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Application of AI in Precision Fertilization and Irrigation Management

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Abstract: With the increasing pressure on global food security and the need for sustainable agricultural development, precision agriculture (Precision Agriculture) has become a key direction in modern agriculture. Artificial intelligence (AI) technology, through data-driven decision-making, shows great potential in precise fertilization and irrigation, and can control runoff pollution. This paper systematically reviews the application models of AI technology in key areas such as soil nutrient management, crop water demand prediction, and variable equipment control. It analyzes the technical advantages, existing challenges, and future trends, aiming to provide a reference for the development of smart agriculture technology.

Keywords: Precision irrigation; Precision fertilization; Artificial intelligence; Runoff pollution.

1. Introduction

1.1. Background and significance

In traditional agriculture, the extensive management of fertilizers and water leads to resource waste, environmental pollution, and soil degradation. By implementing precise fertilization and irrigation techniques, it is possible to dynamically match the specific needs of crop growth with effective resource supply. This not only significantly improves resource utilization efficiency but also brings a series of environmental and economic benefits. In practical applications, precise fertilization can increase both the yield and quality of crops, improving nitrogen fertilizer efficiency by 30-50%. At the same time, the application of precise irrigation technology can effectively conserve water resources and enhance water use efficiency. The adoption of these technologies not only promotes healthy crop growth but also reduces the waste of fertilizers and water resources, which is crucial for promoting sustainable agricultural development. The introduction of AI technology holds promise for further addressing issues such as low data processing efficiency and weak model generalization capabilities in traditional precision agriculture.

1.2. Evolution of AI technology

Before the 2000s, geographic information systems (GIS) and remote sensing technology were widely used in environmental management, mainly manifested as static zoning management. During this period, GIS technology helped managers to classify and manage different regions by collecting and analyzing geographic spatial data.

In the 2010s, the rise of the Internet of Things (IoT) and sensor technology has ushered in a new era of dynamic monitoring for environmental management. By deploying sensors at key points in the environment, managers can collect data in real time and continuously monitor environmental changes to achieve more accurate and timely environmental management.

In recent years, with the emergence of Open AI and domestic DeepSeek, the development of artificial intelligence (AI) and machine learning technologies has brought revolutionary changes to environmental management. They can process and analyze massive amounts of environmental data, enabling real-time decision support for environmental conditions, making environmental management more intelligent. Moreover, they can predict trends in environmental changes, providing scientific evidence for decision-makers.

1.3. Runoff pollution control

Precision irrigation and precision fertilization effectively reduce the risk of agricultural non-point source pollution by optimizing water and fertilizer resource utilization, playing a significant role in controlling runoff pollution. Precision irrigation, leveraging soil moisture monitoring, meteorological data analysis, and intelligent control systems, achieves water supply on demand, reducing soil erosion and surface runoff caused by over-irrigation, thereby inhibiting the entry of nutrients like nitrogen and phosphorus into water bodies through runoff. Precision fertilization, based on crop nutrient requirements, soil nutrient content, and environmental carrying capacity, employs variable-rate fertilization techniques and controlled-release fertilizers to minimize excessive fertilizer application and nutrient loss, reducing the concentration of pollutants such as nitrates and phosphates in runoff. The combined use of these two methods can increase water and fertilizer efficiency by over 30%, reduce runoff pollution loads by 20-50%, and enhance soil retention capacity through root zone moisture regulation, further controlling pollutant migration and providing key technological support for watershed water environment management.

2. Application of AI in precision fertilization

2.1. Sensors collect and process data

Multi-source Data Collection Technology: Advanced soil sensors are used to obtain critical soil information. For example, pH sensors can accurately measure soil pH, providing a basis for determining whether the soil is suitable for crop growth. NPK content sensors can monitor the real-time levels of nitrogen (N), phosphorus (P), and potassium (K) in the soil, which are essential nutrients for crop growth.

Remote sensing image acquisition: Drones equipped with multispectral cameras can obtain image information across different bands. By analyzing these images, the health status, growth trends, and potential nutrient deficiency areas of crops can be identified. For example, under the near-infrared band, healthy crops and nutrient-deficient crops exhibit significantly different reflectance characteristics, which helps to accurately pinpoint problematic areas.

Data Fusion Processing: Spatiotemporal Data Alignment: Data from different sources differ in time and space dimensions, requiring alignment. For example, soil sensor data is measured at fixed points, while multi-spectral images from drones cover an entire area. Using Geographic Information System (GIS) technology, all data can be aligned to the same geographic coordinate system and temporally synchronized based on the acquisition time, providing a foundation for subsequent analysis.

Feature Extraction: Extract valuable features from multi-source data for model training and analysis. For soil sensor data, plot trends in nutrient content changes and the fluctuation range of pH values; for multi-spectral images from drones, extract vegetation indices (such as normalized difference vegetation index NDVI), color characteristics, and texture features; meteorological data should focus on temperature change curves and peak rainfall values. Through feature extraction, raw data is transformed into more representative and analyzable forms, enhancing the efficiency and accuracy of model training.

2.2. Learning model processing

Machine learning models: Random Forest (RF), Support Vector Machine (SVM)

In the task of soil fertility classification, various physicochemical properties of soil (such as pH, NPK content, and organic matter content) are used as input features. The model is trained using a large number of soil samples with known fertility levels, enabling it to predict the fertility level of unknown soil samples. This allows for the assessment of soil fertility conditions in different areas of farmland, thus enabling the formulation of differentiated fertilization plans.

Convolutional neural network (CNN)

CNN analyzes remote sensing image recognition of nutrient-deficient areas by constructing multiple convolutional layers and pooling layers, enabling automatic learning of crop features in remote sensing images. When identifying nutrient-deficient areas, a large number of multispectral image samples of normal and nutrient-deficient crops are collected, with the nutrient-deficient areas labeled. These samples are then fed into the CNN model for training, allowing the model to learn the characteristic patterns of nutrient-deficient crops in the image, such as the color and texture features of yellowing leaves at specific wavelengths. After training is complete, new remote sensing images can be input into the model to quickly and accurately identify nutrient-deficient areas.

Deep learning model: Long Short-Term Memory (LSTM)

LSTM can effectively process time series data. Based on the varying fertilizer requirements of crops at different growth stages, meteorological data, soil nutrient data, crop physiological indicators (such as plant height and leaf area), and fertilizer application rates are used as inputs to construct an LSTM model. The model learns from historical data to predict changes in fertilizer demand at different future growth stages, thereby dynamically adjusting fertilizer application rates and ratios to ensure that crops receive appropriate nutrient supply at all growth stages.

2.3. AI applications

Fertilization based on soil nutrient input variables: AI, through the analysis of large amounts of soil nutrient data collected by soil sensors, combined with machine learning and deep learning models, can generate detailed fertilization prescription maps down to each square meter. The model divides farmland into several zones based on different soil pH values, NPK content, and other nutrient indicators, and formulates personalized fertilization plans for each zone, including types of fertilizer, application rates, and timing. Farmers can apply precise fertilization according to the prescription map, ensuring that each zone receives appropriate nutrient supplementation.

Reducing soil acidification caused by excessive fertilization: Traditional fertilization methods often lead to over-fertilization in certain areas, which can easily cause soil acidification over time, affecting crop growth and soil ecology. AI-based precision fertilization technology can apply fertilizer based on the actual nutrient status of the soil, avoiding the issue of over-fertilization. In areas with low soil pH values, reducing the use of acidic fertilizers and increasing the application of alkaline fertilizers or soil conditioners can gradually improve soil pH levels, maintaining soil health.

3. Application of AI in precision irrigation

3.1. Data perception: build the cornerstone of farmland information Internet of Things

The foundation of precise irrigation lies in the real-time and comprehensive perception of water demand in farmland. The data sensing layer constructs a three-dimensional network for collecting environmental data from farmland through the deployment of various types of sensors and monitoring technologies: including soil moisture sensors, weather stations, and drone remote sensing. This network enables real-time monitoring of multiple dimensions of information such as soil moisture, temperature, wind speed, and rainfall. Soil moisture sensors can penetrate deep into the soil to accurately measure the water content in different layers, helping managers understand the dynamic changes in soil moisture. By setting soil moisture thresholds, the system can automatically trigger irrigation or drainage commands when the soil moisture is below or above the set values, ensuring that crop roots are in an appropriate humidity environment. Weather stations monitor meteorological conditions over the farmland, including temperature, humidity, light intensity, and wind speed, which are used to predict crop transpiration and soil evaporation. In hot and dry weather, crop transpiration increases, requiring more irrigation to meet the water needs of crops; during rainy weather, however, irrigation should be reduced to prevent excessive water from causing crop diseases. Drone remote sensing uses high-resolution cameras and multispectral sensors to obtain information on canopy temperature and vegetation indices, further assessing the water stress status of crops. This helps managers promptly identify and address water deficiency issues, improving the accuracy and efficiency of irrigation.

3.2. Precise monitoring of soil moisture

Using "Time Domain Reflectometry (TDR)" and "Frequency Domain Reflectometry (FDR)" soil moisture sensors, real-time acquisition of parameters such as soil water content and electrical conductivity is achieved, accurately determining the water distribution status in the root zone. These sensors feature high precision and low power consumption, enabling dynamic monitoring of soil moisture at centimeter-level depths, providing fundamental data support for irrigation decisions.

Through long-term monitoring and data analysis, the AI system can identify the water-holding capacity of different soil types and the moisture requirements for crop growth, thereby constructing matching irrigation models. The model can automatically calculate appropriate irrigation amounts and timing based on real-time soil moisture data, combined with real-time meteorological data and the crop growth cycle, achieving demand-driven irrigation. This not only effectively avoids water waste but also ensures that crops receive sufficient and moderate water supply throughout their growth process, improving both quality and yield. Additionally, the AI system can continuously optimize irrigation strategies by comparing historical irrigation data with crop growth conditions, achieving intelligent and precise irrigation management.

3.3. Dynamic tracking of crop transpiration

Using drone remote sensing thermal infrared imaging technology and stem flow sensors, the transpiration rate and water consumption of crops can be monitored in real time. Thermal infrared imaging can non-invasively obtain canopy temperature, which, combined with crop variety characteristics, can infer the transpiration intensity [1]; stem flow sensors directly measure changes in plant stem liquid flow, quantifying root water absorption capacity. Together, these two methods enable bidirectional data collection from "soil water supply" to "crop water demand." Based on phase analysis of multi-source perception data, LSTM models can establish dynamic mapping relationships between crop transpiration and environmental factors such as temperature, humidity, and solar radiation. For example, during the large trumpet stage of corn [2], the system analyzes the continuous 7-day canopy temperature change curve (daily fluctuation range ±1.2°C) and stem flow rate data (daily peak up to 12.5 mL/min), combined with the next three-day weather forecast, predicting that water demand will increase by 35% over the next 72 hours, thus initiating drip irrigation systems for water replenishment in advance. The AI system employs a multimodal data fusion strategy, dividing thermal infrared images into 1m² grid cells, extracting 12 features such as mean temperature and standard deviation for each cell; stem flow data is statistically accumulated hourly, linked to the geographical location information of the corresponding plant. Through attention mechanisms, temporal features are weighted, and when the transpiration rate in a certain area deviates from the normal range by ±15% for three consecutive hours, the system automatically triggers a diagnostic module, combining soil moisture data and meteorological conditions (such as a sudden increase in evaporation when wind speed>4m/s) to determine whether it is physiological water deficiency or environmental stress.

3.4. Intelligent fusion of meteorological data

Integrate meteorological forecast data (such as rainfall probability, evaporation rate, wind speed, etc.) and perform multi-source data fusion through edge computing devices or cloud platforms. For example, use rainfall prediction data to dynamically adjust irrigation plans to avoid flooding caused by cumulative rainwater; combine evaporation rate data to optimize irrigation timing and reduce ineffective water loss.

In the three-dimensional spatial modeling of farmland, the AI system predicts crop water demand [3] using a correction formula based on the Peng-Montessori (Penman-Monteith) formula recommended by the Food and Agriculture Organization (FAO) of the United Nations. When the probability of rainfall over the next 24 hours exceeds 60%, the system automatically applies a reduction factor to the irrigation amount in the control algorithm and adjusts the evaporation compensation parameter according to the predicted wind speed. For sudden meteorological events, the AI system completes spatiotemporal registration of meteorological satellite data, ground automatic station data, and field micro-meteorological observation data within 15 minutes, establishing a dynamic response model for precipitation intensity and soil infiltration rate. In a real-world case study during the winter survival period of wheat in northern Jiangsu, [4], the system successfully predicted the radiation cooling process on January 6, 2023, initiating frost prevention irrigation 12 hours earlier, maintaining the soil temperature at a depth of 0.5°C above 0°C, reducing frost damage area by 63% compared to traditional methods.

The deep reinforcement learning framework demonstrates unique advantages in irrigation decision-making, constructing a state-action value function. The state space includes 12-dimensional features such as soil moisture content (0-100%), crop water stress index (-2.0 to +2.0), and effective rainfall over the next 72 hours (0-30 mm). The action space corresponds to decision variables like irrigation duration (0-240 minutes) and irrigation intensity (2-8 m³/h). After 3,000 iterations of training, the model achieved an irrigation water use efficiency (WUE) improvement of 3.8kg/m³ in a water-saving experiment on cornfields in the Huang-Huai-Hai Plain, which is 28% higher than the benchmark value of an expert system. Particularly in drought warning scenarios, the system leverages transfer learning to migrate feature patterns from historical disaster data (NDVI anomaly dataset from 2000-2020) in the northwest arid region to newly reclaimed irrigation areas, achieving a drought identification accuracy rate of 89.7%[5] despite insufficient training samples.

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