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Toward Demand-Driven Intelligent Perception Paradigm in Agricultural Remote Sensing: From Data Acquisition to Precision Services

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Abstract: With the widespread application of satellite and unmanned aerial vehicle (UAV) remote sensing platforms, agricultural remote sensing has entered an era of big data. However, the "supply–demand mismatch" between data provision and practical application requirements has become increasingly prominent, severely hindering the maximization of data utility. This study has systematically analyzed 3 core bottlenecks in the current application of agricultural remote sensing data: spatiotemporal mismatch, semantic representation gap, and redundant feature construction. To address these challenges, this paper proposes a demand-driven intelligent perception paradigm for agricultural remote sensing. Using the fine-scale monitoring of litchi as a typical case study, this study elaborates on the core architecture and implementation pathways of this paradigm. Centered on the demands of agricultural production applications, the paradigm revolves around 4 key elements (4K: Key Space, Key Time, Key Object, and Key Feature). Driven by end-use requirements, it dynamically designs and iteratively optimizes remote sensing observation strategies, thereby constructing a "Demand-Acquisition-Service-Feedback" (DASF) closed-loop collaborative mechanism. Through continuous iterative optimization of the perception strategy, full-process synergy from data acquisition to information services is achieved. Furthermore, this study analyzes the practical challenges faced by this paradigm, including the accuracy of demand interpretation, multi-source collaborative scheduling, and service-oriented transformation. Future development directions are forecasted, including knowledge graph-driven automatic demand parsing, cloud-edge-end collaborative intelligent acquisition systems, and the "Observation as a Service" (OaaS) model, providing a novel theoretical framework and technical pathway for the application of remote sensing technology in precision agricultural management.

Keywords: agricultural remote sensing; intelligent perception; demand-driven; phenological monitoring; space-air-ground integration

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1 Introduction and Challenges

With the rapid advancement of Earth observation technologies, particularly the widespread adoption of satellite remote sensing and unmanned aerial vehicle (UAV) platforms, agricultural remote sensing has entered an era of big data[1–3]. Currently, thousands of

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satellites in orbit around the world are continuously observing agricultural ecosystems on a large scale and at multiple frequencies, generating massive data resources in various spectral bands, including visible, infrared, and microwave[4–6]. Meanwhile, low-altitude remote sensing technologies, such as UAVs, have scaled down the observation of farmland from a regional scale to a field scale, significantly enhancing the spatial accuracy and temporal flexibility of data acquisition[7,8]. The sustained improvement of high-resolution Earth observation platforms is not only attributed to advancements in satellite design and manufacturing technologies, but also to the significant enhancement of data processing capabilities[9]. Despite the explosive growth in data volume, the efficiency of converting these data into usable information for agricultural management remains low, and massive amounts of data fail to effectively support decision-making. Current agricultural remote sensing still faces core problems at the data application level, including spatiotemporal mismatch of remote sensing data, semantic representation gap, and redundant feature construction. These issues intertwine and collectively constitute the core issue of the "supply-demand mismatch" in agricultural remote sensing, which hinders the practical application of remote sensing technology in agricultural fine-scale management.

1.1 Spatiotemporal Data Mismatch

Current remote-sensing observations mostly adopt strategies of fixed time intervals or maximum spatial coverage, which ignore the phased changes and spatial heterogeneity characteristics of crop phenology, thus resulting in a disconnection between data acquisition and actual needs. In the temporal dimension, optical remote sensing is susceptible to interference from clouds, resulting in a reduction of usable images and making it difficult to capture the critical phenotypic monitoring stage of crops in a timely manner, which affects the monitoring accuracy[10–12]. However, the limitations of observation resolution are the main source of uncertainty in phenological information extraction, making it challenging to accurately characterize the growth differences within the fields[13,14].

The inherent limitations of different observation platforms further exacerbate the spatiotemporal data mismatch. Although wide-swath, high-frequency satellites (such as MODIS and VIIRS) can achieve near-daily coverage, the problem of mixed pixels is prominent, hindering accurate identification of the phenological characteristics of specific crops within heterogeneous areas[15,16]. High-spatial-resolution satellites such as WorldView and the Gaofen series can finely delineate field-level differences; however, their long revisit cycles impede continuous monitoring of phenological transition windows. Medium-resolution data such as Sentinel-2 and Landsat 8/9 offer a favorable balance of spatiotemporal resolution; however, they remain constrained by temporal discontinuities caused by cloud cover[17,18]. UAVs, which are capable of acquiring centimeter-level resolution imagery, are limited by the spatial extent of single-flight coverage and the effective operational time window[19–21].

1.2 Semantic Representation Gap

Currently, there is a significant semantic gap between agricultural information provided by remote sensing and the indicators required for production management, making it difficult to convert data directly into a basis for production decisions. For instance, most existing studies have focused on extracting general phenological indicators, such as the start of the growing season and end of the growing season, from vegetation index time series[22,23], or on a few key transitional stages, such as the maturity stages[24]. These indicators are suitable for large-scale vegetation dynamic monitoring; however, it is difficult to meet the requirements of precise production management for specific crops and cannot directly support decision-making for detailed field operations.

Taking the fine-scale management of a litchi orchard as an example, the core premise is to accurately determine the precise phenological stages, such as the white millete appearance stage, female floral phase, and fruit expansion stage. This determines the timing and specific plans for management measures, such as fertilization, flower and fruit thinning, and pest and disease control[25]. However, owing to the limitations of the spatiotemporal resolution of the data and insufficient dimensionality of the spectral information, traditional remote sensing

methods are unable to achieve precise identification and differentiation of such fine phenological stages[26]. Even with the use of UAV platforms to obtain more accurate phenological information, reliable methods for mapping this information and actual management indicators remain underdeveloped, and differences in the definitions and estimation standards of the same agricultural indicator by different researchers have further exacerbated the semantic gap problem[11,27], greatly restricting the effectiveness of remote sensing technology in agricultural precision production.

1.3 Redundant Feature Construction

The rapid development of data storage technologies has led to the emergence of high-dimensional and large-scale remote sensing datasets; however, they contain a large amount of redundant information, making it difficult to directly serve specific monitoring tasks. In practical applications, feature construction is often guided by data accessibility, and a large number of spectral, temporal, and texture features are indiscriminately introduced, which not only increases data storage and computing costs but may also introduce noise, leading to overfitting of the model, decreased generalization ability, and reduced monitoring accuracy[28].

The requirements for remote-sensing features vary significantly among crops and monitoring tasks. The lack of a targeted feature selection mechanism further exacerbates redundancy. In the study of corn monitoring, the REIP, CRI550, CRI700, and MSBI indices performed the best, and the multi-feature combination effect was superior to that of a single index[29]; in the monitoring of wheat, fAPAR, fCover, EVI, PSRI, and NDVI are more suitable for crop growth management, while ARI2, MCARI, and NDWI are more suitable for crop type identification[30]. From the perspective of task differences, phenological period extraction may only require low-altitude, high-resolution images from UAVs, whereas precise early disease identification requires submeter-level hyperspectral data support[31,32]. Currently, agricultural remote sensing lacks monitoring-specific feature selection, causing a disconnect between features and needs, and building up ineffective ones—raising processing costs, lowering information density, and limiting data utility.

In summary, current agricultural remote sensing suffers from a "supply-demand mismatch" in critical links including data acquisition, semantic representation, and feature construction. The traditional observation mode is oriented toward data acquisition capabilities, resulting in an "data acquisition prior to practical application" model. This leads to a significant supply-demand mismatch and makes it difficult to fully leverage the core value of remote sensing data. In order to address this issue, this paper has proposed a demand-driven intelligent perception paradigm for agricultural remote sensing. Taking the end-use application requirements of agricultural production as the starting point, this paradigm leverages 4 key elements (4K: Key Space, Key Time, Key Object, Key Feature) to guide the dynamic design of observation strategies and construct an intelligent perception system that forms a closed-loop linkage with agricultural decision-making. This approach facilitates the transition of data acquisition from "passive acquisition" to application-oriented "active intelligent perception", thereby achieving full-process optimization from data acquisition to information services.

2 Demand-Driven Intelligent Perception Paradigm for Agricultural Remote Sensing

2.1 Connotation and Core Characteristics

The demand-driven intelligent perception paradigm for agricultural remote sensing refers to a novel data acquisition model that considers end-use application requirements as the starting point, and guides the dynamic design of observation strategies. Unlike the traditional "data acquisition prior to practical application" model, this paradigm emphasizes the active traction effect of demands on acquisition: First, clearly define specific monitoring targets and precision requirements, then specifically determine the optimal observation time, spatial range, observation platform, and feature combination, and finally, use the feedback of service effects to drive the continuous iterative optimization of the acquisition strategy, achieving a

full-chain linkage of "demand defines the task, task guides acquisition, acquisition supports services", breaking the traditional gap between acquisition and application (Figure 1).

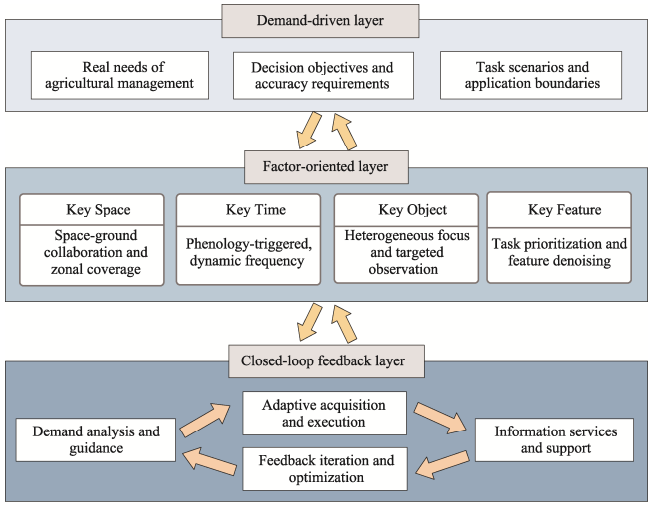


Figure 1 Demand-driven intelligent perception paradigm for agricultural remote sensing

This paradigm has 3 core features that together constitute its key advantages over traditional models. First, demand-driven. It takes the requirements of specific agricultural management decisions (such as precise phenological identification, early disease warning, and yield prediction)—rather than data availability—as the starting point of the entire perception pipeline, thereby ensuring a high degree of alignment between data acquisition and practical application. Second, element-oriented. Through fine-grained analysis of the 4K elements, it achieves precise allocation of acquisition resources, avoids ineffective data collection, and improves data-utilization efficiency. Third, closed-loop feedback. By leveraging the collaborative mechanism of "Demand-Acquisition-Service-Feedback" (DASF), the perception strategy continuously iterates and optimizes in practice, rather than being set statically once and then remaining unchanged. It can respond flexibly to the dynamic complexity and uncertainty of agricultural production.

From a broader perspective, this paradigm is highly consistent with the overall trend in the current field of Earth observation, which is shifting from "data-driven" to "intelligent services". The Asia-Oceania Group on Earth Observations (AOGEO) clearly states that Earth observation systems should provide precise, efficient services for high-quality regional development[9]. The demand-driven paradigm proposed in this study is the specific implementation path for this transformation goal in the agricultural fine-scale management scenario, providing a new concept and theoretical support for the industrial application of agricultural remote sensing technology.

2.2 Four Key Elements (4K) Analysis

The core architecture of the demand-driven paradigm consists of 4K that interact with each other to form a precise definition framework for the acquisition plan. This paper elaborates on the connotations and implementation paths of each element based on a detailed monitoring case of litchi.

2.2.1 Partition-Guided Observation Based on Key Space

Agricultural production space exhibits significant heterogeneity, with systematic differences among plots in terms of soil conditions, crop variety distribution, and field management practices[33,34]. Taking topography as an example, sunny/shady slopes shift phenology by 5–10 d, slope gradient impacts drainage and disease risk; yet traditional uniform sampling under-samples key areas and over-samples others, wasting resources and failing precision monitoring.

Regarding the aforementioned issues, the core strategy for the Key Spatial elements can be summarized as "first divide, then collect". The basis for this division should be directly linked to the agronomic attributes of the crops, such as their phenology and growth status, to ensure that the environmental conditions and growth responses within the same division are highly consistent. For litchi flowering monitoring, DEM derived aspect and slope guide intelligent orchard zoning: sunny slopes for early flowering, shady for late, and low-lying areas for waterlogging risk. Acquisition strategies vary—high frequency UAV flights focus on sunny slopes to capture the white millete and female floral stages; shady slopes get reduced frequency or delayed windows; waterlogged zones intensify disease period monitoring. Medium resolution satellites (e.g., Sentinel 2) further detect macroscopic anomalies (e.g., growth aberrations, disease patches) to refine zoning, directing UAVs to centimeter scale observations in high value areas. This balances macroscopic coverage with microscopic precision, enhancing data acquisition efficiency and targetedness[7,9].

2.2.2 Dynamic Triggering Acquisition Based on Key Time

Different stages of crop growth have varying requirements for the frequency, accuracy, and response timeliness of observations[35]. Taking the growth cycle of litchi as an example, phenological transition periods, such as the white millete appearance stage, female floral phase, and fruit expansion stage, are the most intense periods of phenotypic change and the most critical windows for implementing field management measures[25]. However, these transition periods are short and exhibit rapid changes in growth dynamics, which require extremely high observation timeliness. Traditional fixed-interval observations tend to overlook such opportunities[26]. Moreover, unexpected events such as meteorological disasters (e.g., low temperatures and drought), pest and disease outbreaks, and abnormal growth also constitute Key Time windows that require intensified observations.

Therefore, the Key Time elements abandon the fixed acquisition rhythm of "equal time intervals", and instead focus on the crop growth requirements to achieve on-demand acquisition and precise action[10,12]. For litchi, the white millete stage is a critical window for flower-spike quality, pruning, and pest control—missing it reduces yield and quality. A phenology-based Key Time strategy deploys daily acquisition during this stage, weekly during stable periods, reducing redundant data. It also integrates weather forecasts (e.g., cold waves, drought) and remote-sensing anomalies (e.g., sudden NDVI drops) to auto-trigger intensified observations. This approach precisely captures phenological transitions and sudden risks, providing timely data for field management decisions.

2.2.3 Precise Target Selection Based on Key Objects

Within the same crop category, plants of different varieties, ages, cultivation methods, and growth conditions exhibit significant differences in the selection of observation objects and requirements for the accuracy of information extraction. Traditional observations often consider the crop category (such as litchi) as a unified observation object, ignoring these fine-grained differences, which makes it difficult for the collected data to adapt to the requirements of precise management[36–38].

Therefore, the Key Object elements abandon the "one-size-fits-all" observation approach and refine the observation objects from general land cover type to specific varieties, tree ages, growth conditions, etc., ensuring that the collected data closely match the management requirements. In the monitoring of litchi, the acquisition objects need to be precisely selected based on specific management goals. When estimating yield, priority should be given to mature trees with strong fruit-bearing capacity as the core acquisition objects, and the number and size information of fruits in the fruit-bearing canopy should be focused on when monitoring diseases. Plants with weak growth, low resistance, and dense planting areas should be given priority attention. Early disease spots and abnormal leaf conditions should be accurately captured when evaluating growth. Different varieties, tree ages, and growth vigor of plants should be taken into account, and the nutritional status data of the canopy should be comprehensively collected. In addition, the Key Object strategy can be adjusted based on the spatiotemporal dynamics. For example, in flower identification, different varieties' flower spike morphological differences should be modeled separately,

and in fruit maturity monitoring, priority acquisition should be set for early- and late-maturing varieties in different zones. This precise target selection based on Key Object can enhance the degree of matching between data and management requirements, providing precise targeted data support for fine-scale management.

2.2.4 Optimal Parameter Configuration Based on the Key Features

Feature selection is a core part of remote sensing data applications and a key step in improving the monitoring accuracy of the model. High-quality feature extraction relies on the support of advanced models. These models achieve precise conversion of remote sensing data into agricultural indicators by learning Key Features. Without targeting, stacking many remote-sensing parameters dilutes key information, hindering model focus on core phenological drivers, thus reducing sensitivity to critical stages and boundary resolution.

To address these aforementioned issues, the Key Feature elements require configuring optimal parameters based on task requirements, avoiding redundant stacking of ineffective features[28,30]. Taking litchi monitoring as an example, the selection of satellite observation features focused on the correlation between macrotemporal sequences and spectral responses. In the early disease identification task, the red-edge-related bands were found to be more sensitive to abnormalities in leaf chlorophyll, and hyperspectral imaging data were helpful for capturing spectral changes in the early stage of the disease[29]. The UAV observation platform can obtain ultrahigh spatial resolution images, and its feature extraction strategy focuses on the precise identification and analysis of the microscopic details of the plants. For example, the monitoring of winter shoots length requires an extremely high spatial resolution, reaching 0.01 cm/pixel[39]; while the fine classification of fruit maturity, obtaining a spatial resolution of 0.19–0.25 cm/pixel at a flight height of 6 m can meet the requirements[40]. In contrast, the extraction of tree crown structure parameters (such as perimeter and projection coverage) only requires a centimeter-level spatial resolution (such as 4.1 cm/pixel corresponding to a height of 30 m), and different resolutions have consistency in the measurement results of parameters such as tree crown width[41]. This indicates that for different monitoring tasks, the optimal spatial resolution must be configured according to the target feature scale to avoid the blind pursuit of an excessively high resolution that leads to data redundancy. This method of optimal parameter selection based on Key Features can ensure the precise matching of remote sensing features with actual business needs and achieve the efficient conversion of remote sensing data into management decision information.

2.3 Closed-Loop Collaborative Mechanism Based on Service Feedback

These 4K elements establish a strategic framework for a single acquisition task; however, the static design of the 4K framework alone is insufficient to cope with the dynamic complexity of agricultural production. The other core mechanism of the demand-driven paradigm lies in constructing a closed-loop collaborative DASF mechanism to achieve adaptive iterative optimization of the perception strategy and ensure that the paradigm can dynamically adapt to the changing demands of agricultural production. This closed-loop consists of 4 stages: First, the demand analysis stage, which converts users' agricultural management goals (such as phenological period monitoring, yield estimation) into operational 4K acquisition parameters, clarifying the observation time, space, objects, and features, and forming an initial acquisition plan; Second, the acquisition execution stage, which obtains satellite data as needed based on the parameters and plans the UAV flight route; Third, the service output stage, which preprocesses, extracts features, and makes model inferences on the collected raw data, generating phenological information products (such as monitoring reports, prediction results) for the decision-making; Fourth, the feedback optimization stage, which collects on-site verification results and user evaluations, assesses the deviation of the current acquisition strategy (such as phenological period prediction deviation, unreasonable feature selection, etc.), and accordingly adjusts the 4K parameter configuration for the next round to achieve iterative optimization of the acquisition strategy.

The key to this closed-loop mechanism lies in adaptive iteration. Each observation and

feedback regarding services is a correction to the acquisition strategy, enabling each observation to be closer to the actual demand than the previous observation. In the litchi monitoring scenario, if the prediction of the first white millete appearance stage is too early, the feedback mechanism can automatically adjust the phenological prediction parameters; in the next growing season, the start time of high-frequency acquisition can be corrected; and if the estimation error of the yield in a specific variety area is too large, a special feature selection and model re-training for that variety can be triggered. This "Acquisition-Learning-Re-acquisition" adaptive cycle enables the system to gradually improve the perception accuracy over time, forming a positive cycle of "demand-driven acquisition, acquisition supporting services, and services optimize acquisition", continuously enhancing the practicality and adaptability of the paradigm.

3 Discussion and Conclusion

To resolve the profound contradiction between the "explosion of data volume and the inefficiency of decision support" in the era of agricultural remote sensing big data, this paper has systematically proposed and elucidated a demand-driven intelligent perception paradigm for agricultural remote sensing. With the core objective of addressing the "supply-demand mismatch" problem in traditional agricultural remote sensing, and through an in-depth case analysis of precision monitoring across the full phenological lifecycle of litchi, this paradigm achieves source-level control over the 4 core elements of "Space, Time, Object, and Feature". This alleviates the problems of spatiotemporal data mismatch, semantic discontinuity, and feature redundancy inherent in traditional coarse-grained acquisition, thereby enhancing the utilization efficiency and value realization capability of remote sensing data.

The proposed paradigm successfully breaks the traditional linear observation model of "data acquisition prior to practical application" and establishes a self-adaptive closed-loop collaborative mechanism of DASF. It realizes a fundamental shift in agricultural remote sensing from "passive acquisition" to "active sensing", providing a novel theoretical framework and implementation pathway for the transition of agricultural remote sensing from data supply to intelligent services. With the deep integration of a low-altitude economy, edge intelligence, and large language models, the demand-driven paradigm will progressively mature and become a core engine for future smart agricultural infrastructure. This will help establish a space-air-ground integrated intelligent sensing network and provide solid technical support for precise agricultural management, food security, and the green and high-quality development of agriculture.

However, several practical challenges remain during its deployment, primarily in 3 aspects: demand interpretation, multiplatform coordination, and service-oriented transformation.

3.1 Challenges

3.1.1 Insufficient Precision in Acquiring Demand Interpretations

The primary prerequisite of the demand-driven paradigm is to accurately comprehend and formalize the agricultural management demands of users and subsequently translate them into actionable 4K acquisition parameters. Nevertheless, in practice, user-expressed demands are often vague and domain-oriented. For example, farmers may ask, "Should I spray pesticides on litchi trees now?" rather than issuing a specific instruction such as "Monitor canopy spectral anomalies to identify early pest-induced stress". There is a lack of clear one-to-one correspondence between the precise phenological stages and yield targets on which production managers focus and the spectral features and structural parameters observable by remote sensing, creating a cross-layer gap between the "demand description" and "technical parameters".

Currently, cross-layer mapping relies heavily on manual intervention by domain experts and lacks automated and standardized parsing tools and methodologies. Experts must leverage their experience to convert vague user demands into concrete acquisition

parameters. This process is not only inefficient but also prone to subjective variances among different experts, making it difficult to guarantee the consistency and precision of demand parsing while simultaneously restricting the large-scale promotion of this paradigm. Therefore, constructing a reliable "demand-parameter" mapping mechanism to achieve automated parsing and quantitative transformation of vague demands stands as the primary challenge to the engineering implementation of this paradigm, as well as a critical breakthrough for improving its practicality.

3.1.2 High Complexity of Coordinating Multi-Source Collaborative Acquisition

The demand-driven paradigm requires multiple platforms, such as satellites, UAVs, and ground-based sensors, to coordinate and operate collaboratively in real-time based on dynamic demands. However, significant differences among these platforms in terms of communication protocols, task formats, and operational entities have led to high technical barriers to multi-source collaborative scheduling. Particularly, during critical phenological transition periods of crops, rapid responses and simultaneous acquisition by multiple platforms are required. Under such scenarios, real-time task coordination among platforms is prone to conflicts and delays, affecting the timeliness of data acquisition, and thereby constraining the quality of monitoring services.

Although international cooperative frameworks such as AOGEO have promoted institutional development for data sharing and collaborative observation, real-time scheduling protocols and interface standards across different agencies and platforms remain immature, and a unified collaborative scheduling architecture is still lacking, limiting the large-scale realization of multi-source collaborative sensing capabilities[42]. At the national level, the rapid expansion of commercial remote sensing satellite constellations while increasing data acquisition density also imposes higher management requirements for multi-source data fusion and collaborative scheduling. Consequently, breaking through the technical and institutional barriers of multiplatform collaborative scheduling to achieve efficient integration and dynamic allocation of multi-source observation resources serves as a vital pillar for the implementation of this paradigm.

3.1.3 Technical and Application Barriers to Service-Oriented Transformation

The demand-driven paradigm aims to transition from "data supply" to "intelligent services", enabling users to obtain high-level semantic information and decision support without having to process raw remote sensing data. However, this service-oriented transformation faces several challenges. At the technical level, the chain from high-precision data products to agricultural management decisions is long and involves multiple links such as data processing, model inversion, product generation, and user interface design. Currently, certain links suffer from inadequate automation and the coordination between them is inefficient, making it difficult for data processing and product generation to meet the demands of large-scale, rapid responses. At the user level, most agricultural producers lack professional backgrounds in remote sensing and geographic information systems, and their information technology foundations are relatively weak. This makes it difficult for them to interpret complex data products and translate them into field management actions, creating a "last-mile" barrier to service deployment and thereby constraining the extension of the demand-driven paradigm from research to practice. Moreover, a commercial model for agricultural remote-sensing services still remains unclear. The costs of acquiring and processing high-resolution remote-sensing data are high, whereas the overall profit margin in agriculture is relatively low, and farmers have limited willingness and ability to pay[9]. Striking a balance between technical advancement, economic feasibility, and user acceptance to construct a sustainable commercial closed-loop is a realistic challenge that must be addressed for the large-scale application of this paradigm.

3.2 Future Directions

To address the three major challenges associated with the implementation of the current demand-driven paradigm, and considering the development trends of cutting-edge technologies such as the low-altitude economy, edge intelligence, large language models,

and knowledge graphs, the paradigm will continue to evolve toward "intelligent, collaborative, and service-oriented" systems. Future efforts will focus on the following 3 directions to propel engineering implementation and large-scale application of the paradigm, thereby further unlocking the value of agricultural remote sensing data.

3.2.1 Knowledge Graph-Driven Automatic Demand Interpretation

In order to address the challenge of insufficient precision in demand parsing, a viable technical pathway is to construct an agricultural remote sensing knowledge graph that explicitly structures the mapping relationships between crop phenology, monitoring task types, and acquisition parameter configurations. Such knowledge graphs can integrate multi-source information, including crop physiological characteristics, historical monitoring data, and domain expert experience, thereby transforming expert knowledge into machine-readable inference rules. This enables automated inference from natural language demand descriptions to 4K parameters, substantially reducing the reliance on manual intervention[43]. For instance, when a user submits a request for "litchi flowering stage early warning", the knowledge graph can automatically parse out the trigger conditions (historical phenological windows), key spatial boundaries (coordinates of core producing areas), recommended observation frequency (daily during critical periods), and optimal characteristic spectral bands (red edge and near-infrared). It then outputs a standardized acquisition task order without requiring the user to possess specialized knowledge. Furthermore, the integration of large language models with domain-specific knowledge graphs is expected to enable nonexpert users to rapidly generate complex acquisition demands through natural language interactions. This democratizes agricultural remote-sensing knowledge and significantly lowers barriers to adopting this paradigm.

3.2.2 Cloud-Edge-End Collaborative Intelligent Acquisition System

Leveraging the powerful computing capacity of the cloud and the real-time inference capabilities of the edge, constructing an integrated scheduling system characterized by "cloud planning, edge inferring, and terminal executing" represents a critical pathway to overcoming multi-source coordination challenges. Within this architecture, cloud platforms are responsible for integrating multi-source information, such as satellite orbit predictions, weather forecasts, and phenological models, to perform global planning of cross-platform resource scheduling and optimize the collaborative workflow between satellites and UAVs. The edge (onboard UAVs or ground stations) is responsible for receiving real-time scheduling commands from the cloud and dynamically adjusting tasks based on local environmental perceptions (e.g., real-time weather and terrain changes), ensuring the flexibility and timeliness of acquisition tasks. Terminal sensors execute specific acquisition actions and upload raw data in real-time[5,6]. This Cloud-Edge-End collaboration can markedly improve the scheduling response speed, support large-scale, multiplatform collaborative operations, and enable rapid replanning under dynamically changing external conditions. Driven by the advancement of low-altitude economic policies and the maturation of UAV swarm technologies, multi-UAV coordination and autonomous task allocation are poised to achieve breakthroughs in large-scale monitoring scenarios, paving the way for the scalable application of intelligent agricultural remote-sensing acquisition, while further enhancing the efficiency and precision of multi-source collaborative acquisition.

3.2.3 Implementation and Promotion of the OaaS Model

Translating technological breakthroughs into industrial deployment requires innovations in service models. OaaS encapsulates the demand-driven sensing paradigm into standardized, accessible, and invocable service interfaces, serving as the core pathway to drive service-oriented transformation. Under the OaaS model, users are only required to submit their monitoring objectives and geographic boundaries. The system then automatically completes the entire workflow, including 4K parameter interpretation, multiplatform acquisition planning, data processing, model inference, and result delivery. This model eliminates the need for users to possess a professional background in remote sensing, truly achieving the shift of agricultural remote sensing from "data supply" to "intelligent service" and breaking down the "last-mile" barrier to service deployment. In the future, integrating

OaaS with multi-source information services, such as meteorological forecasts and agricultural product prices, will further amplify its comprehensive value for agricultural decision support. This will form a complete service chain of "sensing-analysis-decision-execution", promoting the widespread adoption of the paradigm across various agricultural scenarios and providing core support for the development of smart agriculture.

Author Contributions

Zhang, Q. N., Wang, Y. Y., and Deng, L. Q. conducted the literature review, summarized relevant research progress, and drafted the initial manuscript. Fu, H. completed the data acquisition and processing work. Shi, Q. and Liu, M. X. contributed to the overall conceptual design, structural optimization, and critical revision and polishing of the paper.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] de Mauro, A., Greco, M., Grimaldi, M. A formal definition of big data based on its essential features [J]. *Library Review*, 2016, 65(3): 122–135.

[2] Wolfert, S., Ge, L., Verdouw, C., *et al*. Big data in smart farming—a review [J]. *Agricultural Systems*, 2017, 153: 69–80.

[3] Chen, M., Mao, S., Liu, Y. Big data: a survey [J]. *Mobile Networks and Applications*, 2014, 19(2): 171–209.

[4] Rosenqvist, Å., Milne, A., Lucas, R., *et al*. A review of remote sensing technology in support of the Kyoto Protocol [J]. *Environmental Science & Policy*, 2003, 6(5): 441–455.

[5] Liu, P. A survey of remote-sensing big data [J]. *Frontiers in Environmental Science*, 2015, 3.

[6] Chi, M., Plaza, A., Benediktsson, J. A., *et al*. Big data for remote sensing: challenges and opportunities [J]. *Proceedings of the IEEE*, 2016, 104(11): 2207–2219.

[7] Huang, Y., Thomson, S. J., Hoffmann, W. C., *et al*. Development and prospect of unmanned aerial vehicle technologies for agricultural production management [J]. *International Journal of Agricultural and Biological Engineering*, 2013, 6(3): 1–10.

[8] Sebastian, C., Fabio, R., Michaela, D. G., *et al*. Evaluating multispectral images and vegetation indices for precision farming applications from UAV images [J]. *Remote Sensing*, 2015, 7(4): 4026–4047.

[9] Wu, J. J., Li, M., Liang, L., *et al*. Progress of high-resolution Earth observation systems [J]. *Journal of Global Change Data & Discovery*, 2024, 8(4): 347–355. https://doi.org/10.3974/geodp.2024.04.02.

[10] Walker, J. J., de Beurs, K. M., Wynne, R. H. Dryland vegetation phenology across an elevation gradient in Arizona, USA, investigated with fused MODIS and Landsat data [J]. *Remote Sensing of Environment*, 2014, 144: 85–97.

[11] Zheng, Y., Wu, B., Zhang, M., *et al*. Crop phenology detection using high spatio-temporal resolution data fused from SPOT5 and MODIS products [J]. *Sensors*, 2016, 16(12): 2099.

[12] Gao, F., Anderson, M. C., Zhang, X., *et al*. Toward mapping crop progress at field scales through fusion of Landsat and MODIS imagery [J]. *Remote Sensing of Environment*, 2017, 188: 9–25.

[13] Zhang, X., Friedl, M. A., Schaaf, C. B. Sensitivity of vegetation phenology detection to the temporal resolution of satellite data [J]. *International Journal of Remote Sensing*, 2009, 30(8): 2061–2074.

[14] Guan, K., Medvigy, D., Wood, E. F., *et al*. Deriving vegetation phenological time and trajectory information over Africa using SEVIRI daily LAI [J]. *IEEE Transactions on Geoscience and Remote Sensing*, 2014, 52(2): 1113–1130.

[15] Zhang, X., Wang, J., Gao, F., *et al*. Exploration of scaling effects on coarse resolution land surface phenology [J]. *Remote Sensing of Environment*, 2017, 190: 318–330.

[16] Vrieling, A., Skidmore, A. K., Wang, T., *et al*. Spatially detailed retrievals of spring phenology from single-season high-resolution image time series [J]. *International Journal of Applied Earth Observation and Geoinformation*, 2017, 59: 19–30.

[17] Zhu, Z., Wang, S., Woodcock, C. E. Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images [J]. *Remote Sensing of Environment*, 2015, 159: 269–277.

[18] Novelli, A., Aguilar, M. A., Nemmaoui, A., *et al*. Performance evaluation of object based greenhouse detection from Sentinel-2 MSI and Landsat 8 OLI data: a case study from Almería (Spain) [J]. *International Journal of Applied Earth Observation and Geoinformation*, 2016, 52: 403–411.

[19] Hassanalian, M., Abdelkefi, A. Design, manufacturing, and flight testing of a fixed wing micro air vehicle

with Zimmerman planform [J]. *Meccanica*, 2017, 52(6): 1265–1282.
[20] Nhamo, L., van Dijk, R., Magidi, J., *et al*. Improving the accuracy of remotely sensed irrigated areas using post-classification enhancement through UAV capability [J]. *Remote Sensing*, 2018, 10(5): 712.
[21] Agrawal, J., Arafat, M. Y. Transforming farming: a review of AI-powered UAV technologies in precision agriculture [J]. *Drones*, 2024, 8(11): 664.
[22] Reed, B. C., Brown, J. F., VanderZee, D., *et al*. Measuring phenological variability from satellite imagery [J]. *Journal of Vegetation Science*, 1994, 5(5): 703–714.
[23] de Beurs, K. M., Henebry, G. M. Spatio-Temporal Statistical Methods for Modelling Land Surface Phenology [M]. Dordrecht: Springer Netherlands, 2010: 177–208.
[24] Zhang, X., Friedl, M. A., Schaaf, C. B., *et al*. Monitoring vegetation phenology using MODIS [J]. *Remote Sensing of Environment*, 2003, 84(3): 471–475.
[25] Wei, Y. Z., Zhang, H. N., Li, W. C., *et al*. Phenological growth stages of lychee (*Litchi chinensis* Sonn.) using the extended BBCH-scale [J]. *Scientia Horticulturae*, 2013, 161: 273–277.
[26] Zeng, L., Wardlow, B. D., Xiang, D., *et al*. A review of vegetation phenological metrics extraction using time-series, multispectral satellite data [J]. *Remote Sensing of Environment*, 2020, 237: 111511.
[27] Lu, L., Wang, C., Guo, H., *et al*. Detecting winter wheat phenology with SPOT-VEGETATION data in the North China Plain [J]. *Geocarto International*, 2014, 29(3): 244–255.
[28] Liu, G., Jiang, X. G., Tang, B. H. Application of feature optimization and convolutional neural network in crop classification [J]. *Journal of Geo-Information Science*, 2021, 23(6): 1071–1081.
[29] Sonobe, R., Yamaya, Y., Tani, H., *et al*. Crop classification from Sentinel-2-derived vegetation indices using ensemble learning [J]. *Journal of Applied Remote Sensing*, 2018, 12: 1.
[30] Vidican, R., Mălinaș, A., Ranta, O., *et al*. Using remote sensing vegetation indices for the discrimination and monitoring of agricultural crops: a critical review [J]. *Agronomy*, 2023, 13(12): 3040.
[31] Kuswidiyanto, L. W., Noh, H., Han, X. Plant disease diagnosis using deep learning based on aerial hyperspectral images: a review [J]. *Remote Sensing*, 2022, 14(23): 6031.
[32] Moghadam, P., Ward, D., Goan, E., *et al*. Plant disease detection using hyperspectral imaging: international conference on digital image computing: techniques and applications (DICTA) [C]. Sydney, 2017.
[33] Araya, S., Ostendorf, B., Lyle, G., *et al*. Remote sensing derived phenological metrics to assess the spatio-temporal crop yield variability [J]. *Advances in Remote Sensing*, 2017, 6: 212–228.
[34] Kousar, R., Lone, A. H., Shah, Z. A., *et al*. Farm-scale soil spatial variability at a mountain research centre in Northwestern Himalayas [J]. *Scientific Reports*, 2025, 15(1): 19705.
[35] Potgieter, A. B., Zhao, Y., Zarco-Tejada, P. J., *et al*. Evolution and application of digital technologies to predict crop type and crop phenology in agriculture [J]. *in silico Plants*, 2021.
[36] Zhu, Y., Yang, G., Yang, H., *et al*. Identification of apple orchard planting year based on spatiotemporally fused satellite images and clustering analysis of foliage phenophase [J]. *Remote Sensing*, 2020, 12(7): 1199.
[37] Mahlayeye, M., Darvishzadeh, R., Nelson, A. Cropping patterns of annual crops: a remote sensing review [J]. *Remote Sensing*, 2022, 14(10): 2404.
[38] Ozdarici-Ok, A., Ok, A. O. Using remote sensing to identify individual tree species in orchards: a review [J]. *Scientia Horticulturae*, 2023, 321: 112333.
[39] Liang, C., Liu, D., Ge, W., *et al*. Detection of litchi fruit maturity states based on unmanned aerial vehicle remote sensing and improved YOLOv8 model [J]. *Frontiers in Plant Science*, 2025, 16.
[40] Shen, Z., Liu, B., Xu, R., *et al*. Evaluation of lychee winter shoot length using UAV remote sensing technology [J]. *International Journal of Agricultural and Biological Engineering*, 2025, 18(6): 241–249.
[41] Johansen, K., Raharjo, T., McCabe, M. Using multi-spectral UAV imagery to extract tree crop structural properties and assess pruning effects [J]. *Remote Sensing*, 2018, 10: 854.
[42] Wu, J. J., Huang, Z. R., Liu, J. L., *et al*. Progress of the Asia-Oceania Group on Earth Observations (AOGEO) Programme [J]. *Journal of Global Change Data & Discovery*, 2024, 8(4): 366–375. https://doi.org/10.3974/geodp.2024.04.04.
[43] Qin, Q. M. AlphaEarth Foundations: the potential and challenges of remote sensing foundation models [J]. *Journal of Geo-Information Science*, 2025, 27(10): 2283–2290.