

Application Scenarios and Research Progress of Remote Sensing Technology in Crop Income Insurance: Postprint

Authors: Chen Ailian, Zhao Sijian, Zhu Yuxia, Sun Wei, Jing Zhang, Zhang Qiao

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Abstract

Crop revenue insurance has become an important form of agricultural insurance in China, and will be implemented in all major producing counties across 13 major grain-producing provinces in 2022. This paper first reviews the overall application history of remote sensing technology in agricultural insurance. Secondly, by elaborating on the business model of existing crop revenue insurance, it presents the current application scenarios of remote sensing technology within this model, and reviews the research progress on key technologies in various application scenarios, including farmland parcel extraction, crop classification, crop disaster assessment, and crop yield estimation. Finally, it enumerates the commonly used remote sensing data sources for crop revenue insurance. Through this review, two most important technical-level issues in the application scenarios of crop revenue insurance are identified: first, parcel extraction and crop classification are not sufficiently automated; second, yield estimation lacks strong mechanistic basis and has low accuracy. This further leads to two industry-level issues: first, the inherent limitations of the remote sensing industry itself; second, compatibility issues between the current insurance industry practices and remote sensing technology integration. To address these, this paper proposes five specific recommendations: establishing a data distribution platform to solve problems of data acquisition, processing difficulties, and initial data standardization; improving farmland parcel and crop type sample databases to promote automation of parcel extraction and crop classification; conducting interdisciplinary research to achieve faster, more accurate, and more scientific yield estimation; standardizing the application of remote sensing technology in agricultural insurance; and contractualizing the application of remote sensing technology. Looking forward, the application model of remote sensing technology in crop revenue insurance and even all agricultural insurance should

be a new model with available data, more automated and intelligent technology, enforceable standards, and contractual backing.

Full Text

Application Scenarios and Research Progress of Remote Sensing Technology in Plant Income Insurance

CHEN Ailian^{1,2}, ZHAO Sijian^{1,2*}, ZHU Yuxia^{1,2}, SUN Wei^{1,2}, ZHANG Jing^{1,2}, ZHANG Qiao^{1,2}

¹Agricultural Information Institute, Chinese Academy of Agricultural Sciences, Beijing 100081, China

²Key Laboratory of Agricultural Information Service Technology, Ministry of Agriculture and Rural Affairs, Beijing 100081, China

Abstract: Plant income insurance has become an important form of agricultural insurance in China. Since 2016, the Chinese government has recommended pilot programs in several counties, and by 2022, implementation is required in all major grain-producing counties across 13 major grain-producing provinces. The measurement of yield for plant income insurance at such scale urgently requires support from remote sensing technology. This paper first reviews the overall application history of remote sensing technology in agricultural insurance. Second, by elaborating on the existing business model of plant income insurance, it demonstrates current application scenarios for remote sensing technology within this model and reviews research progress on key technologies under various scenarios, including cultivated plot extraction, crop classification, crop disaster assessment, and crop yield estimation. Finally, commonly used remote sensing data sources for plant income insurance are enumerated. Through this review, two critical technical problems are identified in the application scenario of plant income insurance: first, plot extraction and crop classification are insufficiently automated; second, yield estimation lacks mechanistic rigor and sufficient accuracy. These technical issues extend to two industry-level problems: the inherent limitations of the remote sensing industry itself, and compatibility issues between current insurance industry practices and remote sensing technology integration. Accordingly, this paper proposes five specific recommendations: establishing a data distribution platform to address difficulties in data acquisition, processing, and initial data standardization; improving cultivated plot and crop type sample databases to promote automation in plot extraction and crop classification; conducting interdisciplinary research to achieve faster, more accurate, and more scientific yield estimation; standardizing remote sensing technology applications in agricultural insurance; and contractualizing remote sensing technology applications. Looking forward, the application model of remote sensing technology in plant income insurance—and indeed all agricultural insurance—should be a new model with readily available data, more automated and intelligent technology, standards to follow, and contractual backing.

Keywords: remote sensing; agricultural insurance; plant income insurance; precise claim settlement; yield estimation; cultivated land extraction; disaster assessment; remote sensing data sources

1 Introduction

Agriculture is a vulnerable industry facing dual risks: production risk from natural disasters and market risk from price fluctuations. As an effective tool for agricultural risk management, agricultural insurance plays a crucial role in avoiding agricultural risks, ensuring stable farmer income, and maintaining rural social stability. Since the implementation of policy-supported agricultural insurance in 2007, China's agricultural insurance has developed rapidly. In 2020, agricultural insurance premiums reached 81.5 billion RMB [?], ranking first in the world for the first time, and continued to grow to 96.5 billion RMB in 2021 [?].

However, China's current policy-supported agricultural insurance is predominantly physical cost insurance, which primarily compensates for yield losses caused by natural disasters at the level of physical input costs. With economic globalization, the correlation of agricultural product prices across countries has increased, and the impact of agricultural market risk has become increasingly prominent. Frequent price fluctuations have seriously affected the stability of agricultural income. Traditional physical cost insurance, also known as yield insurance, can no longer meet the risk protection needs of agricultural producers. International experience shows that agricultural income insurance is an important means of protecting farmers against production and market risks and has become a key agricultural insurance product promoted in developed countries such as the United States, Canada, and Japan [?]. Compared with insurance products that cover only price or only yield, agricultural income insurance compensates producers for income losses caused by dual risks of yield or price. It offers more comprehensive risk protection, lower underwriting risk, stronger risk diversification capacity, and lower entry barriers, making it an inevitable choice for high-quality development of agricultural insurance in China.

Since 2016, China has emphasized the implementation and promotion of agricultural income insurance, particularly plant income insurance. The central government's No. 1 Document has mentioned exploring pilot programs for plant income insurance every year since 2016. Under policy guidance, multiple provinces and cities in China have actively carried out plant income insurance pilots, mostly in the form of area-based income insurance. In June 2021, the Ministry of Finance, Ministry of Agriculture and Rural Affairs, and China Banking and Insurance Regulatory Commission jointly issued the "Notice on Expanding the Implementation Scope of Full Cost Insurance and Plant Income Insurance for Three Major Grain Crops" (Caijin [2021] No. 49) [?], which expanded the 2021 plant income insurance pilot from 4 major grain-producing counties in

each of 6 major grain-producing provinces in 2020 to 500 major grain-producing counties across all 13 major grain-producing provinces, accounting for 60% of major grain-producing counties. The 2022 central government No. 1 Document further clarified the need to “achieve full coverage of full cost insurance and plant income insurance for three major grain crops in major grain-producing counties of major grain-producing provinces,” and added new requirements to “explore full cost insurance and plant income insurance for sugarcane.” Thus, for plant insurance, income insurance has become an important product encouraged by national policy for the current and future periods.

During the pilot and large-scale development of plant income insurance, insurance stakeholders have continuously encountered new challenges in real-time and accurate yield acquisition, claim area delineation, and basis risk identification during claims settlement. Among these, real-time and accurate yield acquisition is the most prominent challenge. Remote sensing (RS) technology has been applied in agriculture for over 50 years, covering agricultural resource surveys, monitoring of the four agricultural conditions (area, growth, disaster, and yield), and agricultural environmental protection [?]. With its advantages of wide coverage, objective recording, and short revisit cycles, remote sensing technology has been introduced into income insurance pilot projects, accumulating certain experience. However, with the rapid development of the insurance industry and government policy guidance, remote sensing technology applications in agricultural insurance face new opportunities and significant challenges. These challenges include: (1) the short history of remote sensing technology application in China’s agricultural insurance and insufficient experience accumulation; (2) varying service demands for remote sensing technology across different insurance products without unified models or standards; (3) uncertainty in recognition of remote sensing technology by agricultural insurance parties (government providing premium subsidies, insurance companies as insurers, and farmers as insured) since its introduction is not mandatory by government or regulators and lacks explicit contract terms; (4) immature integration between remote sensing technology and agricultural insurance, especially loss compensation insurance (as opposed to index insurance); and (5) inherent limitations of remote sensing technology itself [?, ?].

Therefore, this paper first reviews the development history of remote sensing technology in agricultural insurance, elaborates on existing problems in yield acquisition for plant income insurance, and focuses on the plant income insurance product. By presenting the business process of plant income insurance and intervention scenarios for remote sensing technology, it reviews key technologies related to the business, and finally discusses the current application status and future prospects of remote sensing technology in plant income insurance, aiming to promote in-depth application of remote sensing technology and high-quality development of agricultural insurance in China.

2 Development History of Remote Sensing Technology in Agricultural Insurance

2.1 International Development History

Cases of remote sensing technology applied to agricultural insurance can be traced back to 1975. In 1980, Towery et al. [?, ?] used aerial infrared imagery to qualitatively assess the impact of hail and other disasters on crop yield, determining damaged area and location. According to De Leeuw et al.'s [?] review of the potential and actual adoption of remote sensing in insurance, during the 40 years before 2014, remote sensing applications in loss compensation insurance were very limited, almost exclusively restricted to several studies conducted by the U.S. government. De Leeuw et al. [?] also found that remote sensing technology combined better with index insurance, with a much higher maturity level than its combination with loss compensation insurance, mainly used for forage or livestock index insurance. Subsequently, in 2019, Vroege et al. [?] reviewed remote sensing applications in forage index insurance, noting the high potential of remote sensing imagery for different types of agricultural insurance, with high-resolution imagery for loss compensation insurance, medium-resolution imagery for area yield insurance, and low-resolution meteorological parameter-related imagery for weather index insurance.

Around 2014, agricultural insurance in developing countries, especially China, began rapid development. Due to the late start of agricultural insurance in developing countries and severe information asymmetry between insurance parties, remote sensing technology began to be applied in non-index insurance in many countries, such as rice yield estimation in India [?], wheat drought risk assessment in China [?], and rice loss assessment in Indonesia [?]. These studies explored remote sensing technology to assist insurance loss assessment or yield estimation, requiring transformation of remote sensing information into yield loss-related information.

2.2 Development History in China

China is an emerging market for agricultural insurance. Since the Chinese government began providing premium subsidies in 2007, agricultural insurance has entered a stage of rapid development [?], and research on remote sensing applications in agricultural insurance also began during this period. In 2013, the People's Insurance Company (Group) of China Limited (PICC) jointly launched the "National Development and Reform Commission Satellite and Application Industry Development Special Project—Remote Sensing Technology-Based Agricultural Insurance Precision Underwriting and Rapid Claim Settlement Comprehensive Service Platform and Application Demonstration" with Beijing Normal University and other institutions [?], marking a milestone in the integration of agricultural insurance and remote sensing technology. In 2014, Guo and He [?] analyzed the "underwriting by map, claim settlement by map" application model of remote sensing technology in agricultural insurance, detailing the technical

process of underwriting and claim settlement supported by remote sensing.

Since the introduction of remote sensing technology, Chinese researchers have not only learned from foreign experience [?] but also actively explored product design based on remote sensing technology, full-process auxiliary technology applications, and business scheme designs based primarily on remote sensing technology supplemented by Geographic Information System (GIS) and Global Positioning System (GPS) technology, tailored to China's national conditions. Product design is mainly reflected in index insurance, such as Li et al. [?] designing a livestock drought index insurance product based on remote sensing vegetation indices for Nagqu, Tibet. Full-process auxiliary applications based on remote sensing technology involve post-underwriting inspection and yield estimation during claim settlement. Meng et al. [?] conducted a systematic case study applying remote sensing technology to planting insurance underwriting and claim settlement in Kulun Banner, Inner Mongolia, including crop classification, planting area extraction, drought grade assessment, crop growth monitoring, and yield assessment. Specialized case studies have also introduced remote sensing technology into plant income insurance, such as Chen et al. [?] studying soybean remote sensing yield estimation and its application process in regional income insurance based on Sentinel-2 satellite data, and Zhu et al. [?] conducting detailed exploration in Shanxi potato regional income insurance.

Since China's agricultural insurance entered rapid development, various groups including insurance companies [?], research institutes [?], regulatory departments [?], and technology companies [?, ?] have independently or jointly studied the extensive application of remote sensing-centered 3S technology in agricultural insurance. Applications cover both grain crops and economic crops, forestry, and forage insurance; from product perspectives, both loss compensation insurance and index insurance; and data sources include meteorological satellites, medium-low resolution multispectral satellites, radar satellites, medium-high resolution satellites, high-resolution satellites, and UAV aerial data. Meteorological satellite data can be used for disaster assessment, such as NOAA satellite rainfall products for drought assessment [?] and GPM precipitation radar satellite data for yield assessment [?]. Medium-low resolution data can be used for growth assessment, such as Moderate-resolution Imaging Spectroradiometer (MODIS) products [?], and also for yield estimation [?]. Medium-high resolution satellite data can be used for cultivated plot delineation, such as Sentinel-2 [?, ?], crop classification, such as environmental satellites [?], and growth assessment and yield estimation [?]. Ultra-high resolution satellite and UAV data are mostly used for plot extraction, crop classification, and yield estimation [?].

Since plant income insurance generally covers individual farmers or townships, it requires accurate crop classification, area estimation, and yield prediction at district, township, village, and even plot levels, demanding higher resolution. The data used are primarily medium-high and high-resolution satellite data and UAV data [?, ?]. Although the overall technical framework for remote sensing

in agricultural insurance has formed a standard— “Remote Sensing Technology-Based Agricultural Insurance Precision Underwriting and Rapid Claim Settlement Specification” (JR/T 0180-2019)—which stipulates work preparation, remote sensing data acquisition, preprocessing and interpretation methods, overall processes, product content, and accuracy requirements for precision underwriting and rapid claim settlement, the specification is relatively general. It does not address specific remote sensing technologies for different insurance types, data sources, or insurance stages. As De Leeuw et al. [?] noted, remote sensing applications in agricultural loss claims remain concentrated on technical exploration with limited research on insurance business integration. While remote sensing technology can currently meet underwriting and inspection requirements for “precision underwriting,” its application in precision claim settlement faces challenges due to the complexity of crop growth and yield formation mechanisms and influencing factors. Claims settlement remains “one place, one technique, one case” [?], without forming technical standards or application model norms.

2.3 Problems in Crop Yield Acquisition

Plant income insurance requires actual yield and price data at harvest to support claim settlement. While actual price data can reference pricing bureau data, actual yield data sources present a significant challenge. China’s statistical departments typically release yield data with a lag of six months to one year, making it unavailable for timely claim settlement. Therefore, yield estimation methods, specifically manual yield measurement, are currently widely used. Since agricultural production in China remains dominated by smallholder farmers, obtaining individual yields for individual income insurance is extremely costly and difficult to implement. Current plant income insurance mostly operates as area-based income insurance, with claims settled based on regional yield measurements.

Existing manual yield measurement for regional yield acquisition suffers from five deficiencies: high cost, low efficiency, incomplete regional coverage, subjective bias leading to result deviation, and inability to resolve basis risk issues. Remote sensing technology provides a new channel for crop yield estimation, offering growth grading maps for sampling point layout and yield estimation modeling, but it also introduces new problems. First, remote sensing yield estimation is limited by data availability. Optical satellite data are affected by weather, UAV data are constrained by flight range and resolution conflicts and cost [?], and radar data are limited by information content [?]. Second, the reliability and recognition of remote sensing yield estimation remain uncertain. Remote sensing yield estimation relies on ground data support, and remote sensing parameters suffer from “same object, different spectrum” or “different object, same spectrum” phenomena, causing estimation errors. Recognition of remote sensing technology by insurance parties, especially the insured, needs improvement. Third, data acquisition costs vary dramatically across different remote sensing data sources, such as archived vs. programmed satellite data, medium

vs. high-resolution data, and UAV vs. satellite data. If income insurance uniformly requires remote sensing data, the substantial cost differences must be carefully considered.

Thus, remote sensing technology application in plant income insurance is not only a challenge for remote sensing technology itself but also for insurance companies, government, and regulatory departments.

3 Business Process of Plant Income Insurance and Remote Sensing Intervention Scenarios

The following uses plant income insurance as an example to illustrate its business process and remote sensing intervention scenarios, as shown in Figure 1 [Figure 1: see original paper].

From a timeline perspective, plant income insurance begins after target crop emergence, when insurance institutions enter the underwriting stage. Through policy issuance, insurance institutions determine the coverage area and define the operational scope for remote sensing applications. During the crop growth period, remote sensing technology can be used for cultivated plot extraction and crop classification in the insured area. Cultivated plots are fundamental data for income insurance inspection and the basis for subsequent crop classification, while crop classification maps are important references for insurance inspection. During crop growth, remote sensing technology can also record and monitor crop growth status and disaster conditions, enabling growth analysis and disaster assessment. From harvest to claim settlement, crop yield estimation modeling is conducted based on multi-source data including meteorological, remote sensing, and elevation data, calculating the average yield of target crops according to claim area regulations to serve as the yield basis for income insurance.

The business process involves four key remote sensing technologies: cultivated plot extraction, crop classification, crop disaster monitoring, and crop yield estimation. Additionally, data sources and ground sample collection are essential throughout the process. Data sources are prerequisites for business operations, while ground samples ensure the accuracy of remote sensing analysis results. Sample collection primarily relies on GPS technology, GIS technology, internet technology, and sampling techniques. Current sample collection technologies are relatively mature, such as the “e-Agricultural Insurance” system of China Pacific Property Insurance Co., Ltd. [?] and the “Sample Collection Treasure” of the Agricultural Information Institute, Chinese Academy of Agricultural Sciences [?]. Due to space limitations, sample collection technology is not discussed further in this paper.

4 Current Status of Key Remote Sensing Technologies and Data Sources for Plant Income Insurance

Theoretically, all agricultural remote sensing technologies and data sources can be used in agricultural insurance, with selection based on business requirements. The following sections review the overall technical status and the specific technologies and data sources needed for agricultural insurance.

4.1 Cultivated Plot Extraction Technology

Cultivated plots are fundamental data for plant income insurance underwriting and inspection, as well as the framework for crop classification extraction, playing an important role in income insurance and the entire planting insurance application. Cultivated plots can be extracted from existing land use products, such as the 30 m resolution GlobeLand30 [?]. However, land use products are initially produced for land use type classification, and their accuracy generally cannot directly meet the needs of plot-level extraction at the township level required by agricultural insurance. Therefore, extracting cultivated land from land use products often requires supplementation with statistical data or new remote sensing imagery for correction [?], serving as a basis for finer plot extraction or crop classification.

In agricultural insurance remote sensing applications, since policies involve individual farmers, plot extraction often requires supplementation with remote sensing data at resolutions better than 10 m. Methods for plot extraction based on medium-high and high-resolution remote sensing data include traditional indoor visual interpretation, outdoor field delineation based on GPS tracks, pixel-based classification, object-oriented image segmentation, and deep learning methods from artificial intelligence. Currently, practical plot extraction generally combines primary data and methods with supplementary data and methods, completed with some manual correction. Among these, object-oriented image segmentation and deep learning classification are relatively less dependent on manual work, offering higher extraction efficiency and accuracy, and are currently more commonly used methods [?].

Object-oriented methods integrate multiple knowledge sources, such as multi-band gray values, texture, neighborhood features, and geometric shapes of remote sensing imagery, for neighborhood comparison. Combining fuzzy mathematics, they refine similar knowledge into objects [?, ?], identifying cultivated land information with similar texture, shape, and gray values. This method can eliminate pixel islands and “salt-and-pepper” problems in traditional pixel-based classification, reducing extensive post-processing work and improving both classification accuracy and efficiency. The method is mature and available in many commercial image processing software packages, such as eCognition, which can achieve 96% plot extraction accuracy for Sentinel-2A data using object-oriented extraction combined with random forest models [?]. The domestic remote sensing information processing software “Jianyi” provides multi-scale segmentation

modes and is particularly sensitive to texture information [?]. Other common remote sensing software such as ENVI and ERDAS IMAGINE also include object-oriented extraction modules.

Deep learning classification evolved from early machine learning algorithms such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), formally proposed by Hinton et al. in 2006 [?] and introduced into remote sensing classification by researchers. Researchers worldwide have conducted unsupervised or supervised classification using deep learning algorithms with data including multispectral, hyperspectral, and radar remote sensing [?]. Deep learning algorithms have high hardware requirements. Currently, Google' s Earth Engine (GEE) platform provides cloud computing platforms and directly callable code modules for deep learning algorithms, greatly promoting their rapid development and application. Domestic remote sensing information processing software has also embedded deep learning algorithms, promoting their application in China. In addition to GEE, international cloud platforms include Amazon Web Services (AWS), while domestic cloud platform development is accelerating, such as the EarthDataMiner from the Chinese Academy of Sciences and PIE-Engine from Aerospace Hongtu [?].

From a classification method perspective, supervised deep learning classification generally requires tens of thousands of samples for high-accuracy extraction, while unsupervised deep learning requires extensive time for parameter tuning [?]. Currently, deep learning-based plot extraction still requires substantial manual correction in pre- and post-processing. Yang et al. [?] used deep learning classification based on the D-Linknet algorithm with only 84 samples of 1000×1000 pixels, achieving relatively reliable 84% accuracy with manual correction, though the advantages of deep learning were not obvious.

From the perspective of planting insurance applications, the currently mature and rapid plot extraction technology remains object-oriented technology, which requires few samples and lower technical skills from operators. However, with the deepening of deep learning applications, its automation and intelligence characteristics will be continuously exploited, becoming a key technology for future automated and intelligent plot extraction.

4.2 Crop Classification Extraction Technology

China' s agricultural insurance is a policy-supported insurance where premium subsidy amounts are related to crop type. Therefore, crop classification maps are not only the basis for yield estimation but also for insurance inspection. Many crop classification extraction technologies exist, with selection depending on work area size, data used, and regional planting structure characteristics. Large-scale (provincial and above) crop classification often uses medium-low resolution imagery (100-1000 m) such as MODIS and Advanced Very High Resolution Radiometer (AVHRR) data, with classification based primarily on phenological patterns shown in long time-series imagery. Methods can include manual decision

trees or machine learning for crop identification, supplemented by pixel-based soft/hard classification post-processing to improve accuracy [?]. Medium-scale (below provincial or county-level) crop classification generally uses medium-high resolution (10-100 m) imagery, employing object-oriented methods, decision tree classification, or integrated methods [?]. Small-scale (township, village level) or regions with complex planting structures generally require high-resolution imagery (<10 m), using object-oriented or deep learning algorithms [?].

In plant income insurance, before crop classification, satellite remote sensing data should be collected as comprehensively as possible, with methods determined based on data availability and crop characteristics in the imagery. If the target crop shows obvious spectral or texture differences from 同期 crops, classification can be based on single-phase imagery. If spectral features differ significantly, traditional supervised, unsupervised, or object-oriented methods can be used; if texture features differ significantly, object-oriented methods are primarily used. Liu et al. [?] achieved 92% identification accuracy for crops on single-phase UAV imagery using SVM combined with Digital Surface Model (DSM) data.

In practice, to achieve optimal classification accuracy and meet application requirements, multiple data sources and methods are often integrated. For example, Wu et al. [?] conducted crop extraction in Fusui County, Guangxi, using a spatiotemporal collaboration and multi-method integration scheme. The study first used deep learning algorithms to extract plot boundaries from 0.6 m Google Earth data as a mask base map, then combined 45 scenes of Landsat 8 and Sentinel-2 data over two years (8 Landsat 8 and 14 Sentinel-2 scenes in 2018; 7 Landsat 8 and 16 Sentinel-2 scenes in 2019) vegetation indices for full crop classification using random forest methods, achieving 88% crop extraction accuracy. Chen et al. [?] conducted growth grading and disaster assessment during soybean planting identification in Jiayang County, providing effective auxiliary data for improving yield estimation accuracy.

Due to China's extremely complex planting structure with widespread "same spectrum, different objects" crops, decision tree methods are often chosen for classification based on crop phenological patterns—specifically, the growth change rate of target crops at certain stages showing obvious differences from other crops [?, ?, ?].

4.3 Crop Disaster Assessment Technology

Crop disaster conditions directly affect yield, serving as important reference data for yield estimation and insurance claim basis, and are closely related to crop growth monitoring.

Disaster assessment can compare pre- and post-disaster growth conditions, such as using vegetation indices from multi-temporal multispectral satellite remote sensing data [?, ?], comparing height differences in corn monitored by UAV

LiDAR for flood assessment [?], or using spectral transformation based on multispectral or hyperspectral data [?, ?, ?].

In area-based plant income insurance applications, crop growth and disaster assessment directly serve yield estimation. Therefore, disaster assessment is often transformed into growth assessment. Specialized growth monitoring research generally only provides crop growth grades [?], while growth monitoring in income insurance considers not only the grade of certain growth characteristics but also the causes of that grade and its relationship with yield. Crop growth and disaster assessment in plant income insurance are generally conducted during crop classification and field sampling. During crop classification, re-verification of uncertain categories and re-identification of minor spectral differences within confirmed categories are key to growth assessment. Spectral differences between uncertain or confirmed categories, and within individual plots, may be caused by disasters, pests, or different planting habits and management practices. For these anomalous plots and categories, field verification should be supplemented to complete ground growth grading and disaster damage grading. Based on these field samples, optimal remote sensing indices can be identified, such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), or physiological parameters like Leaf Area Index (LAI) and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), for large-scale growth grading and disaster assessment. Growth grading maps and disaster grading maps guide field yield measurement sampling route planning and sample quantity calculation, assisting final yield estimation through weighting and other methods.

4.4 Crop Yield Estimation Technology

Crop yield is the direct basis for income insurance claims. Remote sensing-based crop yield estimation methods can be divided into two categories: statistical modeling and crop growth model simulation assimilated with remote sensing data [?]. Statistical modeling uses parameters obtained from aerial or space remote sensing as input factors for regression analysis with actual yields to develop empirical statistical models for yield estimation. Based on remote sensing data resolution, this method can provide yield estimates at different plot scales, estimating yield on the basis of identified crop planting areas with high accuracy and credibility [?]. The drawback is the need for numerous ground yield samples. Traditional crop physiological model simulation has been studied mainly at single points (including experimental plots) for crop production and development, genetic traits, and variety selection [?], with related research showing increasing trends in recent years [?]. However, remote sensing data-assimilated crop growth model simulation requires numerous crop-related parameters and has not yet produced better results at township and smaller scales.

Currently, remote sensing yield estimation-related standards such as “Technical Specification for Remote Sensing Monitoring of Major Crop Yield Using Medium and High Resolution Satellites” (NY/T 4065-2021) and “Remote Sensing Es-

timization Procedures for Wheat and Corn Yield” (DB61 T 1041-2018) (DB32T 3780-2020) all adopt statistical modeling methods. Statistical modeling seeks remote sensing parameters with strong correlations to measured yields, such as NDVI, crop agronomic parameters [?], or microwave-based radiation parameters [?]. In addition to remote sensing parameters, terrain data, meteorological remote sensing products, and other factors can be incorporated to increase model explanatory power. Zhu et al. [?] found that potato yield in Shanxi regional income insurance correlated best with land surface temperature representing ground potential heat flux.

In remote sensing-based crop yield estimation, field yield samples are critical, and growth and disaster assessment before field sampling is even more critical. Yield estimation should comprehensively utilize multi-source data, including resource satellite remote sensing data, meteorological remote sensing products, terrain data, and socio-economic data, to increase model credibility.

4.5 Remote Sensing Data Sources

Remote sensing data sources are prerequisites for remote sensing-based agricultural insurance business. From the above review of remote sensing technology application history and technical progress in agricultural insurance, it is evident that agricultural insurance uses data from numerous remote sensing platforms, including near-ground (handheld devices), aerial platforms, or space platforms. From an electromagnetic spectrum perspective, both active and passive remote sensing are used. From resolution perspectives, high, medium, and low-resolution data are included (JR/T 0180-2019). However, for plant income insurance, since claim areas generally extend to townships, villages, and farms, higher spatial resolution is required, while the commercial nature of agricultural insurance also imposes certain cost constraints. From perspectives of data availability, technical maturity [?], and low cost, the most commonly used and process-spanning data remain satellite data. Currently, the most commonly used multispectral satellite data and their typical insurance stages are shown in Table 1 .

Radar satellite data, as a supplement to optical satellite data, has shown potential in recent years for retrieving crop growth parameters such as LAI and biomass [?] and can also be applied in agricultural insurance. Currently, commonly used radar satellite data and their typical insurance stages are shown in Table 2 .

5 Problems and Development Recommendations

5.1 Existing Problems

Although remote sensing technology has only been applied in agricultural insurance for just over a decade, the above review shows that technologies involved in plant income insurance applications—including plot extraction, crop classification, growth and disaster assessment, and yield estimation—can all find similar

application cases and experience in agricultural remote sensing. However, two technical problems and two industry-level problems remain in current applications.

The two technical problems are: (1) insufficient automation and intelligence in plot identification and crop classification; and (2) lack of mechanistic meaning and insufficient simplicity and reliability in yield estimation.

The two industry-level problems are: (1) inherent limitations of the remote sensing industry itself, including data source issues, data cost issues, and data preprocessing issues; and (2) compatibility issues between current insurance industry business practices and remote sensing technology integration.

Data source issues refer to optical remote sensing being frequently unavailable due to weather, radar data having limited agricultural information reflection, and high costs for UAVs to cover all major grain-producing counties. Data cost issues mean most data require payment. For commonly used high and medium-high resolution multispectral satellite data in income insurance, except for free U.S. Landsat 8 and its related series and European Sentinel-2 satellite data, all others require payment, with some being quite expensive. Multispectral satellite data acquisition is also severely affected by weather. If insufficient multispectral satellites are available, how to supplement with other data—including commercial satellite programming, radar data, and low-altitude data—and who bears the cost of supplementary data are important considerations. Data preprocessing issues refer to geometric correction, atmospheric correction, and data fusion. For multispectral satellites, except for Landsat 8 and Sentinel-2 with relatively simple preprocessing workflows, other data, including China's Gaofen series, also require laborious preprocessing [?]. China has remote sensing technical specifications for agricultural remote sensing satellite data preprocessing and crop area extraction, but questions of who performs preprocessing, who provides data, and who pays data fees are important factors affecting remote sensing applications in agricultural insurance.

The purpose of remote sensing technology application in agricultural insurance may be a detour. With the goal of automating existing business, many explorations have been conducted in remote sensing applications for agricultural insurance. However, automating existing business may be less convenient than finding a new business approach. As Hammer stated [?], all attempts in the 20th century to automate existing business had low success rates, with the best approach being to replace it with entirely new business models—this is true business innovation based on technology. Currently, exploration of innovative integration models between the two is limited, leading to controversy over the role of remote sensing technology in claim settlement, such as whether remote sensing yield results are completely reliable, whether they can be directly used for claims, what proportion should be adopted, whether remote sensing technology should be standardized and written into insurance contracts, etc.

Although each remote sensing technology involved in the plant income insurance

business process has a certain technical foundation, different crops and insurance products have different business processes and remote sensing technology service requirements. With further development of plant income insurance, demand for data support from remote sensing technology has increased dramatically, and remote sensing technology applications in plant income insurance still require extensive piloting and accelerated application of high-tech to promote the birth of a new agricultural insurance model integrated with remote sensing technology.

5.2 Development Recommendations

Therefore, five recommendations are proposed for the next steps in applying remote sensing technology to plant income insurance:

- (1) Domestic departments with satellite data collection and distribution qualifications should leverage their advantages and resources to play an important role by uniformly collecting and preprocessing data, and establishing standardized satellite data distribution platforms for direct download and use by the agricultural insurance industry or remote sensing application departments.
- (2) In plot identification and crop classification, fully leverage the insurance industry's advantage in field sample collection for loss assessment, continuously accumulate field samples, and improve cultivated land and crop sample databases to provide a foundation for automated and intelligent plot identification and crop classification.
- (3) Fully utilize interdisciplinary research results, integrating agronomy, meteorology, modeling, ecology, and remote sensing science to establish more mechanistic, simpler, more reliable, and multi-scale yield estimation models, reducing time and economic costs of yield estimation processes and improving accuracy and mechanistic understanding.
- (4) Establish relevant standards and specifications for applying mature remote sensing technologies to agricultural insurance as soon as possible to facilitate insurance companies and industry regulators' recognition and application of remote sensing technology, accelerate its promotion, and promote healthy development of the agricultural insurance industry.
- (5) Under the new situation of expanded pilot programs for plant income insurance, the introduction of remote sensing technology should begin at insurance product design and be written into insurance contracts. For future applications of remote sensing technology in plant income insurance and other agricultural insurance, remote sensing technology should fully play its role, strive for piloting, and accelerate the application of high-tech to promote the birth of a new agricultural insurance model with high precision and efficiency.

With further improvements in remote sensing-related technologies, the introduction of standards and specifications for combining remote sensing technology

with agricultural insurance, and explicit provisions for remote sensing technology in agricultural insurance contracts, remote sensing technology applications in agricultural insurance will enter a stage of rapid development. The future application model of remote sensing technology in plant income insurance and all agricultural insurance will be a new model with readily available data, more automated and intelligent technology, standards to follow, and contractual backing.

References

- [1] XUE Jin. Agricultural insurance premium growth outpaces property insurance industry: “customized style” protects rural revitalization [EB/OL]. China Securities Journal, (2021-02-05) https://www.cs.com.cn/bx/202102/t20210205_{6137554}.html. [2022-1-31].
- [2] ZHAO Zhanhui, QU Zhehan. National agricultural insurance premium scale reached 96.5 billion RMB in 2021 [N]. People’s Daily, 2022-01-13(7).
- [3] China Insurance Society. Research on agricultural insurance serving “three rural” development [M]. Beijing: China Financial Publishing House, 2021: 496.
- [4] Financial Department, Ministry of Agriculture and Rural Affairs. Notice on expanding the implementation scope of full cost insurance and plant income insurance for three major grain crops [EB/OL]. [2021-12-31]. http://www.moa.gov.cn/govpublic/CWS/202106/t20210630_{6370731}.htm.
- [5] TANG Huajun. Progress and prospect of agricultural remote sensing research [J]. Journal of Agriculture, 2018, 8(1): 161-171.
- [6] WANG Limin, LIU Jia, JI Fuhua. Status quo and development trend of agriculture remote sensing technology application in China [J]. Chinese Agricultural Science Bulletin, 2021, 37(25): 138-143.
- [7] WU Wenbin, HU Qiong, LU Miao, et al. Agricultural land system remote sensing mapping [M]. Beijing: Science Press, 2020.
- [8] HUANG Bo. Research on the application of unmanned aerial vehicle technology in planting industry insurance [D]. Kunming: Kunming University of Science and Technology, 2019.
- [9] ZHANG Wangfei, CHEN Erxue, LI Zengyuan, et al. A review of applications of radar remote sensing in agriculture [J]. Journal of Radars, 2020, 9(3): 444-461.
- [10] TOWERY N G, EYTON J R, CHANGNON S, et al. Remote sensing of crop hail damage [R]. Illinois State: Illinois State Water Survey, 1975.
- [11] TOWERY N. Some applications of remote sensing of crop-hail damage in the insurance industry [R]. Circular 143/80 of the Illinois State Water Survey, Illinois Institute of Natural Resources: Urbana, IL, USA, 1980.

- [12] DE LEEUW J, VRIELING A, SHEE A, et al. The potential and uptake of remote sensing in insurance: A review [J]. *Remote Sensing*, 2014, 6(11): 10888-10912.
- [13] VROEGE W, DALHAUS T, FINGER R. Index insurances for grasslands: A review for Europe and North-America [J]. *Agricultural Systems*, 2019, 168: 101-111.
- [14] ARUMUGAM P, CHEMURA A, SCHAUBERGER B, et al. Remote sensing based yield estimation of rice (*Oryza Sativa* L.) using gradient boosted regression in India [J]. *Remote Sensing*, 2021, 13(12): ID 2379.
- [15] LI Z, ZHANG Z, ZHANG L. Improving regional wheat drought risk assessment for insurance application by integrating scenario-driven crop model, machine learning, and satellite data [J]. *Agricultural Systems*, 2021, 191: ID 103141.
- [16] MANAGO N, HONGO C, SOFUE Y, et al. Transplanting date estimation using Sentinel-1 satellite data for paddy rice damage assessment in Indonesia [J]. *Agriculture*, 2020, 10(12): 1-18.
- [17] ZHANG Lan. Agricultural insurance “leg-based claim settlement” may end [N]. *Financial Times*. 2013-10-21(005).
- [18] GUO Qing, HE Fei. Research on the application of spatial information technology in agricultural insurance [J]. *Geographic Information World*, 2014, 21(1): 79-84.
- [19] LI Yijia, YE Tao, DEQING Zhuoga, et al. Research on the design of animal husbandry drought index insurance product in Nagqu region of Tibet based on remote sensing vegetation index [J]. *Agricultural Modernization Research*, 2018, 39(4): 680-688.
- [20] MENG Jihua, FU Wei, XU Jin, et al. Application of remote sensing in planting industry insurance loss estimation [J]. *Remote Sensing Technology and Application*, 2017(2): 238-246.
- [21] CHEN Ailian, LI Jiayu, ZHANG Shengjun, et al. Application of satellite remote sensing yield estimation technology in regional revenue protection crop insurance: A case of soybean [J]. *Smart Agriculture*, 2020, 2(3): 139-152.
- [22] ZHU Yuxia, NIU Guofen, CHEN Ailian, et al. Application of potato income insurance based on multi-source remote sensing data [J]. *Chinese Journal of Agricultural Resources and Regional Planning*, 2021, 42(10): 223-232.
- [23] ZHAO Sijian, ZHANG Qiao. The current situation, system and prospect of agricultural insurance technology [J]. *China Insurance*, 2018(7): 28-35.
- [24] ZHAO Sijian, ZHANG Qiao. Research on science and technology boosting the high-quality development of agricultural insurance [J]. *Insurance Theory and Practice*, 2020(8): 7-19.

- [25] LI Le, PAN Yaozhong, WANG Xiaodong, et al. Based on 3S technology agricultural insurance “accurate underwriting and fast claim settlement” [J]. *Satellite Applications*, 2016(3): 66-72.
- [26] QI Xin. Innovation in business models of remote sensing technology applied to agricultural insurance [J]. *Agricultural Technology Service*, 2017. 34(14): 171.
- [27] XU Zhicheng, HAN Zhihua, WANG Dun, et al. Inner Mongolia uses scientific and technological means to carry out the pilot work of agricultural insurance precision underwriting and claims settlement [J]. *Insurance Theory and Practice*, 2020(1): 1-6.
- [28] WU Bo, YANG Na, DAI Weixu, et al. A brief discussion on the application of remote sensing technology in agricultural insurance: Taking the damage determination of corn waterlogging disaster in Shanxian county, Heze city as an example [J]. *Rural Practical Technology*, 2020(5): 37-39.
- [29] HU Yunwei, LENG Wei, CHEN Shumin, et al. Analysis of the whole process of remote sensing in agricultural insurance application: Taking the middle rice calibration and inspection project in Xiaonan district, Xiaogan city, Hubei province as an example [J]. *Satellite Applications*, 2020(11): 30-34.
- [30] DING Wei. Research on land extraction and crop recognition method based on deep neural network [D]. Beijing: University of Science and Technology of China, 2021.
- [31] WU Yanpeng. UAV protects PICC agricultural insurance [J]. *Rural Agriculture Farmers (B Edition)*, 2016(4): 48.
- [32] CHEN Ailian, ZHU Yuxia, SUN Wei, et al. Application of remote sensing technology in the determination of pests and diseases in agricultural insurance: A case study of Rice Blast in Shuanghe Farm [J]. *Remote Sensing Information*, 2021, 36(6): 44-50.
- [33] GAO Yaqin, CHEN Linjie, CHEN Xinlei, et al. Research on agricultural insurance service innovation in the “Internet+” era: Taking Pacific Insurance “e-Agricultural Insurance” application in weather index insurance as an example [G]. (2017) Selected Compilation of Zhejiang Insurance Scientific Research Achievements, 2018.
- [34] CHEN Jun, WU Hao, LI Songnian. Research progress of global land domain service computing: Take GlobeLand 30 as an example [J]. *Acta Geodaetica et Cartographica Sinica*, 2017, 46(10): 1526-1533.
- [35] CHEN Di, WU Wenbin, LU Miao, et al. A review of the research progress of land cover data reconstruction based on multi-source data fusion [J]. *Chinese Journal of Agricultural Resources and Regional Planning*, 2016, 37(9): 62-70.
- [36] NI Ling, SHU Ning. Object-oriented knowledge representation in remote sensing image understanding expert system [J]. *Journal of Wuhan University of Surveying and Mapping Technology*, 1997(1): 34-36, 48.

- [37] ZHANG Dongmei. The land use classification based on multi-scale segmentation: A case in Jinfeng district, Yinchuan city [D]. Nanchang: East China University of Technology, 2017.
- [38] ZHAO Shiyi, YAN Jinfeng, DU Jiaxue. Sentinel-2A image cultivated land information extraction based on object-oriented and random forest model [J/OL]. Journal of Henan Polytechnic University (Natural Science), [2021-03-29]. <https://kns.cnki.net/kcms/detail/41.1384.N.20210327.1413.002.html>.
- [39] LUO Jiansong, ZHAO Nini, LI Shurui. Research on the quick change detection based on Landsat-8 Satellite images [J]. Surveying and Geospatial Information, 2020, 43(12): 116-118, 121.
- [40] HINTON G E, OSINDERO S, TEH Y W. A fast learning algorithm for deep belief nets [J]. Neural Computation, 2006, 18(7): 1527-1554.
- [41] LIU Dawei, HAN Ling, HAN Xiaoyong. High spatial resolution remote sensing image classification based on deep learning [J]. Acta Optica Sinica, 2016, 36(4): 306-314.
- [42] FENG Liying. Research on construction land information extraction from high resolution sensing images with deep learning technology [D]. Hangzhou: Zhejiang University, 2017.
- [43] WANG Bin, FAN Donglin. Research progress of deep learning in classification and recognition of remote sensing images [J]. Surveying and Mapping Bulletin, 2019(2): 99-102, 136.
- [44] DONG Jinwei, LI Shiwei, ZENG Yelu, et al. Remote sensing cloud computing and scientific analysis: Application and practice [M]. Beijing: Science Press, 2020.
- [45] YANG Yingpin, WU Zhifeng, LUO Jiancheng, et al. Parcel-based crop distribution extraction using the spatiotemporal collaboration of remote sensing data [J]. Transactions of the CSAE, 2021, 37(7): 166-174.
- [46] LIU Bin, SHI Yun, WU Wenbin, et al. Crop classification based on uav remote sensing images [J]. Chinese Journal of Agricultural Resources and Regional Planning, 2019, 40(8): 55-63.
- [47] WU Zhifeng, LUO Jiancheng, SUN Yingwei, et al. Research on precision agricultural based on the spatial-temporal remote sensing collaboration [J]. Journal of Geo-information Science, 2020, 22(4): 731-742.
- [48] YANG Yanjun, ZHAN Yulin, TIAN Qingjiu, et al. Crop classification based on GF-1/WFV NDVI time series [J]. Transactions of the CSAE, 2015, 31(24): 155-161.
- [49] DU Baojia, ZHANG Jing, WANG Zongming, et al. Crop mapping based on Sentinel-2A NDVI time series using object-oriented classification and decision tree model [J]. Journal of Geo-information Science, 2019, 21(5): 740-751.

- [50] SUN Chenhong, YANG Guijun, DONG Yansheng, et al. Remote sensing monitoring on seedling conditions of winter wheat growth under double stress of dry and freezing injury [J]. *Journal of Triticeae Crops*, 2014, 34(5): 635-641.
- [51] DONG Yansheng, CHEN Hongping, WANG Huifang, et al. Assessing freeze injury to winter wheat with multi-temporal HJ-1 satellite imagery [J]. *Transactions of the CSAE*, 2012, 28(20): 172-179, 295.
- [52] GAN Ping, DONG Yansheng, SUN Lin, et al. Evaluation of maize water-logging disaster using UAV LiDAR data [J]. *Scientia Agricultura Sinica*, 2017, 50(15): 2983-2992.
- [53] GUO Anting. Research on the methods of wheat yellow rust monitoring based on imaging remote sensing [D]. Beijing: Aerospace Information Research Institute, Chinese Academy of Sciences, 2021.
- [54] WANG Fan. Hyperspectral monitoring of maize leaf blight disease based on wavelet transform [D]. Taigu: Shanxi Agricultural University, 2019.
- [55] HUANG Qing, LI Dandan, CHEN Zhongxin, et al. Rapid extraction and growth monitoring of winter wheat planting area based on MODIS data [J]. *Transactions of the CSAM*, 2012(7): 163-167.
- [56] DU Xin, MENG Jihua, WU Bingfang. Overview on monitoring crop biomass with remote sensing [J]. *Spectroscopy and Spectral Analysis*, 2010, 30(11): 3098-3102.
- [57] HUANG Jianxi, HUANG Hai, MA Hongyuan, et al. Review on data assimilation of remote sensing and crop growth models [J]. *Transactions of the CSAE*, 2018, 34(21): 144-156.
- [58] WANG Liyuan. Estimating winter wheat yield by assimilation of remote sensing data into crop models [D]. Hangzhou: Zhejiang University, 2018.
- [59] CHENG Zhiqiang, MENG Jihua. Research advances and prospects on crop yield estimation models [J]. *Chinese Journal of Ecological Agriculture*, 2015, 23(4): 402-415.
- [60] WU Wei, FAN Li, LI Maofen, et al. Sensitivity analysis of crop growth models to multi-temporal scale solar radiation [J]. *Transactions of the CSAE*, 2012, 28(3): 123-128.
- [61] LU Bihui, YU Kun. Research progress on assimilation application of remote sensing information and crop growth model [J]. *Jiangsu Agricultural Science*, 2018, 46(10): 9-13.
- [62] WANG Ying, GONG Yinxi. Spectral remote sensing technology applied in crop yield estimation: Research progress [J]. *Chinese Agricultural Science Bulletin*, 2019, 35(3): 69-75.
- [63] HAMMER M. Reengineering work: Don't automate, obliterate [J]. *Harvard Business Review*, 1990, 68(4): 104.

Table 1 The parameters of multispectral satellite data commonly used in plant insurance

Satellite	Multispectral Range (nm)	Spatial Resolution (m)	Temporal Resolution (days)	Common Insurance Organization
Sentinel 2 A/B	443~2190	10, 20, 60	15, 30, 100	2015/2017 Underwriting –Claim
Landsat 8	433~1251	15, 30, 100	2012/2014	Underwriting –Claim
Planet constellation	455~860	<3, 3.7	2011/2012	Underwriting –Claim
SPOT 6, 7	455~890	1.5, 6	2013/2018	Underwriting –Claim
Pleiades 1/2	430~940	0.5, 2	Underwriting –Claim	
Rapideye 4	440~850	2, 8, 16	Underwriting –Claim	
Gaofen 1, 6	450~890	2.1, 3.5, 6	Underwriting –Claim	
Gaofen 2	450~890	Underwriting – Claim		
Ziyuan 3	450~890	Underwriting – Claim		

Table 2 The parameters of radar satellite data useful in plant insurance

Satellite	Imaging Modes	Polarization	Spatial Resolution (m)	Launch Year	Common Insurance Stages
TerraSAR-X and constellation	SL, SM, SC, SCW	Single, dual, full polarization	1~100	2007~2013	Underwriting—Claim
RadarSat 2	SL, SM, SC	Single, dual, full polarization	1~100	2016/2021/2022	Underwriting—Claim
ALOS-2	SL, UFS, FS, HSS, SCN, SCI, SCW	Single, dual, full polarization	1~500	2014/2016	Underwriting—Claim
Gaofen 3 (01/02/03stars)	SL, SMSC, WAV, EXT	Single, dual, full polarization	1~100		Underwriting—Claim
Sentinel 1 A/B	SM, IWS, EW, WAV	Single, dual polarization			Underwriting—Claim

Note: SL: Spotlight; SM: Stripmap; SC: ScanSAR; SCW: ScanSAR Wide; UFS: Ultra Fine ScanSAR; FS: Fine ScanSAR; HSS: High Sensitive ScanSAR; SCN: ScanSAR nominal; IWS: Interferometric Wide Swath; WAV: Wave; EXT: Extended Incidence Angle; EW: Extra Wide Swath

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