ProGeo: Geodetic Hardware-Software System for Geospatial Artificial Intelligence Applications

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SUMMARY

Progress Company is developing the ProGeo geodetic system, a high-precision solution for earth surface measurement and analysis. ProGeo utilizes a multi-constellation GNSS receiver (GPS, GLONASS, GALILEO, BEIDOU, IRNSS) achieving up to 8 mm real-time and 2.5 mm post-processed accuracy. The system features a high-stability antenna, radio modems, and GIS-compatible software for data processing and analysis. A cloud-based service is under development.

ProGeoAgro (as part ProGeo software) integrates with computer vision and AI, enabling smart agriculture applications such as optimized resource utilization, field planning, and crop monitoring, leading to improved yields and production efficiency. Specifically, an AI-driven approach for vineyard mapping is presented, utilizing UAV or ground vehicle imagery with GNSS data. Machine learning algorithms analyze images to identify diseases, assess plant health, determine grape density, and verify trellis post inclination. The results are integrated into digital maps for yield prediction and detailed field insights.

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1. INTRODUCTION

Modern agriculture, facing the need to increase yields, efficiency, and sustainability, is actively adopting precision farming technologies based on intelligent data analysis and process automation. A key element of these approaches is the precise determination of coordinates of agricultural infrastructure objects and crop conditions. In this context, GNSS (Global Navigation Satellite System) geodetic equipment and specialized software play a critically important role, providing the necessary spatial referencing for the analysis of data obtained through computer vision and artificial intelligence.

Traditional geodetic methods, while providing accuracy, are often costly and labor-intensive, which limits their application over large areas. GNSS geodetic equipment, on the other hand, offers the possibility of high-precision coordinate determination in real-time, making it an ideal solution for precision agriculture tasks. It is GNSS that provides the spatial context necessary to understand exactly where observed processes, such as plant growth, disease spread, and other important aspects.

Computer vision, using cameras to obtain visual information, is a powerful tool for assessing crop condition, identifying problem areas, and monitoring various parameters. However, images alone, without precise geographic referencing, are fragmented and do not allow for a complete assessment of spatial variability and the scale of phenomena. GNSS positioning provides the necessary basis for the interpretation and analysis of computer vision data, enabling the linkage of visual information to a specific location in the field. Artificial intelligence (AI), in turn, plays a crucial role in processing large volumes of data obtained using GNSS and computer vision. Machine learning and deep learning algorithms enable the automation of complex analytical tasks, including image classification, object segmentation, and yield prediction.

2. GEODETIC HARDWARE-SOFTWARE SYSTEM PROGEO

PROGRESS company actively engages in geodetic solutions and is developing a state-of-the-art geodetic system, which serves as a crucial instrument for precise measurement and analysis of the Earth’s surface. This platform integrates advanced technologies and equipment, enabling

effective solutions across various sectors: construction, agriculture, mining and resource transportation, transportation, telecommunications, cartography, and cadastral surveying.
ProGeo is a cutting-edge system designed for high-precision geodetic measurements using GNSS. This suite includes several key components, each playing a vital role in ensuring measurement accuracy and reliability.

2.1 Hardware products of ProGeo

The high-precision multi-system geodetic GNSS receiver is capable of operating with multiple satellite systems, such as GPS, GLONASS, GALILEO, BEIDOU, and IRNSS, significantly enhancing positioning accuracy and reliability. In real-time mode, measurement accuracy is 8mm + 1mm per kilometer horizontally, while in post-processing mode, it achieves 2.5mm + 1mm per kilometer. It offers high sensitivity and rapid initialization, enabling data acquisition even in challenging environments, such as urban canyons or near tall buildings. The receiver supports various operational modes, including static and RTK (Real-Time Kinematic), making it a versatile tool for diverse geodetic tasks.
ProGeo implements proprietary real-time algorithms, including RTPK (Real-Time Post-Process Kinematic), which, unlike traditional RTK, enhances the reliability and stability of solutions. Leveraging the power of modern microprocessors, RTPK applies truncated post-processing algorithms, achieving results comparable to post-processing directly in the field. In essence, RTPK is the application of robust post-processing algorithms for real-time problem-solving.
The receiver design (Figure 1) is based on unified blocks, facilitating easy upgrades of its functionalities and maximizing ease of repair in case of failure, which is reduced to replacing the faulty module. Furthermore, there are plans to optionally equip the receiver with a monocular camera. This will enable geo-positional determination in challenging environments through advanced computer vision algorithms.
The GNSS antenna is designed to receive signals from satellites and must provide high efficiency across a broad frequency range. A high-quality antenna minimizes the impact of multipath errors and ensures a reliable connection with the receiver, which is critical for precise positioning. A distinctive feature of the antenna is its highly stable phase center, which ensures its effective use in high-precision measurements.
Multiple variations of radio modems provide wireless communication between GNSS receivers (base-rover) in the UHF band (410-470 MHz) over long distances (with a modem variant having a transmission power of up to 35W). These radio modems enable real-time data transmission,

which is essential for dynamic measurements and RTK operations, particularly in areas where mobile cellular connectivity may not be available.

Figure 1: Geodetic GNSS receiver ProGeo with modular design

2.2 Software products of ProGeo

The ProGeo ecosystem currently comprises a suite of software products: ProGeoOffice, ProGeoMobile and ProGeoNet. ProGeoOffice is a powerful desktop application designed to streamline the post-processing and analysis of geodetic data acquired in the field. It provides a comprehensive suite of tools for data management, quality control, adjustment computations, and reporting. ProGeoMobile is a field-ready application designed for use with GNSS receivers and other field equipment. It provides real-time data acquisition, processing, and visualization capabilities, directly on the worksite. Geodetic technicians can utilize ProGeoMobile to collect high-accuracy data efficiently, monitor the accuracy of measurements, and immediately assess the quality of the collected data.

ProGeoNet introduces a transformative approach to the positioning and navigation of both stationary and mobile objects by utilizing sophisticated data processing from global navigation satellite systems GPS, GLONASS, GALILEO, BEIDOU, QZSS, and IRNSS. With advanced methodologies such as RTPK, PPP, and classic RTK or post-processing, ProGeoNet delivers 1cm level of accuracy.

The ProGeoNet offers a comprehensive and robust solution for GNSS data management and processing, distinguished by several key advantages. It seamlessly integrates diverse data sources, providing instant access to the latest satellite orbits, clock corrections, weather data, earth surface velocity models, control point coordinates, satellite receiver antenna databases, and coordinate transformation tools. This comprehensive data integration is complemented by automatic software module updates, ensuring the system remains at the forefront of GNSS technology. Real-time network monitoring with proactive data and station performance analysis allows for swift anomaly detection and resolution. The system's scalability enables network expansion to meet growing demands without compromising performance, while its broad device compatibility ensures seamless data collection and integration from a wide range of field GNSS devices. Secure network management and data access are available via any standard web browser, offering flexibility and convenience. Deployment options include a user-friendly web interface or a console version for advanced users.

Further enhancing its capabilities, the system incorporates a powerful Universal NTRIP Caster (version 2), compatible with both Linux and Windows. This caster efficiently manages GNSS stations and generates a continuous coordinate space, offering both web interface and console versions for versatile applications. It utilizes the enhanced NTRIP protocol version 2 for reliable data transmission and includes comprehensive streaming and connection billing features, supporting RTCM 3.0 and MSM formats for robust corrective information transmission. Robust monitoring features include hourly reference station checks and daily assessments of position and velocity via PPP in ITRF2014, guaranteeing network precision. Finally, advanced RTK solutions, specifically our Network Real Time Kinematic over Virtual Reference Station.

Network Real-Time Kinematic over Virtual Reference Station (NRTK VRS) technology represents a significant advancement in GNSS positioning. It delivers superior accuracy and significantly reduces measurement times, even across vast distances (Figure 2). This reliability extends to challenging environments, including urban areas and regions with dense foliage. Furthermore, NRTK VRS minimizes infrastructure requirements by reducing the number of

necessary base stations and enabling the use of single-frequency and mass-market GNSS modules.
One more distinctive feature of the engine is the ability to perform independent calculations without being linked to GPS. For example, Figure 3 shows the result of the system's operation based only on IRNSS measurements.

trellis

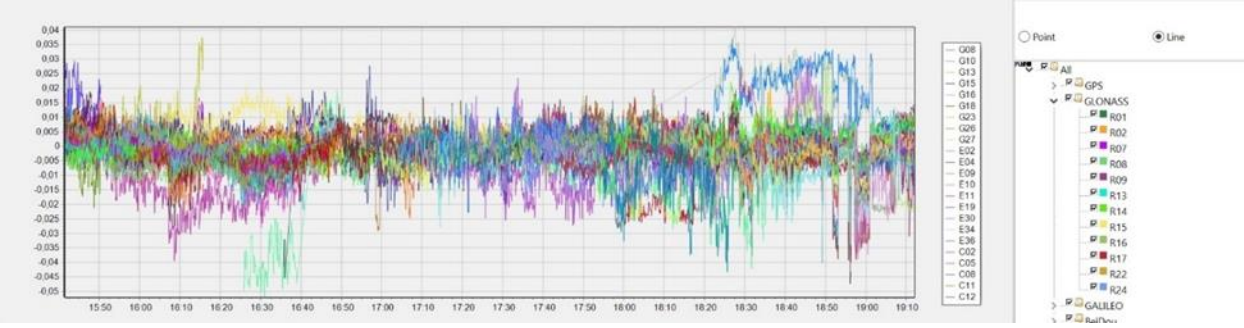

Figure 2: Residuals of RTK solutions for 130 km baseline using VRS

trellis

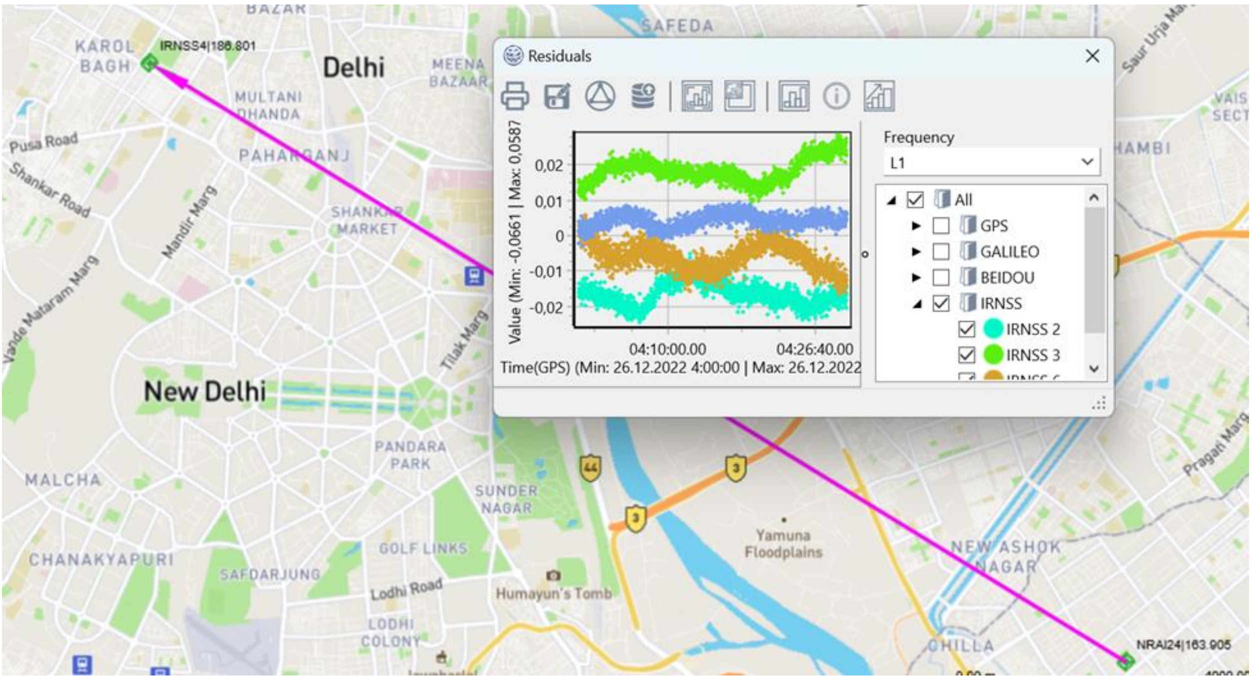

Figure 3: Residuals of IRNSS data processing

3. PROGEOAGRO

One of the potential applications of the ProGeo system is in smart agriculture. In agriculture, geodetic technologies are utilized to optimize the use of land resources, plan planting areas, and monitor the condition of agricultural lands. Geodetic data assists farmers in making informed decisions regarding fertilizer application, irrigation, and other agronomic activities, which contributes to increased yields and production efficiency.
The integration of computer vision and artificial intelligence (AI) in agriculture, coupled with geodetic equipment, opens new horizons for enhancing the efficiency and productivity of the agricultural sector (Patrício D., 2018). This integrated solution enables farmers and agronomists to make more precise and rapid decisions based on data from various sources. Here are some of the key tasks that can be addressed by a combined system (geodetic system + video cameras): defining field boundaries, mapping terrain, monitoring plant and support structure conditions, detecting diseases and pests, assessing and predicting yields (Apolo-Apolo O.E. 2020), and automating planting, watering, and harvesting processes (Olenskyj A., 2022).
At PROGRESS company, research and development efforts are focused on the collaborative use of geodetic receivers and video cameras for mapping agricultural fields – "ProGeoAgro" project. This integrated approach combines precise geodetic measurements with visual information to create detailed maps and analyze field conditions. This paper presents an example of using the geodetic system for mapping vineyards based on computer vision and artificial intelligence algorithms.
The mapping process can be divided into three main stages: data acquisition, data processing, and the creation of digital maps. Let's examine each stage of the problem-solving process.

3.1 Data acquisition

The data acquisition process for vineyard mapping integrates the capabilities of a high-precision GNSS receiver and GoPro video cameras, mounted on a tractor as it performs its routine vineyard operations. This approach minimizes disruption to normal agricultural activities while providing a wealth of georeferenced visual and spatial data. The integration is designed to leverage existing workflows, thereby minimizing additional effort and expenses.

A geodetic-grade GNSS receiver is mounted on the tractor to capture precise positional data. The receiver's data (position and velocity) is recorded at a frequency of 2 Hz to ensure detailed tracking of the tractor's movement. The GNSS receiver is configured to use RTK, which guarantees centimeter-level positioning accuracy. The RTK mode is implemented using either a nearby base station or a network of reference stations via cellular communication, ensuring high data quality even in challenging environments. The GNSS data is stored with a timestamp, which enables precise synchronization with the video data.

Two GoPro cameras are mounted on the tractor to capture different perspectives of the vineyard. Typically, the cameras are positioned to provide lateral views of the vineyard rows.

The cameras are set to record video in high-resolution format (4K) with a wide field of view. Video recording is performed at a frequency of 2 frames per second to optimize the volume of accumulated data. While the GoPro cameras have their own onboard GNSS receivers, their positional accuracy is insufficient for the task at hand. Synchronization between the cameras and the primary GNSS system is achieved using the system time from the primary GNSS system. The recording time and duration are adapted to the length of the tractor's work. The cameras continuously record video during the tractor's operation within the vineyard, capturing the vines, trellis systems, and other relevant objects.

3.2 Video data processing

State-of-the-art neural network architectures have demonstrated significant advancements in object detection, segmentation, and classification tasks, enabling their application to the analysis of agricultural crops, including grapes (Pinheiro, 2023). However, despite this progress, challenges remain regarding the accuracy and robustness of grape cluster detection and classification in real-world vineyard settings, including variations in lighting, viewpoints, and occlusions between clusters. Therefore, an effective approach for automated vineyard image analysis is required to provide accurate yield estimation based on data-driven insights, enabling grape growers to make more informed decisions to enhance productivity and quality.

The ProGeoAgro system incorporates a trained neural network model for precise grape cluster detection in images. This model was trained on over ten thousand vineyard images acquired under diverse lighting conditions, from various viewpoints, and accounting for occlusions between clusters, ensuring robustness and accuracy in real-world scenarios. The model demonstrates acceptable accuracy and reliability (mAP > 90%). In addition to grape cluster detection, an algorithm for precise segmentation of the boundaries of each detected grape cluster, implemented using instance segmentation models, is employed. Beyond segmentation, the system differentiates between healthy and defective grape clusters (Figure 4) based on key features: shape, color, and texture of the berries. The resulting performance metrics of the deep learning system (precision > 88%, recall > 85%) are suitable for generating yield maps and calculating the percentage of defective produce.

Figure 4: Examples of neural network results for detection, segmentation, and classification of grape clusters (blue color – segmented health grapes, red color reflects defected grapes)

The analysis of grapevine diseases using neural networks (Nagi, 2022), based on leaf imagery, enables cost reduction by minimizing the need for manual expertise and optimizing pesticide usage. It enhances efficiency through faster, more objective, and more accurate disease detection at early stages. Within the ProGeoAgro project, a module for automated analysis of grapevine leaf images has been developed for the purpose of early detection of various disease indicators. By employing computer vision and deep learning technologies, this module rapidly and with high accuracy identifies common grapevine diseases, allowing grape growers to take timely measures to protect their plants and prevent significant yield losses. The resulting data is utilized to create maps of problematic vineyard areas, visually representing the spatial distribution of diseases.

For the analysis of grapevine leaf images, the neural network was trained on over four thousand leaf images, annotated as either "healthy" or "diseased," aiming at classifying leaves based on the presence or absence of disease indicators. The system automatically processes uploaded images of grapevine bushes (Figure 5), attempting to detect signs of the most common diseases: downy mildew, powdery mildew, gray mold, and anthracnose. Images are classified based on characteristic disease indicators: the presence of spots of a specific shape, marginal necrosis, color, texture, or changes in leaf shape.

Figure 5: Examples of neural network results for grape leaf's diseases detection (yellow bounding boxes on image)

ProGeoAgro incorporates a module for the automated detection and assessment of the inclination angle of trellis posts in vineyards. Based on computer vision and deep learning technologies, this module allows for the rapid identification of posts in critical condition (with excessive inclination), enabling the prevention of their collapse and, consequently, damage to vines and reduced yields. The resulting data is used to generate vineyard maps indicating the location of posts and highlighting problematic areas, providing clarity and simplifying maintenance and repair processes.

Initially, trellis posts are detected and segmented using a neural network model. The model is capable of simultaneously identifying the location of posts in images and segmenting them, delineating the contours of each post. The neural network model was trained on a comprehensive dataset containing images of thousands of trellis posts constructed from various materials: wood, metal profiles, and reinforced concrete. An image of the vineyard is fed into the neural network. The model processes the image and, as output, generates segmentation masks highlighting the pixels of each post in the image.

Subsequently, a two-stage procedure, incorporating RANSAC (RANdom SAmple Consensus) and the least squares method (LSM), is employed for precise determination of the inclination angle of each post. In the first stage, pixel coordinates belonging to the pillar are extracted from the segmentation mask. To eliminate anomalous points (e.g., points not belonging to the trellis post that were included in the mask due to segmentation errors), the RANSAC algorithm is applied. The RANSAC algorithm iteratively selects random subsets of points and fits a linear model to them. Ultimately, the model with the largest number of “inliers” – points that agree with the model – is selected. In the second stage, the least squares method (LSM) is applied to the set of “inliers” obtained after RANSAC to construct a linear approximation of the post. After obtaining the linear approximation, the inclination angle of the post is determined as the angle between this line and the vertical axis. The inclination angle is estimated in degrees with an accuracy of ±1 degree.

3.3 Digital map creation

The final step in our mapping process involves generating digital maps from the previously processed, geotagged images. This process integrates the outputs of the neural network analysis with precise spatial information to create comprehensive, informative maps. This map provides an interactive and comprehensive visual representation of the vineyard, with information based on precise geographical data, and analyzed by neural networks (Figures 6 and 7).

Currently, the KML (Keyhole Markup Language) format is utilized for our maps, which enables visualization of the results (yield map, diseases area map, pillars map) for Google Earth program. The KML format is an XML-based file format used for storing geographic data and visualizing it in geographic information systems. Utilizing KML ensures compatibility with a wide range of software and platforms, allowing for easy sharing and viewing of spatial data. KML files can contain information about points, lines, polygons, as well as graphic elements, textual annotations and images, which allows for the creation of informative and visually clear maps.

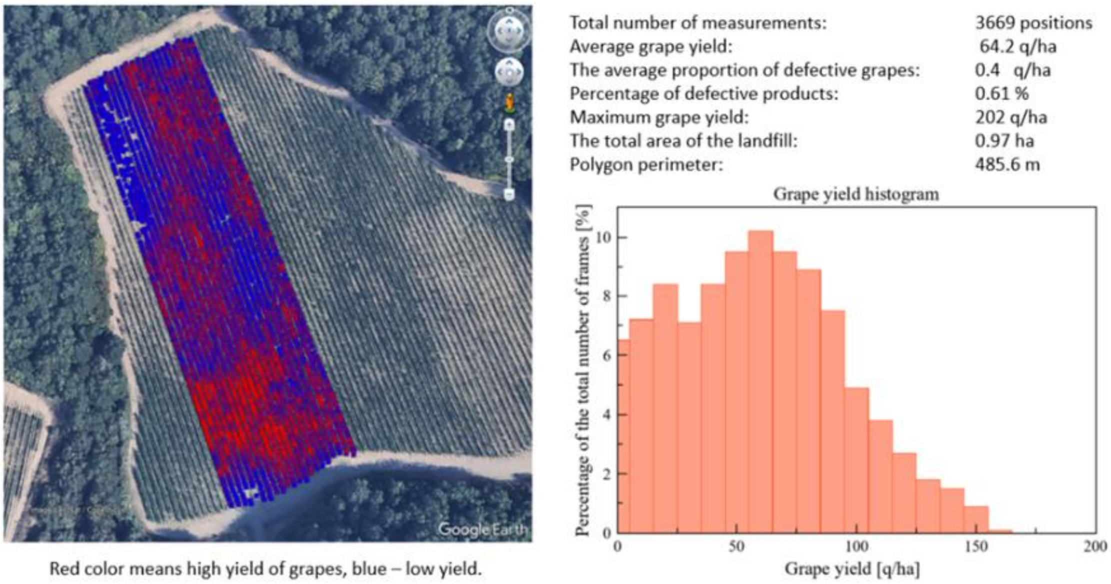

Figure 6: Example of grape yield map with statistics

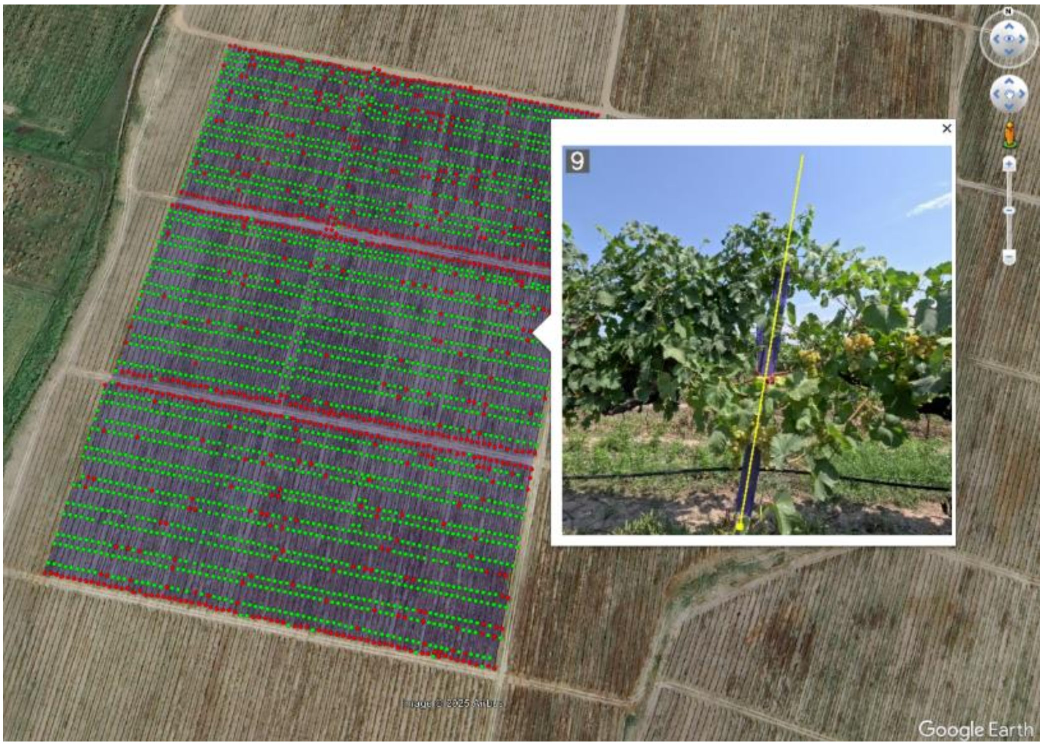

Figure 7: Example of pillars map with the ability to analyze pillars with a significant slope (problematic pillars are marked as red points)

It's worth noting that the mapping of agricultural fields based on AI algorithms offers significant flexibility in customizing the system for different classes of agricultural products, including fruits, vegetables, and berries, and it eliminates the influence of the human factor on the quality of the work performed.

4. CONCLUSION

Combined hardware and software geodetic platform ProGeo, relying on the high-quality hardware components, can solve a wide range of tasks using innovative AI-based approaches. This demonstrates the enormous potential of the system for use in various areas of land resource management.

Mass production of the hardware components of the geodetic system and its market launch are planned for early 2026. Currently, we are seeking potential clients for the software part of the system, which supports digital mapping of agricultural fields. The digital mapping system has undergone initial testing in vineyards in Italy and Russia. We are ready to adapt the system for end-users – thanks to the customization capabilities, the system can be used not only for vineyards but also for fruit orchards and vegetable fields.

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BIOGRAPHICAL NOTES

Zakhar Kondrashov has been the General Director of NIIMA Progress company since August 2020, where he leads the company in its goals of innovation and growth. He holds a degree in “Design and Technology of Radio-Electronic Devices” from Saint Petersburg State University of Telecommunications named after Prof. M.A. Bonch-Bruevich, awarded in 1998, as well as a second higher education degree from the North-West Institute of Management at the Russian Presidential Academy of National Economy and Public Administration obtained in 2016.

Andrey Zimin is the Head of the Mixed-Signal Microwave Module Development Department at NIIMA Progress since April 2023. He holds a degree in Radioelectronics Systems, having graduated from Moscow Aviation Institute (Technical University) in 1999. He possesses extensive experience in the development of microelectronic GNSS equipment, demonstrating a high level of expertise and professionalism in the field.

Alexei Razumovsky is a highly experienced professional with expertise in geodesy and applied mathematics. He graduated from the geodetic faculty of the Moscow State University of Geodesy and Cartography (MIIGAiK) with a degree in "Astronomo-Geodesy" in 1978, and from the Faculty of Computational Mathematics and Cybernetics of Moscow State University (MSU) with a degree in "Applied Mathematics" in 1988. He has had a Candidate of Technical Sciences degree since 1988. His career includes positions at the Central Scientific Research Institute of Geodesy, Aerial Survey and Cartography, Ashtech, the S.A. Lebedev Institute of Precision Mechanics and Computer Engineering of the Russian Academy of Sciences, and Javad GNSS LLC. Since 2022, he has been the Head of Software Department at NIIMA Progress company.

Mikhail Vorobiev is a leading specialist in GNSS and Sensor Fusion technologies with three decades of experience in the field. He earned his degree from the Radio Engineering Faculty of the Moscow Power Engineering Institute (Technical University) in 1995 and holds a Candidate of Technical Sciences degree in 2001. Since February 2024, he has been a key contributor to research and development as Lead R&D Engineer at NIIMA Progress.

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