Global Navigation Satellite Systems in Precision Agriculture

Subjects: Agronomy | Agriculture, Dairy & Animal Science

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Global Navigation Satellite Systems (GNSS) in precision agriculture (PA) represent a cornerstone for field mapping, machinery guidance, and variable rate technology.

GNSS | multi-constellation receivers | precise point positioning | simultaneous localization and mapping

1. Introduction

The successful application of Global Navigation Satellite Systems (GNSS) in precision agriculture (PA) has revolutionized farming practices, offering significant benefits in terms of improved efficiency, productivity, and sustainability [1]. GNSS technologies, such as GPS, GLONASS, Galileo, and BeiDou, have been widely adopted in PA applications worldwide [2]. GPS, originating from the United States, has been utilized since its full operational capability was achieved in 1995. Its development traces back to the 1970s as a military project. Similarly, GLONASS, developed by Russia, reached full operational status in 1995 after a development process initiated in the 1970s for military purposes. Galileo, initiated by the European Union, commenced its services in 2016, offering an independent global navigation system with primary civilian purposes. In contrast, BeiDou, developed by China, initially provided regional services in 2000 and achieved global coverage in 2020. These GNSS systems are a cornerstone in various well-documented aspects of PA, including field mapping [3], agricultural machinery guidance and steering [4][5], variable rate technology (VRT) [6], and yield monitoring [7].

GNSS receivers, in conjunction with Geographic Information Systems (GIS), allow for exact field boundary determination and accurate mapping of field features such as roadways, irrigation systems, and drainage networks [8]. This data provides the foundation for further precision agricultural activities such as VRT, yield monitoring, and crop scouting. A thorough understanding of the field's characteristics and spatial variability allows for the optimization of input utilization, customizing management strategies, and waste minimization, resulting in enhanced resource efficiency and cost savings [9]. The precise guidance and automated steering capabilities of GNSS-based systems contribute to more consistent seed placement, fertilizer application, and other field operations, resulting in improved crop uniformity, optimized input usage, and increased yields [10]. Map-based VRT systems utilize GNSS positioning to deliver site-specific applications of inputs, such as fertilizers, pesticides, and irrigation water [11]. By integrating GNSS data with yield maps, soil maps, and other relevant spatial information, these data are used for the creation of prescription maps that guide VRT equipment to apply inputs at different rates according to the specific needs of different areas within a field [12]. VRT systems further enable optimization of input usage, minimizing environmental impact and maximizing crop productivity by adjusting inputs to the specific requirements of different soil types, nutrient levels, and crop growth stages. Yield monitoring has been significantly improved through the use of GNSS in PA [13]. GNSS receivers integrated with yield monitoring systems precisely measure and map crop yields across the field. By correlating yield data with other spatial information, such as soil maps and management practices, valuable insights for future growing seasons are produced into the factors influencing yield variability within a field [14].

Despite the gains, there are still several research gaps in the use of GNSS in PA that need to be filled. One disadvantage is the reliance on satellite transmissions, which can be hampered by signal blockages and atmospheric conditions [15]. Satellite signals may be obscured or diminished in locations with extensive vegetation, tall structures, or steep terrain, resulting in lower positioning accuracy [16]. Such constraints can have an impact on the dependability and robustness of GNSS-based systems, especially in complicated agricultural settings. As a result, more research and development are required to improve signal reception and processing algorithms in order to offset the impacts of signal blockages and multipath interference [17]. Another GNSS restriction in PA is the requirement for precise and up-to-date georeferenced data for optimal decision-making [18]. While GNSS offers precise location data, the accuracy of other spatial data layers like soil maps, yield maps, and topography data might vary [19]. Therefore, efforts should be made to improve data collection methods, data integration, and data validation processes to ensure the availability of accurate and high-quality spatial data for PA applications. Additionally, there is a need for user-friendly and interoperable PA software and hardware solutions [20]. The complexity of GNSS-based systems and the lack of standardization can present challenges in terms of system integration, data compatibility, and ease of use [21].

While advancements in GNSS technologies have shown great potential in revolutionizing farming practices, there are notable differences in the adoption and acceptance of these solutions globally [6][22]. Among the scientific studies indexed in the Web of Science Core Collection (WoSCC), there is a strong recognition of the benefits of GNSS technologies in PA [23][24][25].

2. GNSS in State-of-the-Art Remote Sensing-Based Solutions in PA

2.1. NDVI

NDVI is the most widely used vegetation index in PA that provides valuable insights into plant health and vegetation vigor [26]. When combined with GNSS technology, NDVI measurements are accurately georeferenced, allowing for spatially explicit analysis and monitoring of crop conditions [27]. While multispectral sensors are traditionally mounted on satellites and unmanned aerial vehicles (UAVs), satellite-based multispectral sensors, such as those onboard satellites like Landsat and Sentinel, provide broader coverage of large agricultural areas [28]. GNSS technology aids in the precise geolocation of satellite images, allowing for accurate mapping of NDVI values across the agricultural landscape [29]. Because satellite imagery is available in near-real-time, it allows for time-series analysis and monitoring of vegetation dynamics throughout the growing season [30]. The handheld or tractor-mounted radiometer is another type of sensor used for NDVI measurements [31][32]. GNSS receivers are commonly supplemented to these portable or tractor-mounted devices, allowing for the exact localization of NDVI readings in specified fields.

2.2. LiDAR

LiDAR is complementary to vegetation indices, such as NDVI, by providing information on the 3D structure of crops and the surrounding environment [33]. The hardware used in PA, LiDAR systems includes a variety of components designed to acquire and analyze precise 3D information, including GNSS for the precise georeferencing of point clouds [34]. Airborne LiDAR sensors, which include lasers, scanning mechanisms, and detectors, are often installed on UAVs [35]. The laser beams image the plant canopy, terrain elevation, and crop structural elements. GNSS technology is critical in these systems because it allows for exact georeferencing of LiDAR data by syncing the sensor's location and orientation with the acquired measurements [36]. The aircraft or UAVs' GNSS receivers should provide precise location and timing information, ensuring that the LiDAR data is spatially aligned with the agricultural area. Ground-based LiDAR sensors provide high-resolution data at a smaller scale, allowing for detailed analysis of crop structure and individual plant characteristics [37]. GNSS technology is employed in ground-based LiDAR systems to precisely georeference the acquired data, linking the 3D measurements to their specific spatial locations within the field.

2.3. Harvesting Robot

Unlike NDVI and LiDAR, harvesting robots provide more tangible hardware-based results in PA, significantly improving the process of crop harvesting by automating labor-intensive tasks [38]. The GNSS technology enables these robots to navigate and operate with precise geolocation information, enabling efficient and accurate harvesting operations. RGB cameras, as one of the key sensors used in harvesting robots, capture high-resolution color images of the crops, allowing the robot to visually identify and locate mature or ripe fruits or vegetables [39]. By integrating GNSS for accurate localization and computer vision with RGB cameras for crop detection and identification, these robots can navigate through fields and perform precise harvesting operations. The use of computer vision with RGB cameras in harvesting robots provides several benefits and opens up new opportunities in the field of PA [40]. RGB cameras image the crops, which are subsequently analyzed with computer vision algorithms to extract the color, shape, texture, and other visual characteristics of crops to differentiate between ripe and immature fruits and vegetables [41]. The force/torque sensor allows the robot to detect how much force is needed to harvest the crops without harming them. When paired with GNSS technology, this sensor guarantees that the harvesting robot delivers the necessary force with accuracy, resulting in safe and efficient harvesting operations.

2.4. Unmanned Aerial Vehicles

PA researchers recognized UAVs during the past decade as a cost-effective and efficient means of data collecting and processing [27][42]. When integrated with GNSS technology and advanced positioning techniques such as RTK and Post-Processing Kinematic (PPK), UAVs provide very accurate and exact geolocation capabilities, which improve the efficiency of data collecting and processing in PA. PPK is a post-processing approach in which the UAV captures raw GNSS data during flight and then refines the georeferencing after the data is downloaded and processed offline [43]. PPK processes raw GNSS data from both the UAV-mounted receiver and the ground-based reference station to provide positioning information. This method reduces the requirement for real-time communication between the UAV and the reference station, allowing for more data-collecting flexibility [44]. PPK is especially beneficial in locations with little or no real-time communication infrastructure since data may be gathered and analyzed later when connectivity becomes available. Furthermore, incorporating RTK or PPK capabilities into UAVs improves their autonomous navigation capability [45]. UAVs may follow predetermined flight paths independently with very accurate positional information, boosting data-collecting efficiency and coverage. This is especially useful when scanning large agricultural regions or doing repeated flights to track crop growth and changes over time [46]. The integration of GNSS into UAV aerial spraying systems reduces the risk of spraying outside the designated zone, minimizing environmental impact and optimizing resource utilization [47]. Moreover, GNSS improves the safety of UAV aerial spraying operations through post-spraying analysis and evaluation. The accurate positioning information recorded during the flight can be integrated with other environmental data to assess the efficacy of the spraying operation, identifying areas that require additional treatment or monitoring and optimizing future spraying strategies.

3. GNSS in State-of-the-Art Computer Processing-Based Solutions in PA

3.1. Geostatistics

The traditional method of soil sampling is collecting a restricted number of samples from a field, as it is an expensive and time-demanding procedure, and evaluating them in a laboratory [48]. To provide an overview of the analyzed soil property in the entire field, geostatistics was proven as an effective method for quantifying soil variability [49]. Kriging is the most well-known geostatistical approach for estimating values at unsampled sites using a collection of observed values at neighboring places [50]. The Kriging approach describes the spatial autocorrelation of the data using a mathematical model called a variogram, which is a measure of how similar the values of the data are as a function of the distance between them [49]. In PA, kriging has been widely utilized to map the spatial variability of soil, vegetation, and topography features [51][52].

Because soil parameters must be precisely georeferenced in order to evaluate spatial autocorrelation, GNSS has become an indispensable instrument in PA for soil analysis [53]. GNSS data may also be used to generate digital elevation models (DEMs), which give information on the field’s topography [54]. DEMs may be used to identify fields prone to waterlogging or erosion and to design drainage systems that reduce exposure to these events [55]. GNSS, combined with geostatistics, may also be used to collect agricultural growth and production variability data. The yield data may be used to generate yield maps that depict crop yield spatial variations across the field using geostatistics, identifying zones with high or low production potential and modifying fertilizer and irrigation rates accordingly [56]. Site-specific management using VRT, for example, is a PA strategy that employs geostatistics and

GNSS to adjust management practices to specific sections of the field [57]. This method makes better use of inputs, eliminates the danger of over-application, and lessens the environmental effect of agricultural activities [58].

3.2. Precise Point Positioning

By providing a real-time centimeter-level accuracy based on a single GNSS receiver, Precise Point Positioning (PPP) provides additional flexibility in positioning in PA [59]. PPP employs a network of reference stations to give precise GNSS satellite orbit and clock information, which is utilized to determine the receiver antenna location [60]. PPP can be utilized in places where no reference stations exist, making it especially beneficial in isolated or rural locations. It is also less susceptible to atmospheric and ionospheric disturbances, which can cause inaccurate positioning with RTK and differential GNSS (DGNSS) [61].

Since PA requires high-precision mapping of soil parameters and crop yields in conjunction with geostatistics, PPP supports the detection of spatial heterogeneity in the field. PPP may also be effectively utilized for agricultural machinery guidance by giving precise real-time location information to agricultural machines along specified courses [62]. This enables VRT of inputs like fertilizer and herbicides precisely where they are required, lowering input costs while also limiting environmental effects. These systems have several advantages over manual steering, including enhanced efficiency, less operator fatigue, and improved safety [63]. While manual guiding systems are simple and inexpensive, they are also susceptible to human mistakes, which can lead to unnecessary inter-row overlaps and skips [4]. Assisted guiding systems are more precise than manual guidance systems, but steering corrections must still be made by the operator. Autosteering systems, on the other hand, take full control of the machinery and direct it along a predefined course automatically [64]. These systems use PPP or other GNSS correlations with a variety of sensors to deliver positioning information and automatically perform steering corrections. In addition to the GNSS receiver, IMUs and cameras are also employed to offer additional information about the vehicle's surroundings and to assist the autosteering system in making precise steering adjustments [65].

3.3. Simultaneous Localization and Mapping

Simultaneous Localization and Mapping (SLAM) is a PA technology that includes building a map of an area while also determining the position of a robot or vehicle within the environment [66]. The positioning information from GNSS signals is used to identify the robot's location inside the surroundings in relation to a set of specified landmarks [67]. Other sensors, including LiDAR, cameras, and IMUs, can also be used by SLAM to produce a comprehensive map of the surroundings. The production of precise maps of fields and orchards is an important use of GNSS-based SLAM in PA [68]. GNSS-based SLAM may also be utilized for precise agricultural machinery guiding [69]. As irrigation is another important part of agriculture, precision irrigation may assist in minimizing water use while boosting crop yields. By producing precise maps of the field topography, it is possible to recognize places within the field that require irrigation and apply water just where it is required [70].

3.4. Internet of Things

The Internet of Things (IoT) has emerged as a critical tool in PA, allowing farmers to collect real-time data from sensors and devices strategically placed across their fields and farms [71]. GNSS technology is vital in IoT-based PA, delivering precise location and timing data that is required by many IoT applications [72]. The collection of environmental data such as temperature, humidity, and soil moisture is one of the key uses of IoT in PA [73]. For these sensors, GNSS technology offers accurate position information, guaranteeing that the data is connected to the proper location inside the field or farm. Monitoring livestock health and well-being is another application of IoT in PA [74]. IoT sensors may be fitted to cattle to monitor vital indications like heart rate, respiration rate, and body temperature, providing early warning of health concerns that could jeopardize the animals' well-being [75]. GNSS technology may be used to track the movement of animals inside the farm, allowing farmers to monitor grazing patterns and detect underused farm regions.

3.5. Deep Learning

Deep learning has emerged as a strong tool for precision agricultural data analysis. GNSS technology offers precise geolocation data for satellite images, enabling deep learning algorithms to monitor crop growth and development across time [76]. Deep learning algorithms may identify parts of a field that may require more irrigation, fertilizer, or pest control methods by evaluating patterns in satellite imaging data [77]. Patterns and trends that may suggest inadequate growing conditions may be recognized by evaluating data acquired with IoT sensors using deep learning algorithms [78]. This data may be used to change irrigation and fertilization schedules, ensuring that crops receive the appropriate amount of water and nutrients at the appropriate time. GNSS technology may be used to geolocate these sensors, giving the sensor data geographical context and allowing for more precise analysis [79]. Convolutional Neural Networks (CNNs) are commonly utilized in PA for image processing, enabling recognition of specific crop traits or growth phases by utilizing GNSS technology to offer precise geolocation information [80]. Overall, deep learning has the potential to improve various present technologies as flexible tools in PA, including UAV imaging [81], satellite imagery analysis [82], and livestock monitoring [83].

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