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DETECTION OF GEODYNAMIC ANOMALIES IN GNSS TIME SERIES USING MACHINE LEARNING METHODS

One of the applied geodetic tasks in geodynamics is the detection of anomalous deviations in GNSS time series, which may indicate deformations of the Earth's surface caused by various geophysical phenomena. It is important to note that geodynamic anomalies may be of a local nature, manifesting at a single GNSS station, or of a regional nature, occurring simultaneously across a group of GNSS time series. The objective of this article is to develop a method for detecting geodynamic anomalies in GNSS time series using machine learning algorithms. The method has been implemented in the Python environment and allows for the semi-automated analysis of large datasets. Among the machine learning methods, the Isolation Forest algorithm was selected for this study. The research provides a detailed step-by-step description of the program's operation and its stages, enabling the analysis of both individual time series for identifying local anomalies and groups of time series for detecting concurrent regional geodynamic anomalies. The developed method was tested on data from 37 GNSS stations of the GeoTerrace network located in western Ukraine. As a result, seven distinct groups of horizontal and vertical anomalies were identified. One of the detected anomalies was established to correspond with previously investigated vertical crustal deformations caused by non-tidal atmospheric loading in December 2019. The study presents maps of the spatial distribution of the detected group height anomalies in November 2022 and January 2013. Some anomalies observed at certain GNSS stations are of unknown origin and may be due to unidentified local geodynamic factors or measurement errors. In addition to its relevance for geophysicists and geologists in detecting collective geodynamic anomalies, the proposed method also demonstrates potential for use in structural health monitoring of large engineering constructuctions using data from GNSS station networks.

Key words: GNSS time series, geodynamic anomalies, anomaly detection, machine learning algorithms, Isolation Forest, GeoTerrace GNSS network

Introduction

The number of permanent Global Navigation Satellite System (GNSS) stations is steadily increasing. These stations serve a variety of purposes: they function as active, continuous operating reference stations (CORS) for real-time applications [Pipitone, et al., 2023], providelocal networks for monitoring the structural state of facilities [Tretyak, et al., 2024a], and are utilizedfor earthquake monitoring and volcanology. Data obtained from GNSS time series can be employed to address important applied geodetic tasks, such as the measurement and analysis of deformations and the modeling of local geodynamic processes.

In addition to the growing number of GNSS CORS, the precision of individual GNSS solutions is continuously improving, which consequently enhances the quality of time series data. The total error in GNSS observations comprises measurement errors, model errors used for parameter estimation, and errors in the estimated parameters themselves [Steigenberger, 2017]. GNSS errors can arise from various sources, including synchronization discrepancies between satellites and receivers, orbital errors, ionospheric delays, the Earth's magnetic field, tropospheric delays, receiver-generated noise, and multipath errors [Bhardwaj, et al., 2020]. Initially, orbital errors were the primary source of inaccuracies during the early stages of GPS development. However, today tropospheric delays and specific multipath effects are considered the dominant contributors to error [Steigenberger, 2017].

The increased precision of GNSS solutions renders the detection of anomalies in time series more relevant, as such anomalies may have previously been undetectable due to insufficient accuracy. Anomalies are deviations from the expected trend values that may arise from various influencing factors. This creates significant challenges in analyzing GNSS time series for geodynamic research, which involves two key aspects. The first concerns the accumulation of large data volumes, emphasizing the need for automated detection of concurrent anomalies across time series. The second pertains to the analysis of geophysical causes of these anomalies.

In addition to the instrumental errors listed above, which directly affect the accuracy of each daily solution, other factors may influence changes in time series. It is essential to exclude operational factors, particularly any alterations to tracking antenna or receivers at each GNSS station. In current GNSS CORS networks, such equipment changes are typically recorded in log files, facilitating the traceability of these events during time series analysis.

Once operational factors have been excluded, specific geophysical causes of anomalies can be considered. By geophysical phenomena, events such as seismic activity, non-tidal atmospheric loading (NTAL) [Brusak & Tretyak, 2021], non-tidal ocean loading (NTOL) [Williams & Penna, 2011], and hydrological loading [Michel, et al., 2021], among others. Identifying and confirming the nature of these anomalies typically requires additional data. Forecasting or even detecting them remains challenging. For instance, the impact of NTAL can be evaluated using models developed by the Earth System Modelling division at GFZ Potsdam, Germany [Earth System Modelling at GFZ]. This online platform also offers up-to-date NTOL and hydrological loading models.

When analyzing anomalies for each GNSS CORS individually, it is also crucial to understand that local geodynamic factors may affect only a specific station. For example, anomalies in time series may be caused by anthropogenic disasters, landslides, karst processes, or other geodynamic phenomena in the given area [Savchyn, et al., 2019]. At the same time, major earthquakes produce abrupt changes in the coordinate time series of several GNSS stations in the affected region. Similarly, while NTOL affects coordinate shifts in coastal GNSS stations, NTAL influences coordinate changes in groups of stations subject to atmospheric variations. For instance, in December 2019, height displacements of up to 2 cm were observed in more than 500 GNSS time series across Europe within ten days [Brusak & Tretyak, 2020]. Accordingly, individual and group anomaly analyses should be conducted concurrently within GNSS time series.

When automatically analyzing large amounts of GNSS data to detect specific anomalies, traditional analytical methods, such as the least squares method and spectral analysis, encounter certain limitations. Although these methods are widely used for parameter estimation and time series analysis [Savchyn, et al., 2021; Savchuk, et al., 2024; Doskich & Serant, 2024], they are not always effective for large and complex datasets, especially when the objective is to identifycomplex and unpredictable anomalies. Spectral analysis allows the examination of periodic components in signals. However, identifying non-periodic or irregular anomalies can be challenging, especially when they are obscured by noise or other signal components [Costantino, et al., 2024]. Moreover, the analysis of long-duration time series with high-frequency measurements presents issues related to computational complexity and highlights the need for automation in the analytical process.

Machine learning methods for time series analysis

Today, researchers increasingly turn to machine learning (ML) methods to address the challenges of automating time series analysis, unlocking new possibilities for anomaly detection. ML enables the identification of complex patterns and interrelationships that are difficult to detect using traditional methods, particularly when dealing with large volumes of GNSS data [Butt, et al, 2021, Ramavath & Perumalla, 2023, Heizmann & Braun, 2022, Breiman, 2001]. Special attention has been given to studies focused on using of specific ML algorithms and ensemble methods to enhance the accuracy of GNSS data analysis. For instance, Özarpacı et al., [2024] demonstrate how different ML algorithms can improve velocity estimation from GNSS data, emphasizing the importance of advanced techniques for analyzing complex time series. Butt, et al., [2021] conducted a comprehensive review of ML applications in geodesy, highlighting the value of such methods in uncovering hidden patterns and improving geospatial analysis through classification, regression, and clustering algorithms. This demonstrates the significant potential of ML in solving geodetic tasks, particularly in the detection of anomalies in GNSS datasets. Moreover, the concept of GeoAI, which integrates geospatial data with artificial intelligence, is gaining prominence in geospatial research [Pierdicca & Paolanti M., 2022]. GeoAI provides tools for automating the analysis of large geospatial datasets, significantly reducing processing time and increasing the precision of results. This is especially important for efficient anomaly detection and GNSS network monitoring, where ML methods facilitate the integration of various techniques for deeper and more accurate analysis.

Machine learning techniques are already being applied to analyzing of time series in regions with high geodynamic activity, detecting both local and group anomalies that point to geophysical processes or anthropogenic changes, such as in Turkey [Özbey et al., 2024].

The Isolation Forest algorithm is among the most effective algorithms for detecting isolated anomalies in time series [Liu, et al., 2008, Liu, et al., 2012, Hariri, et al., 2021]. This algorithm is based on the principle of isolating anomalous data points through recursive partitioning of the data space and offers advantages in speed and efficiency when processing large datasets. Extended versions of the Isolation Forest algorithm further enhance its performance for geodetic applications. A study by Özarpacı et al. [2024] reaffirms the importance of employing advanced ML algorithms, such as the Isolation Forest, to analyze complex GNSS datasets and detect anomalies in time series. The algorithm has also been applied to develop a semi-automated method for detecting isolated anomalies induced by earthquakes using GNSS time series from the Japanese archipelago [Haidus & Brusak, 2024].

Compared to other methods, the Isolation Forest is characterized by near-linear time complexity and minimal parameter tuning requirements. It is particularly well-suited for large network datasets and GNSS CORS observations. Density-based algorithms typically exhibit higher computational complexity and are more sensitive to parameter selection (e. g., neighborhood radius in DBSCAN, number of neighbors in LOF). Similarly, traditional statistical time series models such as ARIMA may offer better interpretability for individual stations but often require the assumption of stationarity and may be less effective under high signal nonlinearity or synchronized multistation deviations [Nguyễn & Tran, 2023; Li et al., 2025].

Furthermore, the Isolation Forest algorithm balances detection accuracy and computational performance, even under dynamic GNSS data conditions that include seasonal effects and periodic outlier surges. While neural network-based methods may sometimes achieve higher detection rates for complex patterns, they typically demand large volumes of training data, greater computational resources, and specialized tuning [Nguyễn et al., 2024]. In contrast, the Isolation Forest method, as applied in the study by Haidus, et al. [2024], does not require complex hyperparameter optimization and yet achieves robust performance in identifying both local and network-level anomalies.

The aforementioned studies confirm the effectiveness of the Isolation Forest algorithm in geodetic applications, particularly for the analysis of large datasets and the detection of complex anomalies that may be associated with geophysical, anthropogenic, or operational factors in GNSS station networks. Building upon previous research in this field, the authors of this article aim to develop an algorithm based on the Isolation Forest ML method for detecting anomalies in GNSS time series. An essential component of this work is the supplementary interpretation of the causes of detected anomalies through comparison with findings from related studies.

Method

A step-by-step algorithm of the method for detecting anomalies in GNSS time series is presented below, and the corresponding block diagram is shown in Fig. 1.

At the initial stage, key Python libraries are imported for numerical operations (***NumPy, Pandas***) and the practical implementation of machine learning methods, notably the Isolation Forest algorithm from the ***scikit-learn*** package [Pedregosa et al., 2011]. The ***Plotly*** module is used for results visualization. While these technical components are critical for method construction, the methodological core lies in the theoretical foundations of the Isolation Forest as an algorithm optimized for isolating anomalous points through strategic partitioning of the feature space.

Unlike density or distance-based approaches, Isolation Forest applies a more straightforward strategy based on the principle that “anomalies are few and different”. Its core involves constructing an ensemble of random decision trees: each tree recursively splits the data using randomly selected attributes and split values. Anomalous observations, those deviating significantly in one or more components (***N, E,*** or ***Up***), are “isolated” faster, as their coordinates lead to partition boundaries at shallower tree depths. The anomaly score is computed as a generalized path length to the node, aggregating estimations from all trees.

After loading and cleaning the GNSS time series (removing gaps and invalid values), the data are grouped by station. Additional statistical features such as moving averages or standard deviations may be calculated for each GNSS CORS to enhance the model’s sensitivity.

The definition of Isolation Forest hyperparameters is preceded by evaluating the typically low rate of anomalous events in geodetic measurements. The ***n_estimators*** parameter sets the number of decision trees: increasing this value improves distribution detail but also lengthens computation time.

The *contamination* parameter *contamination*, the expected fraction of anomalies – is typically set low (e. g., 0.01) because GNSS time series usually exhibit smooth trends with isolated outliers.

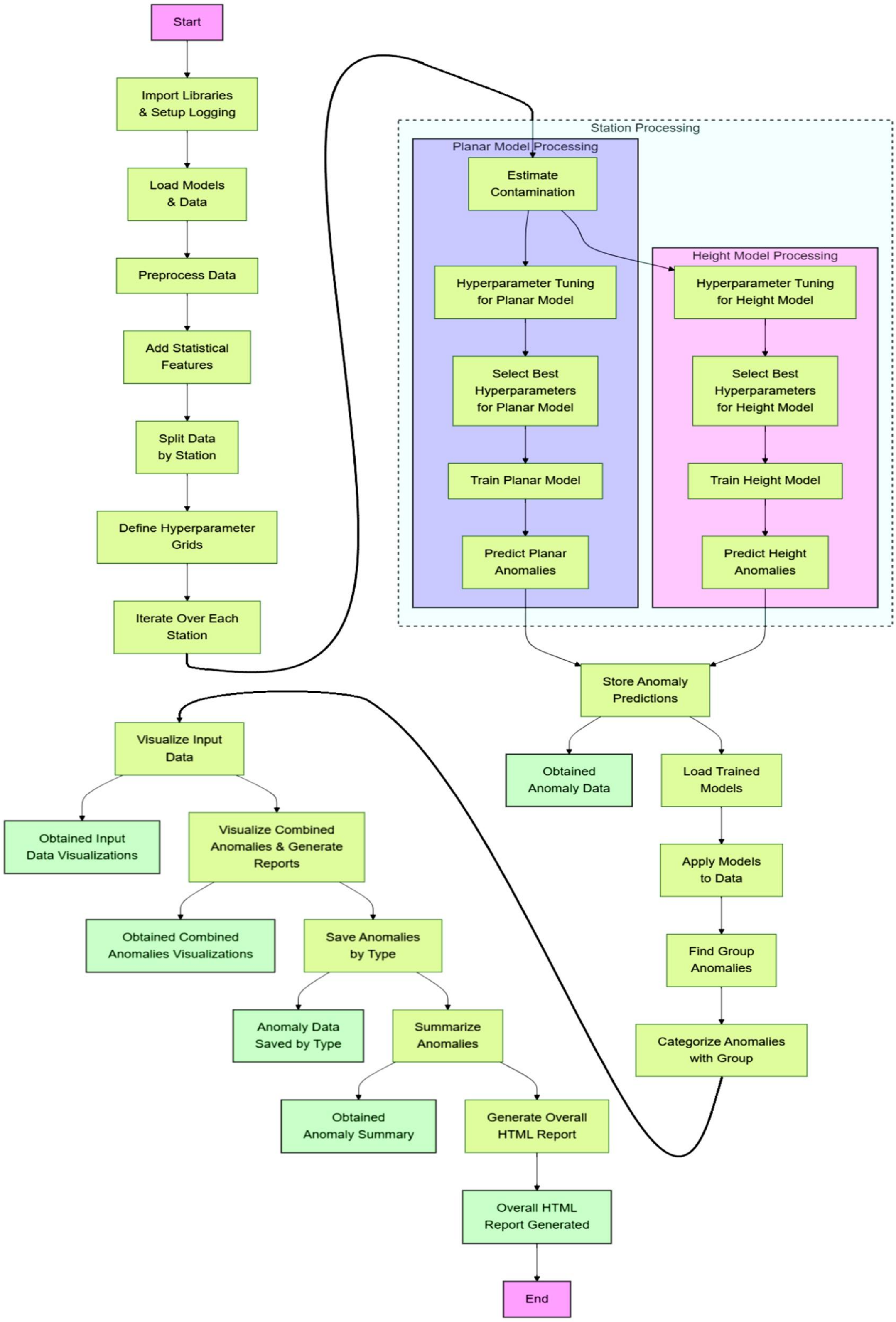

Fig. 1. Block diagram of the proposed method utilizing the Isolation Forest algorithm for detecting geodynamic anomalies in GNSS time series.

Optimal hyperparameter values were selected using a grid search procedure, with particular attention paid to the sensitivity analysis of the contamination parameter. As illustrated by the results for station VARA (Fig. 2), the choice of this parameter is a compromise: increasing it (e. g., from 0.005 to 0.015) leads to an increase in the number of detected anomalies (from 10 to 26), but reduces their average significance, or absolute deviation (from 16.92 mm to 15.86 mm). This pattern, stable even when other hyperparameters are changed, emphasizes the critical role of *contamination* in tuning model sensitivity. Thus, the final parameter value was chosen as a balance between effective detection of significant deviations and avoiding false positives of fluctuations close to the background noise of the signal.

Also, with *contamination* equal to 0.01, the number of expected geodynamic anomalies for the study period corresponds to the authors' experience in this region and for these GNSS data.

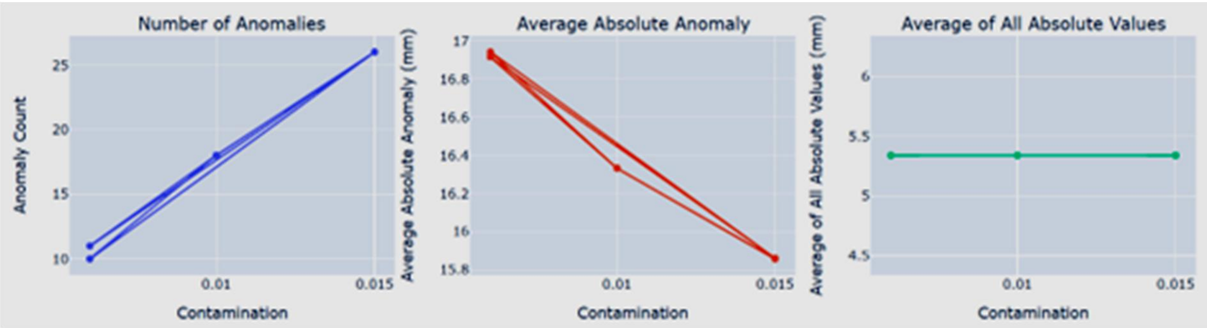

Fig. 2. Dependence of the number and values of detected anomalies on the *contamination* parameter in the Isolation Forest model for Up component on example of VARA GNSS station.

A key advantage of Isolation Forest is that it does not require assumptions about the data distribution, making it particularly suitable for time series affected by seasonal, stochastic, or operational fluctuations. During model training, each daily coordinate solution receives an anomaly score: higher values indicate easier isolation and potential outliers. Alongside local anomaly detection, it is essential to identify group anomalies – synchronous spikes at multiple stations. For this, a four-day sliding window is analyzed: if ≥20 % of stations register outliers within the window, a potential regional geophysical or atmospheric influence is inferred. This threshold is adjustable and tailored to the geodynamic behavior of GNSS time series.

The results are displayed using interactive graphs, where GNSS time series and detected anomalies are overlaid on a single canvas, enabling rapid identification of segments that deviate from the expected trend. Comparing local and group anomalies in the graph facilitates assessment of whether a deformation affects a single or multiple GNSS stations. A final report consolidates all findings for subsequent analysis and comparison with known events.

Ultimately, the "early isolation" principle embedded in Isolation Forest proves highly relevant for GNSS stations, where outliers are typically driven by short-term but significant factors, such as operational changes or geodynamic phenomena. The proposed methodology provides a flexible and robust solution for anomaly detection by combining Isolation Forest with station-specific preprocessing and network-wide anomaly checks. Furthermore, cross-referencing detected anomalies with known events (e. g., seismic events, non-tidal atmospheric loading) significantly supports interpretation. In general, applying the proposed Isolation Forest-based method demonstrates that a data-oriented, distribution-agnostic approach can effectively monitor large volumes of GNSS time series.

Validation of the method

The GeoTerrace GNSS CORS network was selected to validate the proposed method. The Institute of Geodesy at Lviv Polytechnic National University actively developed this national network of GNSS CORS in Ukraine. The development of the GeoTerrace network began in 2007 in the Lviv region and has since expanded to approximately 90 stations, forming a unified network that covers most Ukrainian regions. Real-time network management is performed using the integrated SinoGNSS CDC.NET software. Daily GNSS solutions are computed in post-processing using the Bernese GNSS Software for geodynamic studies. A portion of the processed data was analyzed directly by the authors. In contrast, another portion was obtained from the Institute of geodesy Geodesy laboratory for scientific purposes.

The average distance between adjacent GeoTerrace stations is approximately 70 km, which is effective for differentiating current geodynamic processes across the covered regions. The spatial distribution of the stations is shown in Fig. 3.

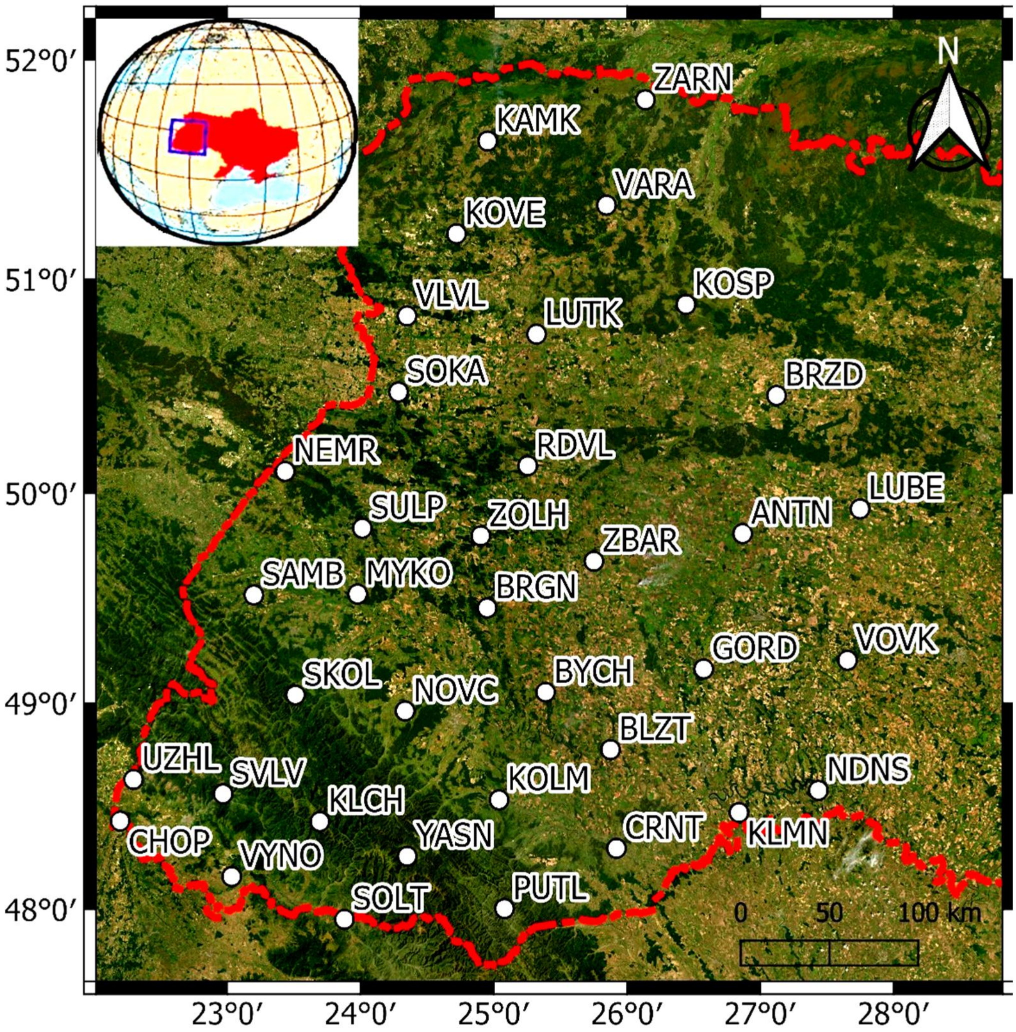

Fig. 3. Location of GNSS stations from the GeoTerrace network used in this study.

Numerous scientific studies utilize data from the GeoTerrace network. Short-term anomalies caused by non-tidal atmospheric loading were identified using data from the GeoTerrace and Dnister Hydro Power Plants GNSS networks [Brusak & Tretyak, 2021]. The validation of GNSS time series for further geodynamic research is currently ongoing [Doskich, 2021; Doskich & Serant, 2024; Brusak, et al., 2024]. These results are employed to identify current geodynamic processes occurring in the Ukrainian region [Tretyak, et al., 2024b; Doskich, et al., 2023]. The data are also provided to the Main Astronomical Observatory of the National Academy of Sciences of Ukraine for forming and disseminating reference frames in Ukraine. Velocity assessments indicate mean repeatability of coordinate components of 1.69 mm (North), 1.40 mm (East), and 3.63 mm (Up) [Khoda, 2024]. Other studies have confirmed seasonal fluctuations at some permanent stations in Eastern Europe [Bem, 2024; Maciuk, 2016; Savchuk, et al., 2023].

For validation, daily GNSS solutions from the GeoTerrace network were analyzed for the period 2019–2024. To confirm anomalies caused by seismic events, USGS data were used [Search Earthquake Catalog at USGS], including event date, type, magnitude, and location. Anomalies associated with non-tidal deformations were compared to GFZ model data [Earth System Modelling at GFZ]. The date difference between the event and anomaly was calculated for each detected anomaly: a maximum difference of 7 days was considered indicative of a potential correlation. A list of matching events was compiled to assess the individual geodynamic impacts on GNSS time series.

Figs. 4 and 5 show the time series of the Up component for GNSS stations VARA and KLCH from the GeoTerrace network. Detected anomalies using the proposed method are marked with vertical black lines: solid lines indicate group anomalies (also present in nearby stations), dashed lines indicate local anomalies affecting only that station.

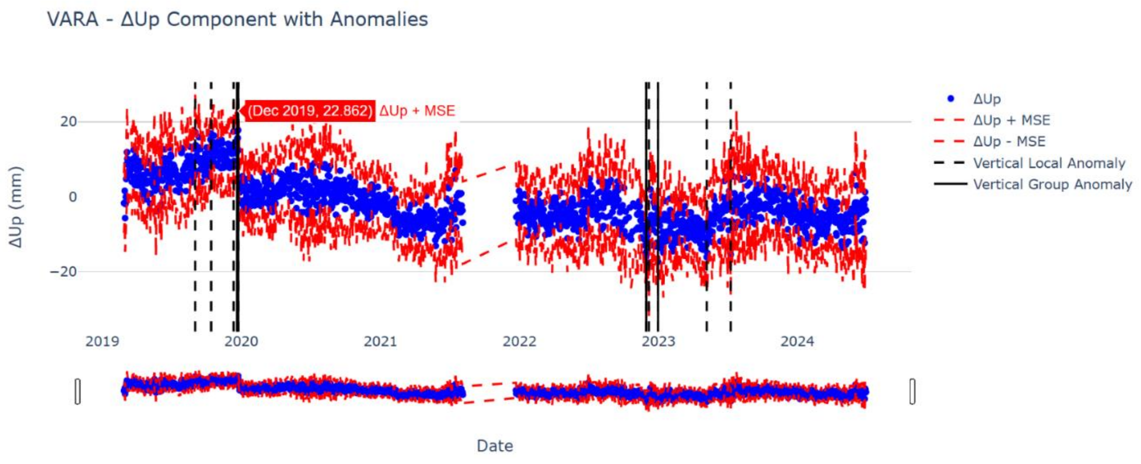

Fig. 4. Time series of vertical (Up) component for GNSS station VARA and detected local and group anomalies using the proposed method.

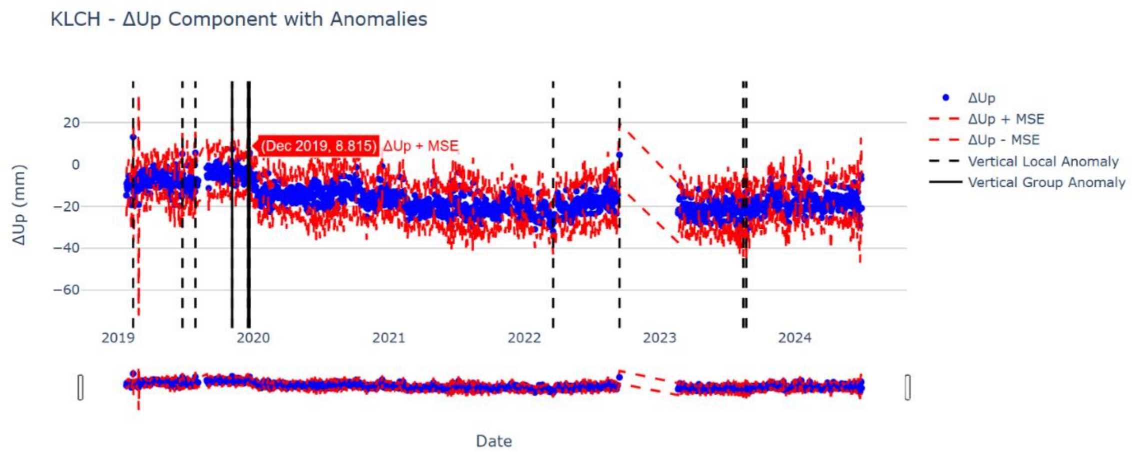

Fig. 5. Time series of vertical (Up) component for GNSS station KLCH and detected local and group anomalies using the proposed method.

A detailed visual analysis of group anomalies revealed clear patterns associated with NTAL anomalies, which correlate with modeled atmospheric pressure variations [Earth System Modelling at GFZ]. In particular, height anomalies identified in December 2019 at stations VARA (see Fig. 4) and KLCH (see Fig. 5) coincide with previously studied NTAL effects [Brusak & Tretyak, 2020], confirming the method's capability to detect such geodynamic influences. Some anomalies are also associated with operational factors, such as equipment replacement. For example, the hardware upgrade (antenna and receiver) at KLCH in early 2022 was identified as a local anomaly (see Fig. 5).

Additionally, Fig. 6 provides a full overview of anomalies recorded at all stations in the western part of the GeoTerrace GNSS network from 2019 to 2024. The horizontal axis displays time, and the vertical axis lists the stations. Blue markers indicate horizontal anomalies (N, E components), and red markers indicate vertical anomalies (Up).

Seven group anomalies were recorded in the period from 2019 to 2024. The determined dates for horizontal anomalies are: August 29, 2020; December 11, 2021; and June 27, 2024. The dates for height anomalies are November 5, 2019; December 20, 2019; November 30, 2022; and January 1, 2023. Summarized data for these periods, including the determined time ranges (where sequential recordings of anomalies of the same type were combined if the gap between them did not exceed 3 days) and a list of stations where the corresponding anomalies were detected, are given in Table.

The detected anomaly in December 2019 that corresponds to the period 2019-12-16 – 2019-12-26 for the Up component (see Table) covers a large number of stations (16 stations, as indicated in Table) and corresponds to a previously documented change in the vertical component under the influence of non-tidal atmospheric loading [Brusak & Tretyak, 2020].

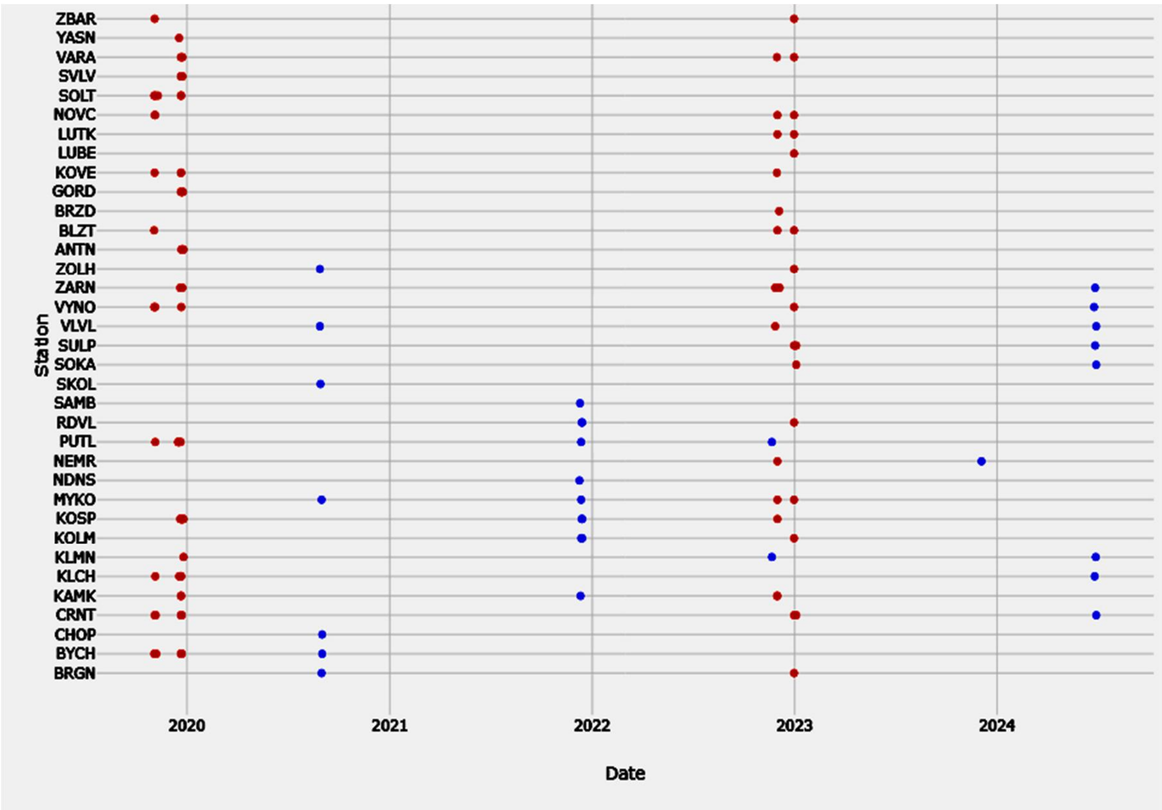

Fig. 6. Horizontal (blue) and vertical (red) group anomalies detected by the proposed method based on the Isolation Forest algorithm for GNSS stations in the GeoTerrace network from 2019 to 2024.

Periods of group anomalies and GeoTerrace network GNSS stations that recorded them (2019–2024)

Anomaly type	Date range	Stations where anomalies were detected (count)
Vertical	2019-11-03 – 2019-11-07	BRGN, BLZT, BYCH, CRNT, KLCH, KOVE, NOVC, PUTL, SOKA, VLVL (10)
Vertical	2019-12-16 – 2019-12-26	ANTN, BYCH, CRNT, GORD, KAMK, KLCH, KLMN, KOSP, KOVE, PUTL, SOKA, SULP, SVLV, VLVL, VYNO, VARA (16)
Vertical	2022-11-27 – 2022-12-05	BLZT, BRZD, KAMK, KOSP, KOVE, LUTK, MYKO, NEMR, NOVC, SVLV, VARA, YASN, ZARN (13)
Vertical	2022-12-31 – 2023-01-04	BLZT, BRGN, CRNT, KOLM, LUBE, LUTK, MYKO, NEMR, NOVC, RDVL, SOLT, SOKA, SVLV, SULP, VLVL, ZBAR, ZOLH (17)
Horizontal	2020-08-28 – 2020-09-01	BRGN, BYCH, CHOP, MYKO, SKOL, VLVL, ZOLH (7)
Horizontal	2021-12-09 – 2021-12-14	KAMK, KOLM, KOSP, MYKO, NDNS, PUTL, RDVL, SAMB (8)
Horizontal	2024-06-24 – 2024-06-28	CRNT, KLCH, KLMN, SOKA, SULP, VLVL, VYNO, ZARN (8)

Let's consider in detail the changes in the vertical GNSS time series during the group events identified in Table. For example, let's consider two recorded cases: the period of activity from 2022-11-27 to 2022-12-05 and the period from 2022-12-31 to 2023-01-04 (see Table). The spatial distribution and magnitudes of vertical anomalies by maximum displacement *dh* (mm) and daily velocity *dV* (mm/day) for these periods are shown in Figs. 7 and 8, respectively.

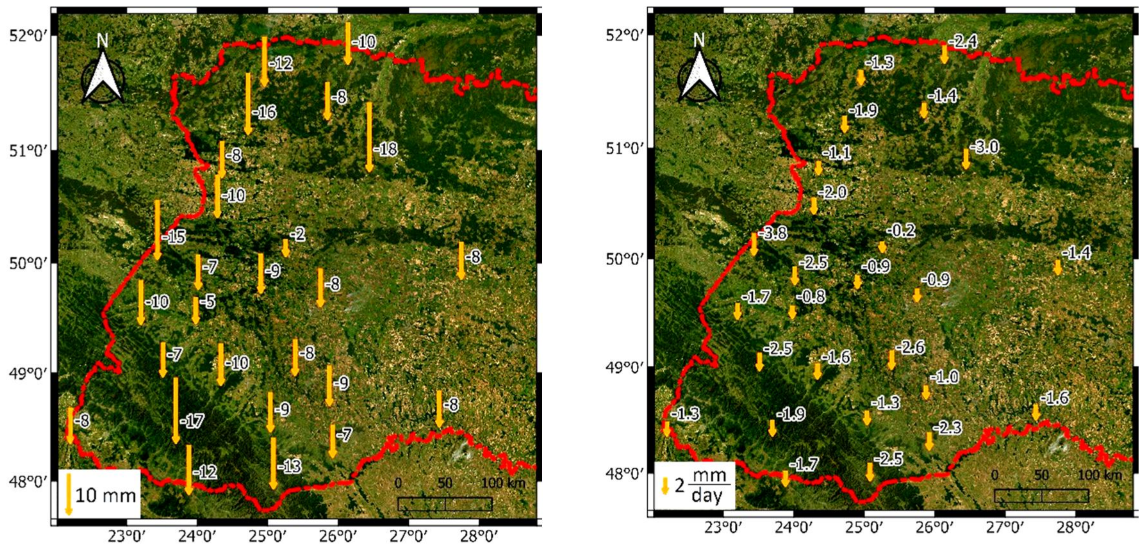

Fig. 7. Spatial distribution of vertical anomaly characteristics at the end of November 2022: maximum subsidence ***dh*** in mm (left) and daily subsidence rate ***dV*** in mm/day (right) detected by the proposed method for GeoTerrace GNSS network stations.

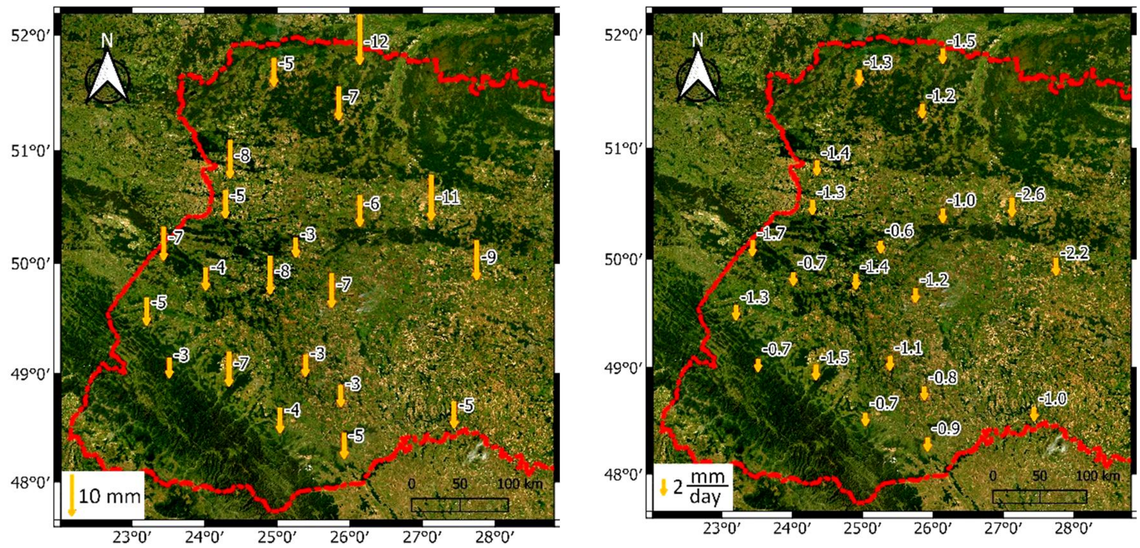

Fig. 8. Spatial distribution of vertical anomaly characteristics at the beginning of January 2023: maximum subsidence ***dh*** in mm (left) and daily subsidence rate ***dV*** in mm/day (right) detected by the proposed method for GeoTerrace GNSS network stations.

The total number of studied GNSS stations is 37, but the figures above show fewer stations due to missing daily solutions during the recorded anomaly. Accordingly, such GNSS stations were excluded. Average data integrity for all GNSS stations is sufficient and is 83.4 % in 2022 and 91.4 % in 2023. Operational problems with GNSS stations were particularly evident in the period from October 2022 to February 2023 due to unstable energy supply caused by russian attacks and missile strikes on Ukraine's energy infrastructure [Brusak et al., 2024]. This period coincides with the anomalies in the Figs. 7 and 8.

In the study, we do not dwell on interpreting the nature of these anomalies, as this is not the purpose of this article. However, it is worth noting that other narrower anomaly clusters may relate to regional geodynamic processes, although their nature requires further investigation. The joint visualization of planar and height anomalies confirms the method's ability to detect synchronous regional geodynamic deformations.

Conclusions

This study presents a method for analyzing GNSS time series using Isolation Forest, one of ML algorithms for geodynamic purposes. The method is fully automated in Python. It can be applied to both individual time series for local anomaly detection and GNSS station networks for identifying synchronous group geodynamic anomalies. Anomalies are categorized into height (Up component) and planar (***N*** and ***E*** components) types.

Data from the Ukrainian GNSS CORS network GeoTerrace were analyzed to validate the proposed method. 37 daily GNSS time series from 2019 to 2024 were examined. Seven group anomaly periods were identified across the network: three planar and four height. One height anomaly period in December 2019 coincided with a known geodynamic anomaly caused by non-tidal atmospheric loading (NTAL) [Brusak & Tretyak, 2020; 2021]. Maps of the spatial distribution of the detected altitude anomalies in November 2022 and January 2023 are presented.

The identified anomalies require further interpretation to ascertain their nature. Group anomalies are particularly valuable, as they appear simultaneously at multiple stations and can only be detected through comprehensive network analysis.

Certain limitations exist, despite the effectiveness of the proposed method. First, generalized model settings may not detect similar anomalies across all stations. For instance, although the December 2019 group anomaly was detected at most stations, it was absent at BLZT, LUTK, NOVC, and ZBAR, potentially due to local effects or data specifics. Nonetheless, previous studies confirm geodynamic deformations at these locations [Brusak & Tretyak, 2020]. Second, the initial setting of the expected anomaly fraction (contamination parameter) significantly impacts result quality. Improper tuning of this parameter can result in either missing significant events or generating false positives. Despite these potential challenges, the model demonstrated satisfactory performance. In the case of the December 2019 NTAL anomalies, it achieved an accuracy of 76 %, validating the method's effectiveness in detecting significant deviations. Group anomaly analysis in height data confirmed successful identification of most abnormal subsidence or trend shifts cases.

Future developments may include preliminary classification of anomaly causes. Even now, the results could interest researchers investigating geodynamic anomalies using GNSS station network data that require further in-depth analysis with complementary geological and geophysical studies.

The proposed approach also promises broader applications, such as structural monitoring of large engineering constructions. When GNSS receivers are installed on critical infrastructure such as dams, hydroelectric power plants, or nuclear facilities, detected local or group anomalies may indicate structural deformations.

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ВИЯВЛЕННЯ ГЕОДИНАМІЧНИХ АНОМАЛІЙ У ЧАСОВИХ РЯДАХ ГНСС З ВИКОРИСТАННЯМ МЕТОДІВ МАШИННОГО НАВЧАННЯ

Одна із прикладних геодезичних задач для геодинаміки – виявлення аномальних відхилень у часових рядах ГНСС, що можуть свідчити про деформації земної поверхні, спричинені впливом різних геофізичних явищ. Важливо зазначити, що геодинамічні аномалії можуть бути локальними та проявлятися лише на одній ГНСС-станції або регіональними і проявлятися одночасно у групі часових ГНСС-рядів. Мета цієї статті – розроблення методу виявлення геодинамічних аномалій у часових рядах ГНСС із використанням алгоритмів машинного навчання. Метод реалізований у середовищі Python та дає змогу аналізувати великі масиви даних у напівавтоматичному режимі. Серед методів машинного навчання для цього вибрано алгоритм Ізоляційного лісу. У дослідженні детально покроково описано роботи програми та її етапи, що дає змогу не лише аналізувати окремий часовий ряд для виявлення локальних аномалій, але й групи часових рядів для виявлення спільних одночасних геодинамічних аномалій. Розроблений метод апробовано на даних 37 ГНСС-станцій мережі GeoTerrace, розташованих у західній частині України. За результатами виявлено сім окремих групових горизонтальних та висотних аномалій. Встановлено, що одна із виявлених аномалій збігається із попередньо дослідженими висотними деформаціями земної кори, спричиненими неприливними атмосферними навантаженнями у грудні 2019 р. Наведено карти просторового розподілу виявлених групових висотних аномалій у листопаді 2022 р. та січні 2023 р. Природа частини аномалій на деяких ГНСС-станціях невідома, можливо, вони спричинені ще не ідентифікованими локальними геодинамічними факторами чи помилками вимірів. Окрім того, що запропонований метод може зацікавити геофізиків та геологів для виявлення спільних геодинамічних аномалій, він має потенціал для використання у структурному моніторингу великих інженерних об'єктів за даними мереж ГНСС-станцій.

Ключові слова: часові ряди ГНСС, геодинамічні аномалії, виявлення аномалій, алгоритми машинного навчання, Ізоляційний ліс, ГНСС-мережа "GeoTerrace".

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