we plan to train the model using an initial period of approximately 10 days of continuous 24/7 data at 1Hz, after which we will transition to a reduced duty cycle to lower power demands while maintaining comparable performance. This will require optimising the model’s ability to generalise from limited data and ensuring it can effectively apply learned patterns to new scenarios. By enhancing these aspects, we aim to develop a more efficient and adaptive AI-driven system that balances data availability, power consumption, and predictive performance.

6 Conclusion

The AIPLAN project has successfully demonstrated the feasibility of integrating low-cost GNSS receivers with AI-driven processing techniques and InSAR for cost-effective, high-precision land deformation monitoring. By utilizing machine learning models to mitigate GNSS errors, enhance multipath correction, and improve positioning accuracy, AIPLAN provides a scalable solution for continuous geospatial monitoring in various environments. The system has been tested in multiple real-world applications, including railway infrastructure assessment and landslide-prone area monitoring, where it has shown reliability and precision comparable to high-end geodetic systems. The integration of InSAR data processed by SatSense has further strengthened the system’s ability to detect and analyze surface movements with high temporal and spatial resolution.

Through the collaborative efforts of Geospatial Ventures Ltd., Loughborough University and SatSense, AIPLAN has demonstrated that AI-enhanced geodetic monitoring can bridge the gap between cost and performance, enabling wider adoption of GNSS-based monitoring solutions. The findings of this project pave the way for future research into adaptive AI models, real-time data fusion techniques, and multi-sensor geospatial integration. As the demand for intelligent land monitoring grows, the continued development and refinement of AIPLAN’s methodologies will be critical in advancing sustainable and resilient infrastructure management.

Acknowledgements

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