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Review

A Review on Soil Nitrogen Sensing Technologies: Challenges, Progress and Perspectives

Jun Liu [1,2], Haotian Cai [2], Shan Chen [2], Jie Pi [2] and Liye Zhao [1,*]

1 School of Instrument Science and Engineering, Southeast University, Nanjing 210096, China; liujun@jaas.ac.cn
2 Institute of Agricultural Facilities and Equipment, Jiangsu Academy of Agricultural Sciences, Nanjing 210014, China; tzcht2008@outlook.com (H.C.); chenshan@jaas.ac.cn (S.C.); pijie@jaas.ac.cn (J.P.)
* Correspondence: liyezhao@seu.edu.cn

Abstract: Nitrogen is a vital ingredient for plant development and growth. It is one of the most crucial indicators of soil fertility and crop growth conditions. For the monitoring of nitrogen loss patterns and the development of crop nitrogen fertilizer application strategies, an accurate determination of soil nitrogen concentration can be a valuable source of information. For the advancement of precision agriculture and the preservation of the natural ecological environment, an accurate, quick, and low-cost determination of soil nitrogen content and its variations is essential. This paper systematically analyzes and summarizes soil nitrogen detection methods by compiling and analyzing the relevant literature, comparing the advantages and disadvantages of various methods, and concluding with a discussion of the most significant challenges and future research trends in this field. This study provides a helpful resource for understanding the current status, application constraints, and future developments of nitrogen-sensing technologies in precision agriculture.

Keywords: soil; nitrogen fertilizer; in-situ sensing; precision fertilization; nitrate nitrogen; spectroscopy; ion-selective electrodes; internet of things

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1. Introduction

Agriculture plays an important part in the global economic growth of nations. In recent years, as a result of a growing population and the impact of local wars, global food security has reached a critical level [1]. The Food and Agriculture Organization of the United Nations (FAO) projects that the global population will reach 9 billion by 2050 [2]. The actual use of fertilizers and pesticides is increasing each year to meet the growing human demand for yield and quality of agricultural products [3]. Taking China as an example, since 2019, due to the adjustment of the planting structure, the sown area of grain and other crops has begun to increase, and the demand for nitrogen fertilizer has also increased, driving the growth of nitrogen fertilizer production. According to the data, China's nitrogen fertilizer output in 2020 will be 37.0248 million tons, a year-on-year increase of 4.1% over 2019, as shown in Figure 1.

Since the turn of the previous century, industrial agriculture has spread around the globe. It is a form of sloppy farming. Throughout this production model, the same production management techniques are utilized in agricultural regions with high degrees of variation [4]. The excessive pursuit of high production efficiency and high yields in the production process has resulted in a series of problems such as environmental pollution and ecological degradation, posing a serious threat to the sustainable development of agriculture [5].

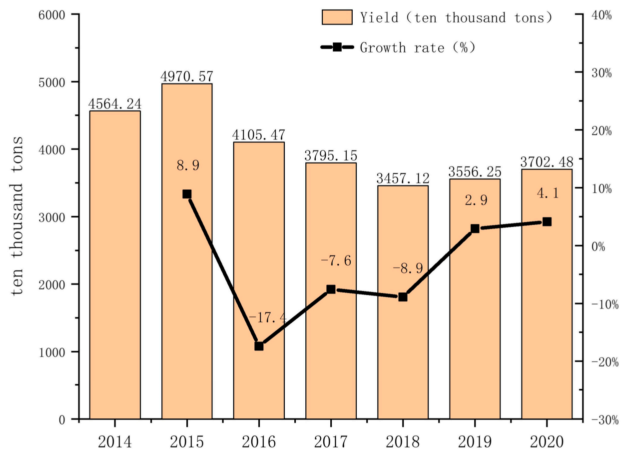

Figure 1. Nitrogen fertilizer output and growth rate in China.

Nitrogen is a crucial ingredient for plant life. It participates in the creation of proteins, nucleic acids, chlorophyll, and enzymes, and is essential for photosynthesis in plants. In places with poor soils, a common practice is to add nitrogen fertilizer to the soil when it does not contain enough nitrogen to meet people's requirements for crop growth and high yields [6]. The literature indicates that the annual use of nitrogen-based fertilizers is approximately 190 million tons [7]. However, the typical nitrogen consumption efficiency of crops is between 40 and 50 percent of the applied nitrogen [1], with the remaining being lost in various forms to the environment [8]. In some countries and regions, over-applied nitrogen fertilizers may enter the natural environment, leading to water pollution, air pollution, species extinction, and other harmful effects [9,10]. High quantities of nitrates that collect on the surface of agricultural products as a result of fertilizer application have also been linked to human disease [11]. Excessive human intake of nitrates and nitrites on the surface of produce, such as leafy vegetables, has become a significant health risk [1,12,13].

Precision agriculture is an advanced agricultural management strategy based on detecting, measuring, and responding to changes in various agricultural production factors in both time and space dimensions, thereby improving the sustainability of agricultural production. In the process of crop cultivation, farmers measure in real time the comprehensive parameters of farm soil to determine the causes of crop yield differences between regions. Then, they take the necessary countermeasures to precisely irrigate, fertilize, and apply pesticides in specific areas to produce high-quality crops while saving water, fertilizer, and other resources [14]. In contrast to conventional crop production, precision agriculture does not use the field or area as a unit of measurement, nor does it treat the soil as an object with uniform crop growth conditions for uniform cultivation and management. Instead, precision agriculture customizes each agricultural material input in each small operating unit of the field according to its unique crop growth conditions and production conditions to achieve the greatest economic and environmental benefit [15].

Precision fertilization is a crucial component of precision agriculture. It entails establishing fertilizer rates and application amounts by assessing the distribution of soil attributes and crop nutrient requirements in order to increase fertilizer usage efficiency, thereby decreasing costs and boosting profitability [16]. Before precision fertilization can be implemented, it is important to determine the types and amounts of nutrients the crop requires, the distribution of soil qualities, and the actual active chemicals in the fertilizer [11]. Before applying nitrogen fertilizer, it is essential to have precise knowledge of the nitrogen elements in the soil in order to reduce nitrogen fertilizer use, boost efficiency, and protect the environment.

There are two basic forms of nitrogen in the soil: organic and inorganic. Organic nitrogen, which constitutes over 90% of total soil nitrogen, is composed of polyphenols and high-molecular-weight amino acids. Although organic nitrogen has various components, only a limited quantity of simple amino acids and amides are directly absorbable by plants. However, most of the organic nitrogen requires microbial conversion before being assimilated by plants. Therefore, the accessibility of organic nitrogen for plant absorption is limited, and its utilization is primarily contingent upon microbial activity. Although inorganic nitrogen is a very small part of total nitrogen, it consists primarily of ammoniacal and nitric nitrogen, which may be utilized directly by the majority of plant species [17]. Fertilizer application on agricultural land has a direct impact on the nitrogen content of the soil, and promotes the transition of nitrogen between soils. Figure 2 illustrates these dynamic changes.

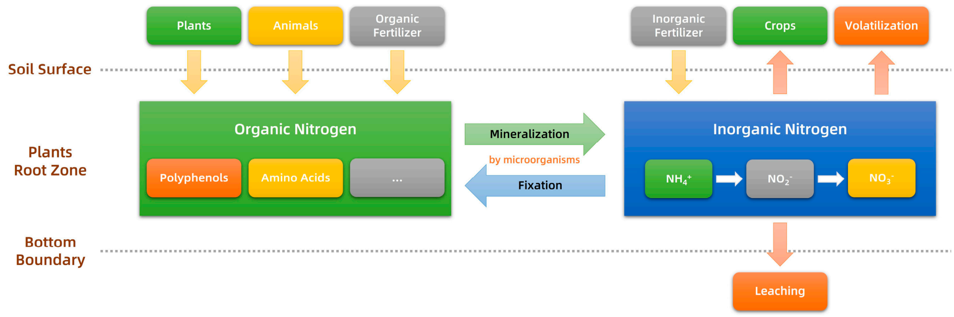

Figure 2. Sources, destinations, and forms of nitrogen in soil.

Soil-available nitrogen is nitrogen in the soil that can be directly absorbed and utilized by plants throughout their normal life cycle. It consists of inorganic mineral nitrogen and the quickly decomposable, relatively simple organic nitrogen contained in some organic matter [18,19]. The amount of available nitrogen in soils is influenced by a number of variables, including the amount of organic matter and total nitrogen in the soil. Soil total nitrogen is an important soil indicator, and its content can, to a certain extent, reflect the reserve capacity of available nitrogen, and is also the basis for deciding the amount of base fertilizer to be applied. Although nitrate nitrogen and other soil-available nitrogen components do not make up a considerable fraction of the total, they are the primary type of nitrogen taken up by plants, and a crucial indication for monitoring soil fertility and managing crop development [20].

With the advent of modern agriculture, scientists have created a large number of novel methodologies and procedures for determining total nitrogen and available nitrogen in a variety of test situations. The new generation of information technology has broadened the capabilities and uses of soil nitrogen determination as well. Rapid, affordable, and field-based determination has become a popular study area. In this study, we examine some of the most recent research findings with great references on the determination of total nitrogen and available nitrogen in soil, discuss the challenges in the current application scenario, and offer some significant future research directions. In accordance with the globally promoted concept of sustainable development, we hope that the development of new technology can provide effective data to facilitate the development of analysis and management in order to select the best crop types, make reasonable fertilization plans, and effectively improve the use of resources.

2. Existing Methods

2.1. Methods for Soil Total Nitrogen Determination

2.1.1. Kjeldahl Method

Established by Kjeldahl in 1883, the Kjeldahl method is recognized and used by the majority of countries and organizations as the international standard for estimating total soil nitrogen [21]. This method requires digestion of the soil sample, conversion of all organic and inorganic nitrogen present in the soil to ammonium nitrogen via a redox reaction, distillation, and titration to determine the amount of ammonium nitrogen, and finally titration to determine the concentration of ammonium nitrogen [22]. The advantages of this technology include the instrument's ease of use and low cost of determination, but the process is laborious and time-consuming.

Digestion of samples is one of the most time-intensive processes in the entire testing procedure. To address this issue, researchers have attempted to decrease the digestion time of soil samples primarily by adjusting the composition of oxidants and accelerators [23,24] and selecting appropriate digestion instruments [25,26]. In order to compensate for the laborious operation and other drawbacks of the standard titration approach, several researchers have attempted to assess the nitrogen content in the digested soil solution via diffusion [27], spectrophotometry [22,28], flow injection analysis [29,30], the ammonia electrode method, etc.

For continuous automation, Kjeldahl-based scale-up control systems have also been created. This type of device enables automated assay process control, and can significantly reduce operational complexity and inspection time [31].

2.1.2. Dumas Method

Jean Baptiste Dumas invented the Dumas technique in 1831. The principle is that the sample is burned at high temperature in a pure oxygen environment; the gas generated by the combustion is carried by the carrier gas through the copper oxide and is completely oxidized, the generated nitrogen oxide is reduced to nitrogen gas by a tungsten filament at high temperature while excess oxygen is combined by this tungsten filament, and the amount of nitrogen gas generated is determined by a thermal conductivity detector following the removal of excess oxygen. The combustion method for analyzing total nitrogen is quick, practical, suited for analyzing large sample volumes, and ecologically benign. However, the costs of experimental analysis and maintenance are much higher [23].

Li et al. (2015) [32] compared the Dumas method to the Kjeldahl method in order to examine the applicability of the Dumas method to the total nitrogen in the soil. They discovered that the results of the Dumas method and the Kjeldahl method did not differ significantly. Wang et al. (2020) [33] analyzed the nitrogen concentration of crop straw using the Dumas and Kjeldahl methods and discovered that the results varied but that there was a considerable linear correlation between them. Currently, the Dumas nitrogen analyzer and other elemental analyzers based on the Dumas method are all being utilized more frequently.

2.1.3. Spectroscopy-Based Methods

Depending on the wavelength band employed for measurement, the most common spectroscopic methods for determining total soil nitrogen are mid-infrared spectroscopy (MIR) and visible-near-infrared spectroscopy (Vis-NIR). A spectroscopic instrument consists of a light source, spectroscopic structure, photoelectric detecting system, control system for the circuitry and mechanical structure, and a spectral data processing system. Spectroscopic detection methods are suited for non-contact detection scenarios, either in a laboratory setting following a flawless pre-treatment of the sample, or in the field using a quick and non-destructive method to conduct measurements at the target detection site. Prior to measurement, sample pretreatment in the laboratory, such as moisture control and particle size management, improves the accuracy of model predictions [34,35]. In contrast, in-situ measurements are susceptible to assay accuracy degradation due to environmental variables [11].

Visible light is an electromagnetic wave with a wavelength between 400 and 780 nanometers, and near-infrared light is an electromagnetic wave with a wavelength between 780 and 2500 nanometers. Vis-NIR spectroscopy, which is based on molecular overtones and combination vibrations, is an indirect analysis method that determines the composition of the corresponding components via selective light absorption. The standard laboratory process is collecting soil samples at the appropriate area, drying and grinding them indoors, then performing spectroscopy to retrieve the raw spectrum data [11,36]. Regarding this premise, researchers have presented a number of spectrum analysis algorithms for predicting and analyzing soil total nitrogen [37–41].

The wavelength range of mid-infrared spectroscopy is between 2500 nm and 25,000 nm, and its absorption characteristics are caused by the molecules' fundamental vibration [42]. Compared to Vis-NIR spectroscopy, MIR spectroscopy has a higher intensity, a greater number of bands, and more information; as a result, it provides a greater number of soil-, mineral-, and organic compound-related features [36]. Utilizing MIR spectroscopy for determining soil total nitrogen is a potential research area with significant implications. Xie et al. (2011) [43] utilized MIR and NIR spectroscopy to simultaneously quantify organic carbon and total nitrogen in soil, and in conjunction with partial least squares regression analysis, they demonstrated that MIR is a more accurate predictor.

The benefits of spectroscopy-based sensors are that they can measure uneven surfaces nondestructively and require minimal or no sample preparation [44], allowing for more intensive and precise sampling [11]. Consequently, spectroscopy-based approaches for estimating total soil nitrogen offer distinct advantages in terms of being real-time, quick, non-destructive, inexpensive, and ecologically benign, and are the preferred non-contact measurement technique.

2.1.4. Other Methods

In addition to the usual analytical chemistry and spectroscopic approaches for determining soil total nitrogen, several researchers have also developed novel technology and instruments. Li et al. (2021) [45] suggested a method for detecting total nitrogen in soil based on pyrolysis and electronic nose. The pyrolysis technique was used to rapidly decompose a small amount of soil sample to produce a large amount of pyrolysis gas, which was then fed into the gas sensor matrix to obtain the sensor response curve, and the neural network algorithm was used to achieve rapid, accurate, and cost-effective detection of soil total nitrogen content. Song (2020) [35] utilizes hyperspectral remote sensing technology for the online monitoring of soil total nitrogen content, and estimates soil total nitrogen content by avoiding the interference of known factors through the development of an inverse model. Infrared attenuated total reflection (ATR) [46], diffuse reflectance infrared Fourier transform (DRIFT) [47], and Raman spectroscopy-based [48] research has also produced some results.

2.2. Methods for Soil Available Nitrogen Determination

Nitrate nitrogen is one of the principal types of available soil nitrogen, and is the primary indicator of nitrogen sufficiency or deficiency in dryland crops. Consequently, the majority of research on available soil nitrogen has focused on measuring nitrate nitrogen concentration. In other investigations, ammonium nitrogen and other inorganic nitrogen compounds were also considered.

According to the literature, there are currently many methods for the determination of soil nitrate nitrogen based on different principles. Some of them are shown in Table 1, and the advantages and disadvantages of each method are comprehensively compared. Commercial sensing devices based on these methods and principles have been applied in real production scenarios, as shown in Figure 3. It is worth noting that some methods can be applied to the determination of both soil nitrate nitrogen content and soil total nitrogen content.

The hotspot methods among them will be elaborated below.

Table 1. Comprehensive comparison of soil nitrate nitrogen detection methods.

Method Name	Estimation Substance	Processing Time	Robustness	Cost	Accuracy	Detection Limit	Specificity	Service Life	Portability	Ease of Use	Reference
Spectrophotometry-based Methods	Nitrate Only	Moderate	Moderate	Moderate	Very high	Moderate–High	Very high	Short–medium	Low	Low	[49–52]
Visible-Near-Infrared Spectroscopy	Both	Very fast	High	Moderate	Moderate–High	Moderate	High	Very long	High	Moderate	[20]
Mid-Infrared Spectroscopy	Both	Fast	Moderate	High	High	Moderate–High	High	Very long	High	Moderate	[20,36]
Attenuated Total Reflectance Spectroscopy	Both	Slow	Low	Moderate–High	High	Moderate	Moderate	Very long	Low–Moderate	Moderate	[53,54]
Raman Spectroscopy	Both	Fast	Low–Moderate	High	Moderate–High	Moderate	Moderate	Short–Medium	Very low	Very low	[44,48,55,56]
Ion-Sensitive Field Effect Transistor	Nitrate Only	Moderate	Moderate–High	Low	High	Moderate	Moderate	Medium	Very high	Moderate–High	[44,57]
Ion-Selective Electrode	Nitrate Only	Moderate	Moderate–High	Low–Moderate	Moderate–High	Moderate	Moderate	Medium	Very high	Moderate–High	[36,53,58–60]

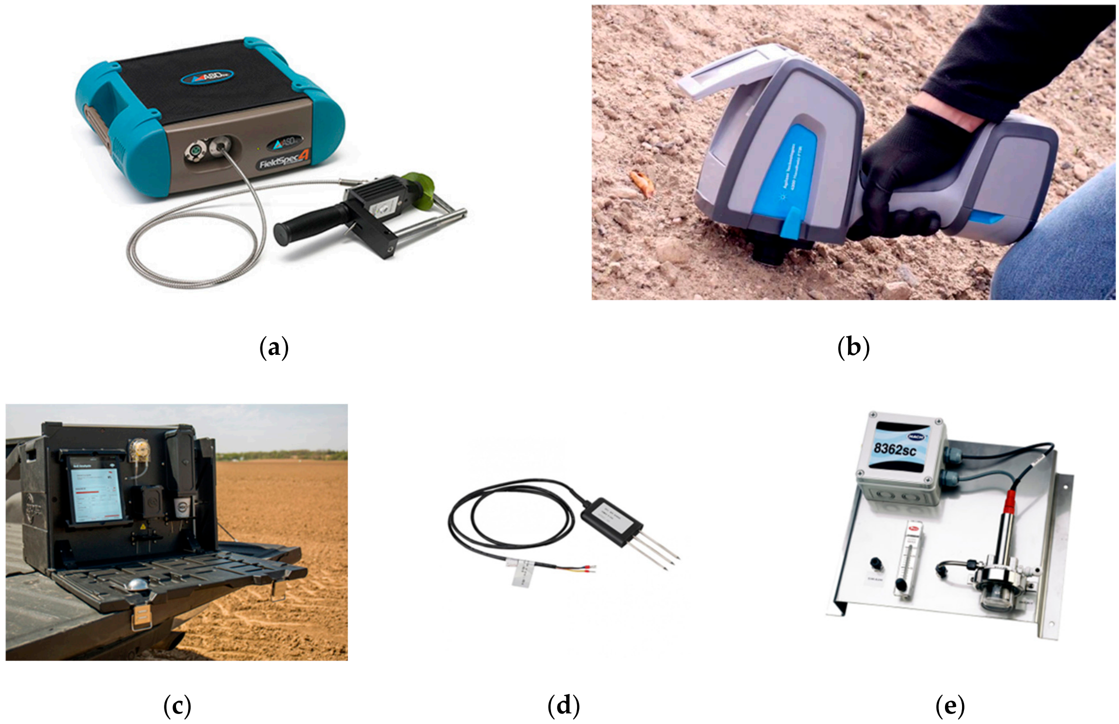

Figure 3. Commercialized soil nitrate nitrogen sensor devices suitable for in-situ determination: (**a**) FieldSpec 4, a portable Vis-NIR spectrometer developed by Malvern Panalytical Ltd., can be used for soil testing; (**b**) Agilent 4300 Handheld FTIR spectrometer can be applied to a variety of test methods including MIR and ATR; (**c**) 360 SOILSCAN, an integrated soil nitrate nitrogen content testing system developed by 360 Yield Center, has a built-in special ISE; (**d**) A low-accuracy but extremely low-cost sensor based on the electrical conductivity method for assessing soil nitrate nitrogen levels that is commonly used in China and elsewhere; (**e**) Nitratax sc, a nitrate nitrogen sensor developed by HACH based on UV spectrophotometry, is often used to measure the nitrate nitrogen content in nutrient solutions in facility agriculture scenarios.

2.2.1. Spectrophotometry-Based and Colorimetry-Based Methods

Traditional chemical approaches for determining available nitrogen in soils involve two steps: extraction and colorimetry. For the extraction of the nitrate nitrogen component of soil, solutions of calcium chloride, potassium chloride, or potassium sulfate are typically employed [49,50]. The nitrate nitrogen in the extraction solution may be measured immediately via a colorimetric reaction with sulfuric acid and salicylate [51], or colorimetrically via reduction to nitrate nitrogen on a metal column and reaction with p-aminobenzosulfamide [51]. Alternately, nitric nitrogen can be converted to ammoniacal nitrogen, and the concentration of nitric nitrogen can be detected by determining the amount of ammoniacal nitrogen [52].

UV spectrophotometry, often known as the optical method, has frequently supplanted the difficult chemical colorimetric method as one of the current standard methods for detecting the nitrate nitrogen content of soil. This approach makes use of the fact that nitrate ions in soil leachates absorb UV light considerably near 220 nm and that the absorbance is proportional to nitrate concentration in order to quantify nitrate content [61]. Additionally, the absorbance of the soil leachate is measured at 275 nm in order to eliminate interference from soluble organic materials [62,63].

Commonly, potassium chloride solutions are used to extract ammonium nitrogen, which is subsequently measured using diffusion-conductivity [64], the Berthelot reaction [65,66], or microdiffusion [67] techniques. This paper will not go into detail because ammonium nitrogen is less prevalent in the soils of most places, and does not correlate well with plant nitrogen uptake [68].

2.2.2. Spectroscopy-Based Methods

Similar to the detection of total soil nitrogen, infrared spectroscopy may detect available soil nitrogen. In the investigation, it was determined that the typical infrared spectral region of nitrate was between 1300 and 1550 nanometers, whereas the characteristic spectral region of carbonate was approximately 1450 nanometers. Therefore, the presence of carbonate in the soil impacts the precision of nitrate detection. Chen (2017) [20] enhanced the accuracy of the model's predictions by employing a neural network in conjunction with principal component analysis to distinguish the soil type prior to the assessment of nitrate concentration, and by introducing various techniques to eliminate interference.

Compared to NIR spectroscopy, nitrate nitrogen has more well-defined spectral features in the mid-infrared region, and the detection of soil nutrients based on mid-infrared spectroscopy has greater development potential and characterization. Mid-infrared spectra are straightforward to examine and calibrate because they are more intense and contain a greater number of soil-, mineral-, and organic compound-related characteristics [36]. The development directions of soil nutrient detection technology based on infrared spectroscopy include constructing a denoising model to reduce the interference of water and carbonate [20], and enhancing the detection accuracy and forecast ability of the nitrate nitrogen model.

In addition, emerging technologies such as infrared microscopic imaging [20,69] and data fusion [46] are beginning to be utilized in the assessment of nitrate nitrogen content.

2.2.3. Electrochemical-Based Methods

The ion-selective electrode (ISE) method is now the most popular method for determining the nitrate nitrogen concentration in soil based on electrochemical principles. It was first proposed in 1906 by R. Creamer. During the operation, the voltage of an ion-selective electrode reflects the concentration of the selective target being measured. The ISE operates by determining the activity or concentration of ions in solution based on the membrane potential. In practical applications, the ion-selective electrode, the reference electrode, and the solution to be measured form a two-electrode system; the relationship between the cell electric potential and the concentration of the ion to be measured is governed by the Nernst equation, and the concentration of the ion to be measured in the solution is determined by measuring the cell electric potential [36,58].

In comparison to conventional detection methods, the ion-selective electrode approach has the benefits of easy operation, rapid reaction time, and low price [59]. Based on ion-selective electrodes, rapid and batch soil nutrient assessment has now been achieved in the laboratory [53]. The ion-selective electrode technology has also been applied to the research of a vehicle-mounted, soil nutrient-field fast measuring device [60] in order to monitor the nitrate nitrogen content of the soil automatically and online.

Additionally, the ion-sensitive field effect transistor (ISFET) is a widely employed ion-concentration-detecting technique based on electrochemical principles. It can be thought of as a mix of an ISE and a field-effect transistor (FET). ISFET has a small size, a high signal-to-noise ratio, and a quick response time in comparison to ISE. The use of ISFET in flow injection analysis (FIA) is one of the main research foci in this area. FIA aids in reducing the drift of ISFET sensors, hence enhancing the efficiency and performance of the sensor system. Using multi-ISFET technology and a rapid extraction technique, researchers have accomplished real-time, on-site measurements of soil nitrogen in under 5 s [44,57].

2.2.4. Other Methods

Along with the development of nanotechnology and electrochemical molecular imprinting technology in recent years, new nanocomposite mediating materials and polymer-specific sensitive membrane technology have made significant strides [60], and ion-selective electrodes have attained significant improvements in sensitivity, stability, lifetime, and electron transfer rate. Electrochemical sensors, such as the ammonia sensor based on a paper substrate, can be produced using inexpensive materials [70].

In addition, printable sensor platforms that can be mass-produced using standard industrial printing techniques are beginning to be employed for real-time analysis of soil nutrients. Some printed electrodes have been commercialized, which are small in size and highly integrated. Baumbauer et al. (2022) [71] produce and manufacture nitrate potentiometric sensors utilizing only printed sensor technology, such as the printed nitrate ISE and the printed RE. The sensor consists of an ion-selective electrode and a reference electrode with a polymer membrane providing functionality. The printed sensors were not significantly impacted by ions such as sulfate, chloride, etc., but calcium ions interfered with the sensors' performance. In comparison to conventional sensors, these printed sensors require little amounts of electricity to function, which facilitates their incorporation into wireless sensing nodes.

3. Key Problems

The determination of soil nitrogen is a complex task due to the intricate nature of soil composition. Currently, there is no technique that combines a simple approach with precise results. Even widely adopted and extensively researched methods for determining soil nitrogen have inherent limitations and are subject to challenges that can compromise their effectiveness. These challenges are influenced by both the underlying principles of the techniques and the specific manner in which they are applied. Thus, the accurate determination of soil nitrogen remains an ongoing challenge in soil science.

3.1. Insufficient Accuracy

Some studies have noted that the Kjeldahl method, which is now the most popular method for assessing soil total nitrogen, produces inaccurate results. The typical Kjeldahl method with conventional reagents can identify organic nitrogen and ammonium nitrogen in a sample but cannot detect nitrate nitrogen or nitrite nitrogen [20,33]. This may be owing to the Kjeldahl method's inability to convert nitrate nitrogen into ammonium nitrogen during the process. At the reaction temperature of the Kjeldahl method, a portion of the nitrate in the sample is vaporized, decomposed, or transformed into nitrogen gas and volatilized, and therefore cannot be quantified [72]. In theory, the Dumas method circumvents the issue that nitrogen cannot be totally transformed, but the homogeneity of the sample and the degree of combustion can influence the precision and accuracy of its measurement results [23]. In addition, the measuring devices based on the Dumas method utilized in certain investigations had a tiny injection capacity, resulting in greater measurement result variation [73].

When measuring available nitrogen, various approaches based on electrochemical principles typically face significant interference issues. Relevant research has demonstrated that soil conductivity, temperature, pH, chloride ions, and other variables can alter nitrate nitrogen measurement results [59]. Researchers employ neural networks [20,35,74], the standard addition method (SAM) [75,76], multi-parameter fusion [59], and other techniques to limit the interference of non-target factors on the detection findings as much as possible; however, the error of the final result remains between 5 and 15% [58,77,78]. This level of precision is adequate for providing supplementary decision-making information for accurate fertilization [78], but there is much opportunity for improvement.

3.2. Limited Scenarios

Traditional soil nitrogen detection methods based on colorimetry, spectrophotometry, or combustion are inconvenient due to their time-consuming nature, high cost, bulky equipment, limited automation, high maintenance costs, and use of toxic reagents. Furthermore, it is impossible to implement long-term automatic detection in the field if measurements are conducted on-site. Due to the benefits of small equipment and simple integration, spectroscopy and electrochemistry-based detection approaches have become the focus of in-situ soil nitrogen detection research. In the majority of investigations, however, the detection system is still intended for the laboratory setting and does not fulfill the features and functional needs of field applications.

On the one hand, the design of these sensing devices focuses primarily on measurement precision and efficiency, while structural strength, reliability, and other parameters required by the sensing system for field applications are frequently disregarded. Using near-infrared spectroscopy as an example, it is necessary to bury the conductive optical fiber in the ground or remove the soil sample while analyzing soil at different depths in the field [11]. Due to the complex composition of the soil, gravel and other particles are frequently present in the soil and can easily harm the instrument probe or alter the measurement findings [79].

On the other hand, despite the fact that some sensing devices possess the outward qualities necessary for field applications, the entire measurement procedure still requires human intervention. Using ion-selective electrodes as an example, in hydroponic situations, fixed electrodes can be used to measure the concentration of nitrate nitrogen in the nutrient solution; however, the electrodes must still be manually calibrated on a regular basis. This procedure is distinct from the on-site detection procedure, which is not only time-consuming and tedious, but also not conducive to the production of online ion-concentration-detecting equipment [78].

Morgan et al. (2009) [80] noted in their research that despite the fact that in-situ measurements eliminate sampling, drying, sieving, and other processing steps, the measurement accuracy will drop due to the impact of environmental conditions on the measurement data.

3.3. Poor Versatility

In the majority of existing soil nitrogen monitoring systems, data extraction and modeling are required processes. As a type of mixed system, the physical and chemical composition of soil is extraordinarily complicated. Most measurement techniques will be affected by non-target soil variables. Soil nitrogen detection faces the challenge of how to extract nitrogen-related indicators from vast amounts of data, reduce the influence of interfering factors, and limit the loss of data quality [36]. The establishment of a fair and reliable model to represent the link between sensory information (such as spectral and electrochemical data) and soil nitrogen content—in order to accomplish accurate prediction of soil nitrogen content—is therefore an essential topic in this field.

Before testing, soil samples must typically be dried, powdered, sieved, etc., whether electrochemical or spectroscopy-based procedures are used. Several studies have demonstrated that physical properties such as the sample's water content and particle diameter influence the prediction accuracy, while detection conditions such as the sample's rotation angle and the installation height of the detection equipment influence the prediction effect [3]. However, there is always a lack of comparable techniques and evaluation standards for the pretreatment of soil samples throughout different research, preventing the horizontal comparison of soil samples and measurement data across investigations.

Principal component analysis, partial least squares regression analysis, backpropagation neural network use, and other techniques are commonly employed in research to extract the portion of the original experimental data pertaining to soil nitrogen content. Among them, a number of methods including neural networks require artificially specified parameters which are typically derived from the researcher's prior experience [45,76,81]. As a result, the processing results are highly influenced by the researcher's subjective factors, and the processing methods are not easily applicable to other samples.

The influence of the universality problem is more apparent in modeling. Using near-infrared spectroscopy as an example, Yu (2015) [3] and Fan et al. (2018) [82] discovered that commercial near-infrared spectroscopy instruments are used in all types of contemporary research, and that the quality of the results is entirely dependent both on the performance of the instruments, as well as the fact that the data and models established between different instruments are not universal. When the same type of near-infrared spectroscopy device is modeled using the same data processing approach, the prediction results for different types of soil will also exhibit significant variation. The established spectrum model cannot produce good forecast results due to variations in measurement time, spectral acquisition equipment, ambient temperature, and test sample soil type. This issue is referred to as the calibration transfer problem. Different types of soil samples have a direct effect on the selection of characteristic bands and modeling methods required by spectroscopy, and the best prediction bands or best prediction models calculated by different types of soil are highly distinct. This significantly restricts the usefulness of spectroscopic techniques. One of the primary reasons why there is no NIR spectral analysis model database for soil organic matter and total nitrogen content in the world is the challenge of calibration transfer [81].

3.4. Unsuitable for Practical Applications

Current research on soil nitrogen detection frequently focuses on enhancing the accuracy of the measurement method, but there is a dearth of study on the sampling procedure and practical application practicality. In many studies, the in-situ measurement of soil nitrogen has not been implemented, and soil sample collection and preparation are still completed manually. Li et al. (2017) [53] noted that the automatic design of soil sample pretreatment and the adjustment of process parameters are essential for determining the efficiency of soil nutrient detection using the ion-selective electrode method and the viability of in-situ determination. Amina et al. (2018) [83] claimed that the inability to acquire data quickly and affordably on soil properties and crop quality—owing to a lack of autonomous sampling and processing—is one of the most significant barriers facing smart agriculture today. To extract and model data, researchers often employ a range of techniques, such as partial least squares, extreme learning machine algorithms, and error backpropagation neural network algorithms. Typically, a considerable amount of data is required for these strategies to achieve success. Before modeling, the data must be manually labeled and categorized into a training set and a test set [45,74]. In addition to requiring a great deal of time and people, the majority of this process requires a high-performance computing platform. In addition, when soil samples change, researchers are unable to determine the optimum model to use and must redo their comparison studies [11]. Due to these issues, the current state of research on soil nitrogen quantification provides few guidelines for field use.

3.5. Low Level of Informatization

With the development and promotion of the concept of smart agriculture, Internet of Things, big data, and artificial intelligence technologies have begun to be implemented in agricultural production. Internet of Things technology facilitates the connectivity of field devices and the cloud, giving the soil nutrient sensor system the ability to visualize and share data in real time [44]. Regarding the detection of soil nitrogen levels, the sensor may broadcast data to the cloud, which can subsequently be analyzed using machine learning and neural networks to estimate the soil's nutrient need and give fertilization countermeasures [84]. However, modern research focuses primarily on fields such as material science, spectroscopy, and machine learning; research objects are typically separate links such as sensor principles and data analysis techniques. Less research exists for the whole system-level design of soil nitrogen determination and the data communication methods between multiple links.

In India and elsewhere, the application of IoT technology to soil nitrogen sensing has emerged as a research hotspot in recent years. In general, researchers have developed detection platforms mainly based on the colorimetric principle, automated the uploading of detection results, and some even created smartphone applications that allow users to view results stored on the server side [84–90]. While these studies have successfully implemented the uploading and online storage of sensor data, the on-site inspection process remains incomplete, and there is limited discussion on how to maximize the value of cloud data and its impact on production practices. In fact, effectively acquiring, managing, and utilizing data remains a common challenge in agricultural IoT research. Current research on the application of IoT technology to soil nitrogen sensing focuses primarily on validating each basic technology independently and testing the feasibility of the process on a small scale over a short period of time. Overall, the level of information provided by soil nitrogen sensing is still relatively low.

3.6. Limitations Due to Soil Variability

Regional data depend on the construction of sample densities, which must be representative of the full statistical population to be reliable. In order to distinguish changes in soil qualities and their spatial patterns, each "point" and the transitions between them must be defined by sampling points in the agricultural area. The majority of current research on soil nitrogen measurement employs conventional laboratory techniques to develop standard models that explain the link between sensor output and soil characteristics. Nevertheless, according to the research of Rossel and Bouma [91], the nutrient content in soil is a dynamic property influenced by many factors such as environmental conditions and soil-plant interactions, so the results of analyses based on different soil extracts cannot accurately represent the soil nutrients available to crops. according to Nawar et al., no single sensor can properly characterize the complexity of soil [92]. Obviously, precision agriculture requires consideration of the spatiotemporal variability and large-scale diversity of soil nitrogen distribution, necessitating the development of a sensing model that accounts for these factors.

4. Future Research Directions

4.1. New Principles, New Equipment, and New Materials

With the advancement of chemistry, material science, and information technology, there are an increasing number of innovative techniques for determining the soil's nitrogen concentration. Concerning test equipment, one of the primary research topics focuses on how to make the equipment more compact and automated in order to better suit the requirements of field measurement.

Ozhikandathil et al. (2018) [93] created a lab-on-a-chip using microfluidic technology, incorporating light-emitting diodes and photoresistors to quantify changes in absorbance and detect amounts of ammonia and amino acids. The microfluidic gadget reportedly responds to a wide range of concentrations and has a detection limit as low as two parts per million. Li et al. (2017) [53] created an in-situ soil pretreatment system for ISE nitrate nitrogen detection that automatically performed the four phases, including soil moisture measurement, weighing, liquid injection and leaching, and high-speed centrifugation, thereby enhancing the timeliness of the determination. Kodaira et al. (2020) [94] created and upgraded a sensor system capable of collecting real-time subsurface soil reflectance in the field. They also employed a complete Vis-NIR reflectance and PLS-R to forecast ammonium nitrogen and nitrate nitrogen, and they obtained positive results.

In terms of detection principles, researchers have enhanced the response performance of commonly used detection technologies, such as ion-selective electrodes and near-infrared spectroscopy, by improving and introducing new materials. In the meantime, several researchers are also actively investigating the possibilities of implementing novel measurement instruments in the field of soil nitrogen sensing.

Solid-state ion-selective electrodes have become a research hotspot in recent years because of their good stability and long life. Zhang (2015) [60] produced a novel solid-state nitrate ion-selective electrode with graphene as the solid-contact layer, glassy carbon electrode as the substrate, and nitrate-doped polypyrrole as the sensitive material. This novel type of electrode has excellent anti-interference performance for interference ions such as chloride ions, and the measurement results are also accurate.

For near-infrared sensing, the near-infrared photoactive materials have the greatest impact on the sensor's performance. Traditional photoactive materials, such as lead sulfide, are constrained by their inherent characteristics, leaving little possibility for performance enhancement. New organic optoelectronic materials have attracted the interest of scientists throughout the globe. The wavelength coverage of these materials is sufficient, and the response range is maximized by improving the material parameters. Nonetheless, there are disparities in the spectrum response range and detection rate of various materials that prevent their commercial adoption [3].

Attenuated total reflectance spectroscopy (ATR) is one of the new techniques for measuring the nitrogen content of soil. It is similar to near-infrared spectroscopy in theory, but uses a crystal in direct contact with the sample to receive the signal, requiring minimal pre-treatment of the soil sample [53,54]. Due to the high cost and fragility of ATR devices, this method has not been extensively researched. Raman spectroscopy utilizes the variation in wavelength and intensity of the sample's scattered light to determine its chemical makeup. It can immediately detect nutrients in both dry and wet soil [44], and has a broader variety of applications than conventional approaches. Miniaturized and field-tested Raman spectroscopy equipment is now available [48,55,56].

Numerous nanomaterials for nitrogen detection in nano(bio)sensors, such as metallic and magnetic nanoparticles, nanorods, nanotubes, nanocomposites, graphene, etc., have been documented in the scientific literature. However, the use of these nanostructured (bio)sensors is still in its infancy, as they have only been studied under laboratory conditions [83].

4.2. Optimization of Data Processing and Analysis Methods

Due to the fact that characteristics such as the particle diameter and water content of the tested samples cannot be identical, the measurement accuracy of the instrument will also lead to mistakes in the provided spectrum data as a result of the varying use settings, such as temperature and humidity. Some researchers have attempted to improve the quality of data by using advanced algorithms to pre-process the raw data obtained from measurements to reduce the influence of various extraneous factors present in the sample itself and in the environment on the measurement results.

According to Morellos et al. (2016) [37], using Vis-NIR spectroscopy to forecast the properties of fresh soil samples necessitates the employment of increasingly sophisticated models to convert raw data into measurement findings. In terms of predictive ability, both the least-squares support-vector machines (LS-SVM) and the Cubist model outperformed the multivariate linear technique. Dotto et al. (2018) [95] examined the prediction accuracy of soil organic matter content with nine models, including partial least-squares regression (PLSR), principal components regression (PCR), multiple linear regression (MLR), support vector machines (SVM), the random forest (RF) ensemble learning method, and artificial neural networks (ANN), under seven different pretreatment procedures, providing guidelines for the selection of data models and pretreatment methods for future studies.

Some academics have also focused on the previously mentioned pervasive model migration problem. The primary solutions include developing a spectral analysis model suitable for detecting a range of various soil total nitrogen levels [96], realizing model migration of different spectra acquired from the same soil sample under different states and different measurement settings of the same measuring instrument by wavelet transform and other methods [97], and employing the direct correction algorithm and the canonical correlation analysis algorithm to realize model migration research work [98]. The challenge of spectral calibration transfer remains within the purview of machine learning; therefore, other machine learning modeling techniques can be used. Ren et al. (2015) [59] substituted a multi-parameter fusion model for the classic Nernst model, significantly boosting the measurement's versatility. Some studies have also demonstrated that by increasing the number of samples in the modeling sample set and the source of sample regions, the prediction error of soil nitrogen content in various locations can be successfully reduced, and the predictive performance of the model can be enhanced [81].

In addition, given the complexity of the overall data extraction and modeling process, a number of academics have begun experimenting with new data measurement and analysis techniques. Lu et al. (2021) [76] constructed an automatic platform for determining soil nitrate nitrogen and incorporated the standard addition method into the detection procedure. This method's concept is straightforward, and it may be executed on a low-performance platform. The influence of the test solution's background on the detection potential of the ion selective electrode can be disregarded, and neither a significant number of modeling experiments nor repetitive data calibration are required during the detection process. Compared to other neural network techniques, it has a larger range of applications and a lower cost per application.

4.3. Deep Application of IoT Technology

As agricultural productivity and production scale continue to increase, traditional Internet of Things systems centered on limited areas and relatively simple tasks can no longer match human needs. People must urgently implement new Internet of Things technologies and investigate new application models in order for technology to enhance agricultural production.

Today, in some sectors of precision agriculture production practices, real-time in-situ sensors and other modern IoT technologies are utilized not only to monitor environmental parameters, but also to construct decision support systems that guide and optimize agricultural production processes. Decision support systems examine the impact of multiple data variables, including climate, irrigation, crop genetics, energy, land topography, human activities, and economic resources, on agricultural productivity and their interrelationships [44,99]. On this basis, decision support systems provide users with intervention and adjustment recommendations for agricultural production measures, as shown in Figure 4. Globally, decision support systems are currently playing a greater role in helping farmers achieve precise fertilization, enhanced yields, and higher incomes [100].

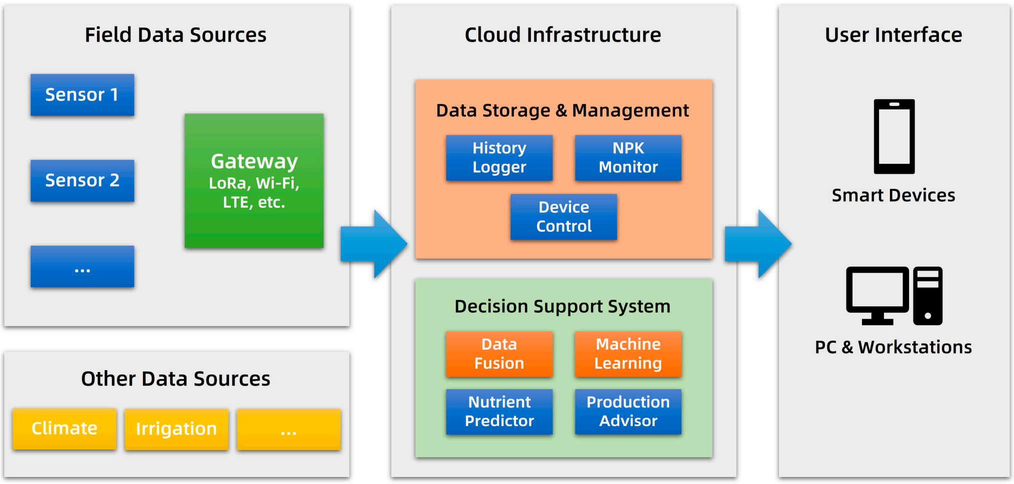

Figure 4. Architecture of a typical modern agricultural IoT system with a decision support system.

As the direct source of soil nutrient data, the soil nitrogen sensor is an essential component of the agricultural Internet of Things, supplying the data and infrastructure necessary for the operation of the decision support system [101]. To enable effective operation of these decision support and information systems, sensors must provide highly precise and timely data. Moreover, in order to promote widespread utilization, sensors should also possess features such as low cost, high dependability, and a high degree of automation.

5. Conclusions

This paper reviews the need and current state of soil nitrogen sensing, describes the current mainstream detection means for total and available soil nitrogen, then describes current deficiencies in sensing technology and application models. Finally, in light of the literature and existing research, several important future research directions in this field are suggested.

The integration of various soil nitrogen detection methods and sensors, discussed in this paper, with practical application scenarios, is of the utmost importance to showcase their unique advantages. Moreover, it is imperative that researchers delve into joint research on detection technology and emerging technologies such as the Internet of Things and big data to enable real-time monitoring and control of agricultural systems, enabling farmers to make informed decisions and minimize resource waste. The traditional laboratory methods of soil chemical analysis are highly precise, providing a robust data foundation for scientists to propose soil improvement strategies. However, the integration of soil nitrogen sensors with in-situ measurement and real-time feedback with emerging technologies has the potential to result in the development of portable and low-cost solutions for end-users. As technology progresses, it is expected that the ease of use and cost-effectiveness of all nitrogen detection methods and corresponding sensors will continue to improve, thereby fostering precision agriculture, reducing resource waste, and protecting the environment.

In the framework of the modern era, the application of information technology—especially the newest generation of Internet of Things technology—to agricultural output is increasing. To increase the value of precision agriculture production methods such as soil formula fertilization, it is necessary to integrate the advantages of objective conditions in the new era based on information technology combined with materials science, analytical chemistry, and other means, address practical needs, and continuously improve the practicality and reliability of soil nitrogen sensors from multiple dimensions. Through the introduction of decision support systems and other means, the application boundary and application value of soil nitrogen sensors can be expanded to achieve an overall and accurate perception of soil conditions, to provide better technical guidance and information reference for the promotion and implementation of precision agriculture, and to contribute to the sustainable development of humans.

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