Research on Key Technologies for Intelligent Monitoring and Early Warning of Agricultural Disasters Based on Multi source Meteorological Data Fusion

Qiang Li[1,2], Ting Zhang[3], QingYi Yang[1], Quan Xia[1], Fan Liu[4], Jun Lei[5]
[1]Meteorology School, Lanzhou Resources & Environment Voc-Tech University, Lanzhou 730021, Gansu, China
[2]Key Laboratory of Arid Climate Resource and Environment of Gansu Province (ACRE), Lanzhou 730021, Gansu, China
[3]Gansu Fengyun Meteorological Equipment Co., Ltd.,Lanzhou 730021, Gansu, China
[4]Meteorological Bureau of Xianyang city, Xianyang 712000, Shaanxi, China
[5]Dingxi Meteorological Bureau, Dingxi 743000, Gansu, China

Corresponding author: Ting Zhang (e-mail: charslee67@126.com)

ABSTRACT In response to the frequent occurrence of agricultural meteorological disasters in China, insufficient monitoring accuracy from a single data source, low timeliness and spatial resolution of early warning, and difficulties in identifying multiple disaster types, this article focuses on the full chain of multi-source meteorological data fusion, intelligent disaster identification, precise early warning, and business application. Construct an integrated multi-source meteorological data acquisition system for space-based, space-based, and ground-based systems, propose spatiotemporal registration and quality control methods, and design a multimodal data fusion algorithm based on dynamic weights and deep learning; Develop intelligent identification models for major agricultural disasters such as drought, floods, low-temperature freezing damage, dry hot winds, and pests and diseases, and establish a dynamic assessment index system for disaster risks by crop, growth period, and region; Build a seamless intelligent early warning model and multi-level early warning release mechanism for long, medium, and short periods, forming a technical system that integrates data fusion, monitoring and identification, risk assessment, early warning release, and decision support. The fusion framework is compatible with satellite remote sensing, weather radar and farmland sensor networks.

INDEX TERMS multi-source meteorological data,data fusion,agricultural disasters,intelligent warning,remote sensing

I. INTRODUCTION

A. RESEARCH BACKGROUND AND SIGNIFICANCE

CHINA is one of the countries with the most severe agricultural meteorological disasters in the world. Drought, floods, low temperature freezing damage, high temperature heat damage, dry and hot winds, continuous rain, hail, pests and diseases, and other disasters cause an average of over 20 million hectares of crop damage per year, resulting in a reduction of 10% to 30% in grain production and economic losses exceeding 100 billion yuan. With the frequent occurrence of global climate change and extreme weather events, agricultural disasters have shown a trend of frequent, concurrent, and severe occurrences. The traditional monitoring and early warning model, which mainly relies on ground observation and supplemented by manual recognition, is no longer able to meet the needs of modern agriculture for precision, real-time, and intelligence[1-3].

B. MAIN RESEARCH CONTENT AND TECHNICAL ROUTE

1) Research Content

1. Construction and preprocessing technology of multi-source meteorological data system for agricultural disasters;

2. Multi source meteorological data spatiotemporal registration, quality control, and deep fusion algorithms;

3. Intelligent recognition and feature extraction technology for typical agricultural disasters;

4. Dynamic assessment model for disaster risk by crop and region;

5. Integrated intelligent early warning technology and threshold system for long, medium, short, and shortterm emergencies;

6. Research and development of technology integration systems and empirical verification in typical regions;

7. Technical optimization path and promotion application strategy[4].

2) Technical roadmap

Adopting the technical route of "data collection preprocessing fusion computing intelligent recognition risk assessment warning modeling system integration empirical verification", based on multi-source heterogeneous meteorological data, with deep learning and spatiotemporal fusion algorithm as the core, and agricultural disaster formation mechanism and crop response law as the basis, a full process technical system is constructed. Through experimental verification in typical agricultural areas such as North China, Huang Huai, and the middle and lower reaches of the Yangtze River, standardized technical solutions and business application models are formed[5].

C. RESEARCH INNOVATION POINTS

1. Propose a dynamic weight fusion algorithm for multi-source meteorological data from space-based and ground-based sources, achieving high-precision spatiotemporal registration and noise suppression for heterogeneous data;
2. Build a multi disaster coupling intelligent recognition model that couples crop growth periods to improve the accuracy of disaster identification in complex scenarios;
3. Establish seamless early warning and grid based precise release technology for long, medium, and short term emergencies, to achieve disaster early warning and precise push at the field level;
4. Form a business oriented technical system that integrates monitoring, identification, evaluation, warning, and decision-making, which can directly support grassroots agricultural meteorological services[6].

II. CONSTRUCTION AND PREPROCESSING TECHNOLOGY OF MULTI-SOURCE METEOROLOGICAL DATA SYSTEM FOR AGRICULTURAL DISASTERS

A. ANALYSIS OF TYPES AND CHARACTERISTICS OF MULTI SOURCE METEOROLOGICAL DATA

Space based remote sensing data

The Fengyun series meteorological satellites, Gaofen series satellites, and Sentinel series satellites provide visible light, infrared, and microwave remote sensing data to invert parameters such as surface temperature, vegetation index NDVI/EVI, soil moisture, precipitation intensity, and cloud cover. They have the advantages of large-scale and continuous observation, with a spatial resolution of 50m~1km and a time resolution of 1-24h[6].

Airborne observation data

The weather radar obtains reflectivity factors, echo top height, and vertically accumulated liquid water content, and monitors short-term heavy precipitation, hail, and strong winds; The drone is equipped with multispectral and thermal infrared sensors to obtain information on crop growth and stress at the field level, with spatial resolution ranging from centimeters to meters and strong flexibility. Please refer to Table 1 for details[7].

TABLE 1. Multi-source Meteorological Data Types and Characteristics

Data Type	Spatial Resolution	Temporal Resolution	Main Observation Elements
Satellite Remote Sensing	50 m–1 km	1 h–24 h	LST, NDVI, SM, Precipitation
Weather Radar	0.5–1 km	6 min	Reflectivity, VIL, Echo top
Ground Meteorological Station	Point data	5 min–1 h	T, RH, Precipitation, Wind
Numerical Weather Prediction	1–9 km	1 h	Forecast elements

Foundation observation data

National level ground meteorological stations, regional automatic meteorological stations, farmland micro climate stations, soil moisture stations, and IoT sensors monitor temperature, precipitation, wind speed, humidity, air pressure, sunshine, soil temperature and humidity, and crop physiological indicators with high data accuracy, good continuity, and significant differences in point density[8].

Numerical forecast data

ECMWF, GRAPES, WRF and other numerical models provide forecast data for temperature, precipitation, wind speed, humidity and other factors, with a spatial resolution of 1-9km and a forecast time of 0-240h, providing support for medium and long-term early warning.

1) Special Data

Historical disaster datasets, crop planting structures, soil types, terrain elevations, irrigation conditions, pest and disease monitoring data, crop growth period data, etc. provide prior knowledge for disaster assessment and early warning[9-10].

B. ANALYSIS OF SPATIOTEMPORAL CHARACTERISTICS AND HETEROGENEITY OF MULTI SOURCE DATA

Multi source data has problems such as inconsistent spatiotemporal resolution, inconsistent observation benchmarks, missing and abnormal data, noise interference, and scale differences: the spatial scale difference between satellites and radars can reach hundreds of times, ground stations are point data, remote sensing is surface data, and the time sampling interval ranges from minutes to days; The observation error of different sensors, system deviation, cloud, rain and snow interference lead to inconsistent data; Some regional sites have sparse data gaps[11].

C. KEY TECHNOLOGIES FOR DATA PREPROCESSING

1) Format Standardization

Unified data formats are NetCDF, GeoTIFF, CSV, and a coordinate system framework (WGS84/CGCS2000) is established to standardize feature naming, units, and timestamps, achieving readability, computability, and fusion of multi-source data.

2) Spatiotemporal Registration

Using bilinear interpolation, inverse distance weight interpolation, and kriging interpolation to achieve spatial scale unification; Time series synchronization is achieved through linear time stretching and sliding window alignment; Build a grid based spatiotemporal benchmark to unify point, surface, and volume data into a 1km × 1km grid with hourly time steps[12].

3) Data Quality Control

1. Boundary value check: Remove outliers that exceed the physically reasonable range;

2. Time consistency check: Remove mutation and jump data;

3. Spatial consistency check: Remove data that deviates significantly from the surrounding spatial pattern;

4. Sensor deviation correction: Linear correction and segmented fitting are used to eliminate system errors;

5. Missing value filling: LSTM, K-nearest neighbor, and spatiotemporal interpolation are used to fill continuous missing data[13-14].

4) Feature Normalization

Perform MinMax normalization and ZScore normalization on characteristics such as temperature, humidity, vegetation index, and soil moisture to eliminate dimensional differences and improve the stability of subsequent fusion and model training[15].

D. DATA PREPROCESSING PROCESS DESIGN

Design a standardized preprocessing process: raw data access → format conversion → spatiotemporal registration → quality control → missing filling → feature extraction → database storage, to construct a high-quality multi-source meteorological dataset, providing a reliable data base for subsequent fusion and intelligent analysis. See Table 2 for details.

TABLE 2. Evaluation Indexes of Data Fusion Effect

Index	Full Name	Evaluation Standard
MAE	Mean Absolute Error	The smaller, the better
RMSE	Root Mean Square Error	The smaller, the better
R	Correlation Coefficient	The closer to 1, the better
NSE	Nash-Sutcliffe Efficiency	The closer to 1, the better

III. KEY ALGORITHM FOR DEEP FUSION OF MULTI-SOURCE METEOROLOGICAL DATA

A. DATA FUSION HIERARCHY AND FRAMEWORK

Adopting a data level feature level decision level three-level fusion framework:

1. Data level fusion: Directly fuse raw observation data while preserving detailed information;

2. Feature level fusion: Extract disaster sensitive features and fuse them to improve computational efficiency;

3. Decision level fusion: Perform decision fusion on the recognition results of multiple models to improve robustness[16].

B. TRADITIONAL DATA FUSION ALGORITHMS

Weighted average fusion

The weight is determined based on the reciprocal of the historical error variance, which is simple to implement, computationally efficient, and suitable for scenarios with high real-time requirements.

1) Kalman Filter Fusion

Based on the linear system state equation and observation equation, recursively update the optimal estimation value, effectively suppress Gaussian noise, suitable for continuous fusion of time-series meteorological data, and improve the observation accuracy of factors such as soil moisture and temperature.

2) Bayesian Estimation Fusion

Combining prior probability and observation likelihood function to calculate posterior probability, processing highly uncertain and non Gaussian distribution data, suitable for disaster probability monitoring and risk assessment[17].

C. MULTI MODAL DATA FUSION ALGORITHM BASED ON DEEP LEARNING

Integration of spatiotemporal attention mechanisms

The proposed CNN-LSTM-Attention network consists of three 2D-CNN layers (kernel size 3×3, 64 filters) for spatial feature extraction, followed by two LSTM layers (128 hidden units each) to capture temporal

dependencies. A self-attention layer is integrated to dynamically allocate weights to high-value features. Comparative testing indicates that while GCN performs best in sparse mountainous regions (R=0.88), the Transformer architecture excels in multi-hazard coupling scenarios (R=0.92), and the CNN-LSTM-Attention model provides the best balance of real-time efficiency and accuracy (R=0.91)[18].

Transformer cross modal fusion

Based on the Transformer architecture, a multi-source data encoding and decoding model is constructed to uniformly represent remote sensing, radar, ground, and numerical forecast data, capture long-range spatiotemporal dependencies, and solve the problem of data mismatch in multi disaster coupling scenarios.

1) Graph Convolutional Network Space Fusion

Construct a spatiotemporal graph with meteorological stations and grid points as nodes and spatial correlations as edges, and use graph convolution to achieve accurate fusion of sparse station data and grid point data, improving the reliability of data in mountainous areas and sparse station regions. See Table 3 for details[19-20].

TABLE 3. Typical Agricultural Disasters and Sensitive Indicators

Disaster Type	Key Sensitive Indicators	Critical Threshold	Vulnerable Period
Agricultural Drought	SM, SPI, VCI	SM $<$ 60%	Jointing, Booting, Filling
Flood Disaster	Hourly rainfall, Waterlogging depth	$>$ 50 mm/3 h	Seedling, Late growth
Low Temperature Freeze	Minimum temperature, Cooling range	$<$ 0 $^{\circ}$C for 3+ days	Overwintering, Heading
Dry Hot Wind	Tmax, RH14, Wind speed	T $\geq$ 32 $^{\circ}$C, RH $\leq$ 30%	Grain filling stage

2) Dynamic Weight Adaptive Fusion Algorithm

Propose a dynamic weight fusion method driven by real-time quality assessment:

1. Establish real-time quality evaluation indicators for data sources (bias, variance, coverage, consistency);

2. Use entropy weight method+analytic hierarchy process to calculate dynamic weights;

3. Combine weighted fusion with deep learning output results for decision level fusion;

4. Establish a closed-loop feedback mechanism and update the fusion model parameters in real-time. This algorithm can dynamically adjust the contribution of each data source based on weather conditions and data quality. Multi cloud and rainy weather increases the weight of radar and ground data, while clear weather increases the weight of remote sensing data. The overall fusion error is reduced by more than 15%.

D. FUSION EFFECT EVALUATION INDICATORS

Selecting mean absolute error (MAE), root mean square error (RMSE), correlation coefficient (R), and Nash efficiency coefficient (NSE) as quantitative evaluation indicators, and combining spatial consistency and temporal smoothness for qualitative evaluation, to ensure that the fused data meets the accuracy requirements of agricultural disaster monitoring.

IV. INTELLIGENT IDENTIFICATION AND RISK ASSESSMENT TECHNOLOGY FOR AGRICULTURAL DISASTERS

A. TYPICAL AGRICULTURAL DISASTER MECHANISMS AND SENSITIVE INDICATORS

Agricultural drought

Less precipitation, insufficient soil moisture, and vigorous evapotranspiration lead to crop water stress. Sensitive indicators include precipitation anomaly percentage, relative humidity index, soil relative humidity, vegetation drought index VCI, and crop water deficit index.

Flood disasters

Short term heavy rainfall and continuous rainfall lead to waterlogging in farmland and excessive soil moisture. Sensitive indicators include hourly rainfall, cumulative rainfall, waterlogging depth, duration of surface flooding, and saturated soil moisture content.

Low temperature freezing damage/late spring cold

Sudden temperature drops and sustained low temperatures suppress crop growth. Sensitive indicators include minimum temperature, cooling amplitude, duration of sustained low temperature, critical temperature at which crops are affected, and accumulated temperature anomaly.

Dry hot air

The combination of high temperature, low humidity, and strong winds leads to premature senescence of crops due to water loss. Sensitive indicators include daily maximum temperature, relative humidity at 14:00, wind speed, number of dry and hot wind days, and cumulative stress intensity.

Agricultural pests and diseases

Appropriate temperature and humidity can lead to the outbreak of pests and diseases. Sensitive indicators include the number of insect sources, effective accumulated temperature, field temperature and humidity, precipitation conditions, and crop growth index. Please refer to Table 4 for details.

TABLE 4. Agricultural Disaster Early Warning Level Standard

Warning Level	Color	Risk Grade	Probability Range	Recommended Response
Level IV	Blue	Low Risk	$<$ 30%	Routine monitoring
Level III	Yellow	Medium Risk	30%–50%	Preventive preparation
Level II	Orange	High Risk	50%–80%	Emergency defense
Level I	Red	Extremely High Risk	$>$ 80%	Full-scale disaster relief

B. DISASTER INTELLIGENT RECOGNITION MODEL BASED ON DEEP LEARNING

Single disaster identification model

1. CNN model: Processing remote sensing images and radar echoes to extract spatial features of disasters;

2. LSTM/GRU model: Processing meteorological time-series data to predict disaster development trends;

3. XGBoost/LightGBM model: Integrating multi-source features to achieve rapid disaster classification.

Multi hazard coupling identification model

Build a multi task learning network that simultaneously outputs identification results for multiple disaster types such as drought, floods, low temperatures, and heat damage. Introduce prior knowledge of mutual exclusion and symbiosis of disasters to solve the problem of concurrent misjudgment of multiple disaster types. Validated against a dataset of 5,000 historical disaster samples (2018–2025) across North China, the multi-hazard coupling model achieved a comprehensive recognition accuracy of 92.4%, with a Precision of 91.2%, Recall of 89.8%, and an F1-score of 0.905, significantly outperforming single-task models.

Small sample disaster identification

Using transfer learning and data augmentation techniques, the general meteorological pre training model is transferred to regional agricultural disaster scenarios, combined with SMOTE oversampling to expand small sample disaster data and enhance the ability to identify rare disasters.

C. DYNAMIC ASSESSMENT INDEX SYSTEM FOR DISASTER RISK

Construct an evaluation system from four dimensions: disaster risk, vulnerability of disaster bearing bodies, exposure, and disaster prevention and mitigation capabilities:

1. Disaster hazard: disaster intensity, duration, impact range, probability of occurrence;
2. Exposure of disaster bearing bodies: crop planting area, crop type, growth period;
3. Vulnerability of disaster bearing bodies: crop disaster sensitivity coefficients at different growth stages;
4. Disaster prevention and mitigation capabilities: irrigation conditions, drainage capacity, agricultural insurance coverage, technical service level.

D. RISK ASSESSMENT MODEL AND GRADING STANDARDS

Using multi-source fusion data as input and historical disaster situations as labels, train a random forest model and output grid based disaster risk probabilities to achieve dynamic and high-precision risk mapping.

Divide disaster risks into four levels: low risk (I), medium risk (II), high risk (III), and extremely high risk (IV), corresponding to different warning levels and disaster prevention measures.

E. COUPLING EVALUATION TECHNOLOGY FOR CROP GROWTH PERIOD

Establish a disaster response database for major crops such as wheat, corn, rice, and cotton during their growth stages. Dynamically couple the risk assessment model with the key growth stages of crops (sowing, tillering, jointing, heading, filling, and maturity) to achieve differentiated risk assessment based on different growth stages, and enhance the pertinence and practicality of the assessment.

V. INTELLIGENT EARLY WARNING MODEL AND RELEASE TECHNOLOGY FOR AGRICULTURAL DISASTERS

A. TIME DIVISION AND TECHNICAL FRAMEWORK FOR EARLY WARNING

Build a four level seamless warning framework for short-term (0-6h), short-term (1-3d), medium-term (4-10d), and long-term (10-30d), using differentiated models and data inputs for different time periods:

1. Short term warning: radar, ground truth, microwave remote sensing data, extrapolation forecast;
2. Short term warning: multi-source fusion of real-time data and numerical forecast correction;
3. Mid term warning: power mode+machine learning statistical correction;
4. Long term warning: climate trend prediction+historical similar scenario matching.

B. SHORT TERM WARNING TECHNOLOGY

Extrapolation of radar echoes

Using optical flow method and cross-correlation method to extrapolate radar echoes from 0 to 2 hours, predict short-term heavy precipitation, hail, and strong wind areas and intensities.

Real time mutation monitoring

Based on threshold triggering and slope mutation detection, real-time identification of disaster precursors such as sudden drops in temperature, sudden increases in precipitation, and rapid changes in soil moisture is achieved, achieving minute level response.

1) Short term and Medium term Warning Models

Numerical forecast correction model

Using machine learning models to correct the forecast bias of ECMWF and GRAPES models, eliminate systematic errors, and improve the accuracy of temperature, precipitation, and wind speed forecasts.

Time series prediction model

Build a multi factor time-series prediction network based on LSTM, Transformer, and Informer models, input historical fusion data and model forecasts, and output the probability of disaster risk in the next 1-10 days.

2) Crop Disaster Critical Warning Model

Establish a critical threshold library for disasters in different crops and growth stages, and automatically trigger warnings when the predicted meteorological elements reach the critical value, with a warning advance of 3-7 days.

C. LONG TERM WARNING AND TREND PREDICTION

Based on climate indices (ENSO, PDO, South Asian monsoon), sea surface temperature anomalies, and circulation characteristics, a climate prediction model is constructed. Combined with historical disaster sequences, the probability and overall trend of quarterly scale disasters are predicted to provide support for agricultural production layout and disaster prevention planning.

D. MULTI LEVEL WARNING THRESHOLD AND GRADING STANDARDS

Develop four levels of warnings based on risk assessment results: blue (general), yellow (heavy), orange (severe), and red (particularly severe). The probability thresholds for these levels (30%, 50%, and 80%) were determined by analyzing the historical frequency distribution of disasters in the study areas from 2018 to 2025, combined with the Analytic Hierarchy Process (AHP) involving agricultural meteorology experts. These thresholds are dynamically adjusted based on regional climate sensitivity to ensure local applicability and minimize arbitrary classification.

E. GRID BASED PRECISE WARNING RELEASE TECHNOLOGY

1km grid based warning product

Discretize the warning result space into 1km $\times$ 1km grid points to achieve precise positioning at the field level and avoid the extensive problem of traditional area based warning.

F. MULTI CHANNEL INTELLIGENT PUBLISHING

Build an integrated publishing platform of web end, mobile end APP, applet, SMS, official account, radio, and large screen terminal, support accurate push by region, crop, and planting subject, and achieve quick access to early warning information.

Warning closed-loop management

Establish a closed-loop mechanism for optimizing the evaluation model of disaster reporting effectiveness based on the feedback of warning release receipts, disposal scheduling, and continuous improvement of warning accuracy and practicality.

VI. SYSTEM INTEGRATION AND EMPIRICAL ANALYSIS

A. OVERALL ARCHITECTURE OF TECHNICAL SYSTEM

Design a five layer system using microservice architecture:

1. Data access layer: real-time collection and standardization of multi-source data;
2. Data fusion layer: spatiotemporal registration, quality control, deep fusion;
3. Algorithm service layer: disaster identification, risk assessment, intelligent warning;
4. Application service layer: monitoring and mapping, risk warning, decision support;
5. Terminal display layer: multi-channel visual publishing and interaction.

B. CORE FUNCTIONAL MODULES

1. Multi source data management module; 2. Spatiotemporal fusion calculation module; 3. Disaster intelligent recognition module; 4. Risk dynamic assessment module; 5. Hierarchical warning release module; 6. Disaster reporting and statistics module; 7. Decision support and scheduling module.

C. EMPIRICAL REGIONS AND DATA

Selecting the winter wheat region in North China, the summer corn region in the Huang Huai region, and the rice region in the middle and lower reaches of the Yangtze River as empirical areas, collecting multi-source meteorological data, crop data, and disaster data from 2018 to 2025, and conducting business operation experiments.

D. FUSION EFFECT VERIFICATION

Compared to a single data source, multi-source fusion data reduces RMSE by 18% to 25%, increases R to above 0.9, and achieves NSE above 0.85, significantly improving spatial continuity and regional consistency.

E. DISASTER IDENTIFICATION AND WARNING EFFECTIVENESS

Using an independent test set of 4,500 samples and addressing class imbalance via the SMOTE algorithm, the model achieved accuracies of 93.2% for drought, 92.7% for floods, 91.5% for low-temperature freezing damage, and 90.8% for dry and hot winds. To evaluate operational practicality, the False Alarm Rate (FAR) was controlled below 8.5% and the Missing Alarm Rate (MAR) was kept under 6.2%, effectively mitigating the “cry wolf” effect in early warnings.

F. ANALYSIS OF DISASTER REDUCTION BENEFITS

After adopting this technology in the empirical region, a comparative analysis with historical trends and synchronized control areas using the Difference-in-Differences (DID) method showed that the average agricultural disaster losses were reduced by 12% to 18%. Even after accounting for the system’s deployment and maintenance costs, the net economic benefit remained significant, with a cost-benefit ratio exceeding 1:5, while the disaster response efficiency of farmers was improved by 50%.

G. TECHNICAL APPLICABILITY AND OPTIMIZATION DIRECTION

The technology is applicable to major agricultural areas in China and has good scalability for complex terrain, facility agriculture, and characteristic economic crops; In the future, it can further improve the real-time performance of edge computing, strengthen the learning ability of small sample disasters, and improve the multi disaster coupling early warning logic.

VII. CONCLUSION AND PROSPECT

A. MAIN CONCLUSIONS

1. Build an integrated multi-source meteorological data system for space-based and ground-based numerical forecasting, establish standardized preprocessing and spatiotemporal registration processes, and effectively solve the problem of inconsistent heterogeneous data.
2. Propose a multi-source data fusion algorithm that combines dynamic weights with deep learning, which significantly improves the fusion accuracy compared to traditional methods and provides a high-quality data foundation for disaster monitoring.
3. Establish a multi hazard intelligent identification and risk dynamic assessment model that couples crop growth periods, achieving high-precision and high timeliness disaster identification and risk mapping.
4. Build an integrated grid based intelligent early warning technology system for long, medium, and short term, with extended warning advance, improved spatial resolution, enhanced release accuracy, and outstanding business application effects.
5. Develop replicable and scalable intelligent monitoring and early warning technology solutions for agricultural disasters, empirically verify significant disaster reduction benefits, and provide key technical support for food security.

B. INSUFFICIENT RESEARCH

1. There is still room for improvement in the model’s generalization ability due to insufficient samples of extreme

rare disasters;

2. The accuracy of data fusion and monitoring in complex terrains such as plateaus and mountains needs to be further improved;

3. The research on the coupling warning of disaster chain and secondary disasters is not deep enough;

4. The deployment of lightweight models at the edge and real-time computing efficiency still need to be optimized.

C. FUTURE OUTLOOK

1. Integrating big models and digital twin technology to build a virtual simulation and accurate prediction system for agricultural disasters;

2. Promote the construction of an integrated intelligent observation network for air, space, and earth, and achieve centimeter level and kilometer level multi-scale collaborative monitoring;

3. Deepen the research on the chain evolution law of multiple disasters, and construct a full chain disaster warning and emergency dispatch system;

4. Promote the deep integration of technology with agricultural insurance, financial credit, and agricultural machinery scheduling to form a smart disaster prevention and mitigation ecosystem;

5. Establish national standardized technical specifications to support the full coverage of intelligent monitoring and early warning services for agricultural disasters nationwide.

AUTHOR CONTRIBUTIONS

Conceptualization – Li Qiang, Zhang Ting, Yang QingYi, Xia Quan, Liu Fan and Lei Jun; methodology – Li Qiang, Zhang Ting, Yang QingYi, Liu Fan and Lei Jun; investigation – Li Qiang, Zhang Ting, Yang QingYi, Xia Quan, Liu Fan and Lei Jun; writing-original draft preparation – Li Qiang, Zhang Ting, Yang QingYi, Xia Quan, Liu Fan and Lei Jun. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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