Scientific Papers. Series E. Land Reclamation, Earth Observation & Surveying, Environmental Engineering. Vol. XV, 2026
Print ISSN 2285-6064, CD-ROM ISSN 2285-6072, Online ISSN 2393-5138, ISSN-L 2285-6064

REAL-TIME PATHOGEN RISK MAPPING IN CEREAL FIELDS THROUGH INTEGRATED UAV, GIS AND SMART FORECASTING TOOLS

Dragoș Andrei CÎRCIUMARIU[1], Mirela PARASCHIVU[2], Constantin ȘULEA-IORGULESCU[1], Dorin SENDRESCU[1]

[1]University of Craiova, Faculty of Automatics, Computer Science and Electronics, 107 Decebal Blvd, Craiova, Dolj County, Romania
[2]University of Craiova, Faculty of Agronomy, 19 Libertății Street, Craiova, Dolj County, Romania

Corresponding author email: paraschivumirela@yahoo.com

Abstract

Cereal crop production faces persistent threats from biotic stresses caused by pathogenic organisms, resulting in significant yield loss and increased management costs. Conventional disease monitoring methods are often limited by spatial resolution, labor intensity, and delayed detection. Integrating unmanned aerial vehicles (UAVs), geographic information systems (GIS), and smart forecasting tools offers potential for real-time, spatially explicit pathogen risk mapping in cereal fields. This review synthesizes state-of-the-art methodologies in UAV remote sensing, GIS spatial analysis, and predictive modelling, emphasizing advances in machine learning for disease detection and risk assessment. Current challenges including data integration, operational constraints, and technological gaps are identified, and future research directions are outlined to facilitate adoption within precision agriculture and environmental engineering frameworks.

Key words**:** *cereal crops, GIS, pathogen detection, risk mapping, smart forecasting, UAV remote sensing.*

INTRODUCTION

Cereal crops such as wheat, barley, and maize represent a fundamental component of global food security; however, their productivity is significantly threatened by plant pathogens that can cause severe yield and quality losses. Globally, crop losses in wheat due to plant diseases are estimated to cause economic damages of approximately US$ 4-10 billion annually, highlighting the significant impact of pathogens on global food security (Chai et al., 2022). As the global population is projected to approach nearly 10 billion by 2050, the pressure on agricultural systems to ensure stable and sufficient cereal production will intensify (United Nations, 2019). Wheat and other staple crops will be required to maintain high productivity under increasingly variable climatic conditions, where plant diseases remain a major constraint to yield stability (Savary et al., 2019). In this context, conventional reactive approaches to crop protection are insufficient to meet future food demands.

Fungal diseases such as Rusts (RSTs), Powdery Mildew (PM), Septoria Leaf Blotch (SLB) and Fusarium Head Blight (FHB) are among the most destructive diseases affecting cereal production worldwide, often developing rapidly under favorable environmental conditions and spreading across large agricultural areas (Chaloner et al., 2021; Cotuna et al., 2021, 2022; Kouadio et al., 2023; Paraschivu et al., 2023). The increasing frequency of plant disease outbreaks, driven by global trade and climate variability, highlights the need for more efficient monitoring and early warning systems capable of supporting timely crop protection strategies. Thus, phytosanitary management of wheat (*Triticum aestivum* L.) represents a major challenge in the current context of climate change and the ongoing transition toward more sustainable and environmentally friendly agricultural systems (Velea et al., 2021; Bonciu, 2022). The resilience of wheat crops to pathogen attacks does not depend on a single factor but rather results from complex interactions among plant genetics, nutritional status, and crop management practices. Understanding these interactions is essential for developing effective strategies aimed at improving plant health and reducing disease incidence in cereal production

systems (Păunescu et al., 2022, 2023; Iacob et al., 2025).

Recent studies have shown that plants subjected to prolonged water stress, often expressed through increased rates of water loss at the level of the flag leaf, exhibit greater susceptibility to pathogen infections (Atkinson and Urwin, 2012; Naz et al., 2021). This increased vulnerability is associated with physiological imbalances and a weakened plant defense system, which may compromise the plant's ability to respond effectively to biotic stress factors (Pandey et al., 2015). Consequently, environmental stress conditions can significantly influence the epidemiology and severity of diseases affecting wheat crops. In addition, the choice of cropping system and the optimization of plant physiological status through the application of foliar fertilizers play an important role in strengthening the plant's natural defense mechanisms. These practices contribute not only to maintaining high yield potential but also to improving grain quality and overall crop performance (Roșculete et al., 2023).

Despite these advances in agronomic management, early detection and spatial monitoring of plant diseases remain critical challenges in modern cereal production systems. Conventional field scouting methods are often limited by time, labor requirements, and restricted spatial coverage, making it difficult to detect early disease symptoms or accurately assess the spatial distribution of pathogens within large agricultural fields. In this context, digital agriculture technologies have emerged as valuable tools for improving crop monitoring and disease detection (Seelan et al., 2003; Mahlein et al., 2012; Barbedo, 2019).

Recent progress in remote sensing technologies, particularly the use of unmanned aerial vehicles (UAVs), has significantly enhanced the capacity to monitor crop health at high spatial and temporal resolutions. UAV platforms equipped with RGB, multispectral, or hyperspectral sensors enable rapid acquisition of detailed crop imagery, allowing the detection of subtle physiological and structural changes associated with plant stress and early disease development (Feng et al., 2021; Neupane & Baysal-Gurel, 2021; Bouguettaya et al., 2023). When combined with geographic information systems (GIS), these datasets can be integrated with environmental variables, crop management information, and historical disease records to generate spatially explicit maps of crop health and pathogen risk. Moreover, the integration of remote sensing data with predictive disease forecasting models based on meteorological parameters and epidemiological indicators can further improve the accuracy of disease monitoring systems. Such integrated approaches enable the development of real-time pathogen risk maps that identify areas with increased probability of infection, thereby supporting targeted crop protection measures and optimizing the use of phytosanitary treatments.

In this context, the present study aims to develop an integrated framework for real-time pathogen risk mapping in cereal fields through the combined use of UAV-derived imagery, GIS-based spatial analysis, and smart forecasting tools. By linking high-resolution spatial monitoring with predictive disease modeling, this approach seeks to improve early detection of plant health risks and provide decision-support tools for precision phytosanitary management in cereal production systems.

MATERIALS AND METHODS

The present study adopts a qualitative, information-oriented research design, based on an extensive review of diverse sources, including academic books, peer-reviewed journal articles, technical reports, news publications, and relevant online databases. The available literature was systematically identified, critically evaluated, and synthesized to provide a comprehensive overview of the current state of knowledge, as well as to highlight emerging trends and future research directions related to the topic (Tranfield et al., 2003). This systematic quantitative review of the scientific literature was conducted in accordance with the methodological framework proposed by Pickering and Byrne (2014). A defined set of search keywords ("UAV", "plant", "disease", "GIS") was employed to systematically explore the literature within the Scopus and Web of Science databases, with the

aim of identifying relevant studies published in peer-reviewed, English-language academic journals focusing on UAV-based applications for plant disease detection and monitoring.

In order to achieve the objectives of this study, a combination of systematic, semi-systematic, and integrative review methodologies was employed. This approach involved a rigorous comparative analysis of existing scientific publications, empirical studies, reports, and statistical datasets, with the aim of generating robust insights and identifying gaps within the existing body of knowledge (Snyder, 2019). Furthermore, text-mining techniques were applied as an analytical tool to process large volumes of textual data, facilitating the extraction of meaningful patterns, relationships, and thematic structures. The reviewed literature and associated sources are organized and presented in the following sections of this paper.

RESULTS AND DISCUSSIONS

Pathogen Dynamics in Cereal Cropping Systems

Many previous studies indicate that tillage practices, cultivation technology, fertilisation levels, and cultivar selection influence the incidence of fungal diseases in cereals (Elen, 2003; Korbas et al., 2008; Horoszkiewicz-Janka et al., 2012; Cotuna et al., 2013; Paraschivu et al., 2021, 2022; Różewicz et al., 2021; Richard et al., 2022; Chețan et al., 2025). Nevertheless, the prevalence of these pathogens is determined mainly by weather conditions throughout plant growth and development (Cotuna et al., 2018; Paraschivu et al., 2017, 2019; Miedaner & Juroszek, 2021; Asfew & Bedemo, 2022; Ahmad et al., 2024; Rubayet & Hossaint, 2024). In many production regions, disease pressure is intensifying due to warmer temperatures, irregular rainfall patterns, changing cropping systems, and the expansion of pathogen dispersal routes through trade and atmospheric movement (Różewicz et al., 2021; Velea et al., 2021).

Rust fungi in wheat (stem rust - *Puccinia graminis* f. sp. *tritici*, leaf rust -*Puccinia triticina* and stripe rust - *Puccinia striiformis* f. sp. *tritici*) are among the most destructive pathogens of cereals worldwide. These obligate biotrophic fungi can spread rapidly over long distances through airborne urediniospores and may cause severe yield losses when susceptible cultivars are grown. Cool to moderate temperatures and prolonged leaf wetness typically favour stripe rust, whereas leaf rust often develops under mild temperatures with intermittent moisture. Stem rust generally thrives under warmer conditions and can become highly aggressive when night time humidity supports infection. Recent studies indicate that climate change may shift the geographic suitability of rust diseases and alter the effectiveness of host resistance genes (Juroszek & von Tiedemann, 2013).

Fusarium species, especially *Fusarium graminearum* and related taxa, are major pathogens of wheat, barley, and maize. In small grains, they cause Fusarium head blight (FHB), while in maize they are associated with ear and stalk rots. Beyond yield reduction, Fusarium diseases are particularly important because they contaminate grain with mycotoxins such as deoxynivalenol and zearalenone, creating serious food and feed safety risks. Epidemics are strongly linked to humid weather during flowering, frequent rainfall, and warm temperatures that favor spore production and infection (Cotuna et al., 2022). Crop residues from maize or cereals also serve as major inoculum reservoirs, making reduced tillage and cereal-intensive rotations important risk factors. In several European regions, recent weather extremes have further emphasized the interaction between local microclimate and Fusarium contamination patterns (Różewicz et al., 2021; Cotuna et al., 2022; Martínez et al., 2022).

Leaf blotch diseases caused by *Zymoseptoria tritici* (Septoria tritici blotch), *Parastagonosporanodorum*, and *Pyrenophora tritici-repentis* (tan spot) are major constraints in temperate cereal systems. These pathogens survive on infected crop residues and initiate new epidemics through splash-dispersed spores. Their development is promoted by extended periods of leaf wetness, dense crop canopies, moderate temperatures, and frequent rainfall events (Downie et al., 2021; Prahl et al., 2023). Conservation tillage practices, while beneficial for soil health, may increase residue persistence and therefore early-season inoculum pressure when rotations are narrow.

Because these diseases often begin in lower canopy leaves before progressing upward, they are strongly influenced by canopy microclimate and crop architecture (Laribi et al., 2024).

Powdery mildew, caused by *Blumeria graminis* formae speciales, affects wheat, barley, and other cereals globally. Unlike many foliar pathogens, powdery mildew does not require free water for infection and frequently develops under high relative humidity combined with moderate temperatures. Dense stands, excessive nitrogen fertilization, and prolonged periods of humid air circulation within the canopy can accelerate epidemic development (Różewicz et al., 2021; Farda et al., 2026).

Consequently, understanding the major cereal pathogens and the environmental factors that drive epidemics has become a priority for sustainable crop protection.

Spatial and Temporal Characteristics of Disease Spreadand Implications of Environmental Monitoring

The epidemiology of cereal diseases is inherently dynamic, as infection processes evolve across space and time in response to host phenology, pathogen biology, agronomic practices, and environmental variability. Thus, pathogens in cereal crops are typically distributed unevenly within fields, generating clusters, gradients, or patchy infection zones rather than homogeneous disease incidence. heterogeneity reflects variation in soil properties, topography, moisture retention, plant density, nutrient availability, and the proximity of primary inoculum sources. Residue-borne pathogens such as *Zymoseptoria tritici*, *Pyrenophora tritici-repentis*, and *Parastagonosporanodorum* are often established near infected residues, from which disease expands progressively through splash dispersal and short-range spore movement (Petit-Houdenot et al., 2021). By contrast, airborne pathogens such as rust fungi (*Puccinia* spp.) may initially appear in scattered hotspots before rapidly colonizing large areas under favourable atmospheric conditions (Radici et al., 2022; Hovmøller et al., 2023). Recent geostatistical studies have demonstrated that spatial autocorrelation of disease intensity can be used to identify infection hotspots and optimize sampling strategies in cereal fields (Amoghavarsha et al., 2022; Mergenthaler et al., 2022; Singh et al., 2023).

The temporal development of cereal diseases is closely linked to crop growth stage and seasonal weather patterns. Many pathogens require specific host tissues or phenological stages to complete infection successfully. For example, Fusarium head blight risk increases markedly during anthesis and early grain filling when spikes are highly susceptible, particularly under humid and warm conditions. Stripe rust epidemics may accelerate during cool and moist spring periods, whereas powdery mildew often develops earlier in the season under moderate temperatures and high relative humidity.

Disease progress over time is frequently described by sigmoidal epidemic curves characterized by an initial latent phase, exponential increase, and saturation stage (Chandran et al., 2025). The duration of each phase depends on inoculum availability, host susceptibility and environmental conduciveness (Dhavale et al., 2025). Shortened latent periods under optimal temperature and moisture conditions can lead to explosive epidemic growth, while intermittent drought or heat stress may suppress some pathogens but predispose plants to others. Consequently, accurate timing of disease risk is as important as identifying where disease occurs.

Disease spread in cereals occurs across multiple spatial scales, from individual leaves to continental regions (Gutaker & Purugganan, 2024). At the field scale, splash dispersal, contact transmission, and short-distance wind movement drive local spread (Karisto et al., 2022). At the landscape scale, crop mosaics, field connectivity, alternate hosts, and topographic corridors influence epidemic connectivity among farms (Fernandes et al., 2022). At regional and transboundary scales, long-distance atmospheric transport can move rust spores hundreds or thousands of kilometers, while seed trade may introduce emerging pathogens such as wheat blast into new production areas.

These scale-dependent processes have important management implications. Local outbreaks may be controlled through field-level interventions, whereas highly mobile pathogens require coordinated surveillance networks and

regional forecasting systems. Integrating multi-scale epidemiological knowledge is therefore critical for resilient cereal disease management.

UAV-Based Technologies for Pathogen Detection

Recent advances in remote sensing and geospatial analytics have expanded the capacity to monitor cereal diseases spatially. Unmanned aerial vehicles (UAVs), satellite imagery, and proximal sensors can detect changes in canopy reflectance, temperature, and structural traits associated with disease stress. When linked with geographic information systems (GIS), these observations can be transformed into disease distribution maps, hotspot analyses, and spatial decision-support layers.

Traditional detection methods - field scouting and laboratory diagnostics - often fail to identify outbreaks at early, asymptomatic stages when interventions are most effective. Conventional ground-based sampling provides limited spatial coverage and is temporally discontinuous, yielding insufficient insight into pathogen dispersion across heterogeneous agricultural landscapes (West & Kimber, 2015). While satellite remote sensing offers broad coverage, its utility for early, localized disease detection is constrained by fixed revisit intervals, coarse spatial resolution, and susceptibility to cloud cover.

Unmanned aerial vehicles (UAVs) bridge the observational gap between satellite and ground-based sensing by enabling rapid, repeated, high-resolution monitoring of crop canopies at user-defined temporal windows. Drones equipped with multi-modal sensor payloads can detect pre-symptomatic stress signatures invisible to the naked eye, with advantages including flexible deployment, comparatively low operational cost, and the capacity to acquire multi-sensor data (visual, spectral, thermal) at sub-centimeter resolutions unattainable by satellite platforms (Joshi et al., 2024; Xing et al., 2026).

However, most current UAV applications in agricultural phytopathology detect indirect disease signatures - spectral anomalies, canopy temperature deviations - rather than causal organisms directly. These responses are frequently non-specific, as similar patterns may arise from drought, nutrient deficiency, or thermal injury (Su et al., 2018). Molecular detection approaches (e.g., UAV-mounted spore traps for downstream DNA analysis) offer definitive identification but remain experimental, constrained by payload limitations and the absence of standardized airborne bioaerosol collection protocols (West & Kimber, 2015). These considerations position UAV-based monitoring as a critical component within a multi-layered surveillance architecture integrating aerial screening, geospatial risk modeling, and targeted ground-truth validation.

UAV Platforms and Sensor Types

Platform selection for cereal disease monitoring is governed by four interrelated constraints: area coverage per sortie, payload capacity, aerodynamic stability under field wind conditions, and operational simplicity for routine deployment. Three airframe categories are relevant:

Fixed-wing UAVs offer superior endurance (45-90 min) and area coverage for landscape-scale screening of large contiguous fields, though they require launch infrastructure and cannot hover for close inspection (Tsouros et al., 2019) (Table 1). **Multi-rotor UAVs** (quadcopters, hexacopters) provide vertical take-off/landing, precise hovering and ground sampling distances below 1 cm, making them ideal for repeated diagnostics over fragmented parcels, but endurance is limited to 20-40 minutes (Agrawal & Arafat, 2024). **Hybrid VTOL fixed-wing systems** combine deployment flexibility with cruise efficiency, increasingly relevant for operational monitoring networks with mixed field geometry (Joshi et al., 2024).

Sensor choice determines the detectable signal domain. **RGB cameras** are the most accessible, supporting canopy coverage metrics and texture-based ML classification, but lack sensitivity to early biochemical changes. **Multispectral sensors** (NIR and red-edge bands) represent the operational core of farm-scale monitoring, enabling vegetation index computation linked to chlorophyll dynamics and stress detection (Su et al., 2018). **Hyperspectral sensors** provide dense spectral fingerprints capturing subtle pre-symptomatic biochemical shifts, but impose greater payload,

cost, and processing demands (Mahlein, 2016). **Thermal infrared cameras** map canopy temperature fields revealing disease-associated thermal anomalies, particularly when interpreted with meteorological context (Khanal et al., 2017; Liu et al., 2024). **LiDAR** complements spectral sensors by providing 3D canopy structure data (Joshi et al., 2024). Emerging **biological/environmental samplers** (spore traps, VOC detectors) offer definitive identification potential but remain experimental (West & Kimber, 2015).

Table 1. UAV platform classes and pathogen detection suitability for cereal systems

UAV Class	Capabilities	Common Sensors	Detection Suitability
Micro/Mini Multi-rotor (<5 kg)	VTOL; 20-40 min; GSD <1 cm	RGB; compact multispectral; mini thermal	Plot-level diagnostics; limited area coverage
Small Multi-rotor (5-25 kg)	VTOL; 25-45 min; heavier payloads	Multispectral; hyperspectral; LiDAR; dual thermal-RGB	Field-scale multi-sensor missions
Small Fixed-wing (<25 kg)	45-90 min; 200–500 ha/flight	Multispectral; RGB; compact hyperspectral	Landscape screening; lower spatial detail
Hybrid VTOL Fixed-wing	VTOL launch; cruise efficiency; 40-75 min	Multispectral; RGB; thermal	Operational networks; mixed geometry

No single platform-sensor combination dominates all use cases; value is maximized when the sensor stack is fitted to the decision question - screening, risk ranking, or trigger for confirmatory sampling - while preserving measurement repeatability across campaigns.

Vegetation Indices and Spectral Indicators

Vegetation indices (VIs) transform multi-band reflectance into interpretable metrics of canopy physiology and serve as the primary screening tools in UAV-based disease monitoring. NDVI remains widely used due to simplicity and cross-study comparability, but exhibits well-documented saturation in dense cereal canopies during mid-to-late growth stages, limiting sensitivity to early physiological changes (Li et al., 2025). NDRE, exploiting the red-edge region (~700-750 nm), provides significantly improved responsiveness in medium-to-high biomass conditions and has been shown to outperform NDVI for detecting subtle chlorophyll degradation associated with rust and *Septoria* infections (Su et al., 2018). PRI captures short-term changes in photosynthetic light-use efficiency, offering complementary early-warning capability since biotic stress frequently affects photosystem function before structural damage is evident (Șulea et al., 2010; Mahlein, 2016).

Recent advances have introduced disease-specific indices with improved diagnostic precision. The Chlorophyll Absorption Ratio Index (CARI) isolates chlorophyll absorption effects while mitigating soil interference and canopy structural heterogeneity; models utilizing CARI have demonstrated substantial improvements over traditional RGB-based configurations for detecting early-stage fungal infections in cereals (Ali et al., 2025; Goluguri & Baik, 2026). Specialized narrow-band indices for specific pathosystems (e.g., rice blast, wheat rusts) have also shown classification accuracies exceeding 95% in controlled evaluations, significantly outperforming broad-band alternatives (Mahlein, 2016; Su et al., 2018). A fundamental limitation remains spectral ambiguity: similar VI decreases may result from water limitation, nutrient deficiency, thermal stress, or mixed interactions. State-of-the-art pipelines therefore combine spectral indices with texture descriptors, thermal signatures, phenological stage and meteorological context within multivariate ML frameworks to improve classification robustness (Su et al., 2018; Kavhu et al, 2021; Srivastava & Jain, 2025). However, temporal consistency - standardized radiometric calibration, acquisition timing, and preprocessing - is essential for reliable trend detection across campaigns.

Data Acquisition and Processing Challenges

The transition from research experiments to operational monitoring confronts several non-trivial challenges. At mission level, operators must negotiate trade-offs among spatial resolution, overlap, coverage, and flight duration within battery, weather, and regulatory constraints. Very high-resolution surveys (GSD < 1 cm) improve lesion detectability but dramatically increase data volume and processing burden. Radiometric consistency is a persistent challenge: illumination variability from solar angle changes and cloud transients, sensor drift, and wind-induced canopy

movement introduce errors degrading multi-temporal spectral comparability unless rigorous calibration using reflectance panels and atmospheric correction is applied (Fu et al., 2024).

Temporal acquisition strategy is critically important yet frequently under-optimized. Pathogen infection dynamics are driven by microclimate variables that change within hours; acquisitions that are too sparse or poorly timed may miss actionable disease development phases (Hossain et al., 2024; Kumar & Mukhopadhyay, 2025). The processing chain - orthomosaic generation, radiometric correction, feature extraction, model inference - can create substantial computational latency. Scalable deployment requires semi-automated pipelines, edge computing architectures, and clear quality-control checkpoints to reduce turnaround from days to hours. Supervised models require accurately labeled training data, but field annotation is labor-intensive and subject to inter-operator variability. Domain shift between cultivars, phenological stages, and regional conditions reduces model transferability without local recalibration (Kamilaris & Prenafeta-Boldú, 2018). Fragmented data formats and proprietary tools impede integration with GIS and decision support systems, necessitating community-accepted standards and interoperable workflows.

Contribution to Environmental Engineering Applications

UAV-based pathogen monitoring supports spatially explicit, risk-informed intervention strategies that reduce the ecological footprint of crop protection. Conventional management relies on calendar-based uniform fungicide applications - inherently inefficient, applying chemicals where pressure may be negligible, accelerating resistance development, and increasing off-target environmental exposure. Spatially explicit risk maps from UAV observations enable site-specific interventions directed exclusively to zones exceeding action thresholds. Empirical studies demonstrate that integrating UAV and satellite remote sensing can substantially decrease agrochemical application volumes alongside measurable reductions in irrigation water usage without yield penalties (Xing et al., 2026). This precision approach is particularly impactful in heterogeneous landscapes where disease-conducive microenvironments are influenced by soil texture gradients, drainage infrastructure, and micro-topographic variation. UAV-derived products improve mechanistic understanding of soil–water–plant–pathogen interactions and, when integrated with GIS layers (parcel boundaries, DEMs, drainage networks), become actionable planning tools supporting environmental compliance and evolving IPM policy frameworks (Wolfert et al., 2017). Environmental value is maximized when UAV surveillance is embedded in a three-step loop: rapid aerial screening, spatial risk synthesis in GIS, and targeted confirmatory sampling before intervention escalation.

GIS-BASED SPATIAL ANALYSIS AND RISK MAPPING

GIS as a Core Tool for Disease Risk Assessment

Geographic Information Systems (GIS) have become a cornerstone of plant disease risk assessment, owing to their capacity to integrate, manage, and analyze heterogeneous spatial datasets across multiple spatial and temporal scales. In cereal cropping systems, GIS facilitates the seamless fusion of UAV-derived remote sensing products with soil properties, climatic variables, and topographic information, enabling a comprehensive representation of disease–environment interactions (Geldsetzer et al., 2023).

A major strength of GIS lies in its ability to harmonize datasets originating from diverse acquisition platforms and temporal resolutions. High-resolution UAV imagery can be accurately georeferenced and spatially aligned with ancillary datasets such as soil surveys, digital elevation models (DEMs), cadastral boundaries, and meteorological observations. This spatial coherence is essential for reliable disease risk modeling, as pathogen development is strongly influenced by fine-scale variability in moisture availability, temperature regimes, and terrain-induced microclimatic conditions (Zhu et al., 2024). Within GIS environments, spatial interpolation techniques - including inverse distance weighting (IDW), ordinary kriging, and regression kriging - are widely employed to

convert discrete disease observations or point-based environmental measurements into continuous disease risk surfaces. These interpolated layers support field-scale visualization of infection probability gradients and enable spatially explicit decision-making (Cressie, 1993; Haggag et al., 2023). Recent studies demonstrate that GIS-based integration improves model robustness by explicitly accounting for spatial autocorrelation and reducing uncertainty in disease risk estimation, particularly in heterogeneous cereal landscapes (Shafay et al., 2025).

Critical assessment:
Advantages: Integration of multi-source spatial data; high-resolution field-scale mapping; generation of continuous disease risk surfaces.
Limitations: Strong dependence on data density and quality; reliance on static datasets that may fail to capture rapid disease dynamics; limited representation of temporal variability.
Improvement opportunities: Integration of near-real-time data streams; adoption of spatio-temporal GIS modeling approaches; development of standardized workflows to enhance cross-regional transferability.

Risk Mapping Techniques
Disease risk mapping in GIS relies on a combination of deterministic, statistical, and decision-support techniques aimed at classifying, quantifying, and spatially delineating areas susceptible to pathogen outbreaks. Zoning and classification approaches are commonly used to categorize agricultural land into discrete risk classes (e.g., low, moderate, high) based on vegetation indices, environmental variables, and crop phenological stages (Ahmed & Yadav, 2023). These methods provide intuitive outputs that facilitate the interpretation of complex datasets and support operational decision-making at farm level. Multi-Criteria Decision Analysis (MCDA) has emerged as a prominent framework for integrating multiple disease risk factors into composite spatial indices. MCDA allows the explicit weighting of criteria such as temperature accumulation, relative humidity, canopy density, soil moisture, and topographic attributes, reflecting their relative influence on pathogen development. When implemented within a GIS environment, MCDA offers transparency, flexibility, and adaptability to different crops, pathogens, and agro-climatic contexts (Malczewski, 2006).
Beyond classification-based methods, spatial statistical techniques—including hotspot and cluster analysis—play a critical role in identifying localized zones of disease intensification. Indicators such as Moran's I and Getis–Ord Gi* statistics enable the detection of spatial dependence and statistically significant disease clusters, supporting early warning systems and targeted intervention strategies (Getis & Ord, 1992; Haggag et al., 2023). These approaches underpin the transition from uniform treatment practices toward precision disease management.

Critical assessment:
Advantages: Intuitive spatial outputs; MCDA enables structured integration of multiple risk factors; hotspot analysis identifies disease clusters.
Limitations: Classification thresholds are context-dependent; MCDA weighting schemes may introduce subjectivity; reliable statistical inference requires historical datasets.
Improvement opportunities: Hybrid MCDA frameworks incorporating machine learning-based weighting; dynamic risk classification schemes; explicit uncertainty quantification in risk maps.

Integration with Land Reclamation and Surveying Data
Integrating land reclamation and surveying datasets into GIS-based disease risk mapping substantially enhances the operational relevance of spatial analyses. Cadastral data provide legally defined parcel boundaries, ensuring alignment between disease risk maps and farm management units and facilitating the implementation of precision interventions at parcel scale (FAO, 2007).
Drainage infrastructure maps, land capability assessments, and soil reclamation records offer valuable insights into soil–water dynamics, which are critical determinants of pathogen proliferation in cereal cropping systems. Areas characterized by inadequate drainage, specific soil textures, or unfavorable microrelief conditions are frequently associated with

elevated disease pressure, particularly for fungal pathogens. Incorporating these datasets into GIS-based models improves explanatory capacity and enhances the accuracy of spatial risk predictions (Bielecka & Burek, 2019; Tsouros et al., 2019). Furthermore, the integration of surveying and land-use data supports site-specific intervention planning by linking disease risk zones to field accessibility, land-use constraints, and environmental protection areas. This capability is increasingly important in the context of sustainable land management, where disease control strategies must reconcile productivity goals with regulatory compliance and environmental protection requirements (Zhu et al., 2024).

Critical assessment:

Advantages: Alignment with farm management units; improved understanding of soil–water–disease interactions; support for precision interventions.

Limitations: Outdated or inconsistent cadastral and reclamation datasets; limited interoperability; uneven availability of high-resolution data.

Improvement opportunities: Digital modernization of cadastral systems; adoption of open geospatial standards; coupling with UAV-derived micro-topographic models.

Epidemiological and Agro-Meteorological Models

Epidemiological and agro-meteorological models constitute the traditional backbone of disease forecasting in cereal cropping systems, as they explicitly describe the interactions between pathogen development, host susceptibility, and environmental drivers. Weather-based disease forecasting models are typically driven by key meteorological variables such as air temperature, relative humidity, precipitation, leaf wetness duration, and wind dynamics, all of which exert a strong influence on pathogen life cycles, infection efficiency, and dispersal mechanisms (Misra et al., 2020; Sangeetha et al., 2025).

Classical agro-meteorological approaches rely on threshold-based or cumulative indicators, including degree-day accumulation, prolonged canopy wetness, and specific temperature–humidity combinations favorable to infection (González-Domínguez et al., 2023). These models have been widely applied to major cereal diseases, such as rusts, fusarium head blight, and leaf blotch complexes, offering early warning capabilities that support timely disease management decisions.

The principal advantage of epidemiological models lies in their biological interpretability and relatively modest data requirements, as they can operate using standard meteorological observations or gridded climate datasets (Rahman et al., 2023). Their mechanistic foundation facilitates transparency and acceptance among agronomists and land managers. However, these models often rely on simplified assumptions regarding host uniformity and pathogen behavior, and they may insufficiently represent spatial heterogeneity at field scale. Furthermore, their predictive performance may decrease under conditions of increasing climate variability or when applied outside the agro-ecological contexts for which they were originally calibrated (Martínez-Cadena et al., 2026).

Recent research emphasizes the integration of agro-meteorological models with GIS-based spatial layers to improve spatial resolution and contextual relevance (Chandel, 2025; Rawat et al., 2026). Nevertheless, the inherent limitations of purely mechanistic approaches highlight the need for complementary data-driven and hybrid modeling strategies.

Critical assessment:

Advantages: Biologically interpretable; low computational requirements; effective for early warning.

Limitations: Limited spatial resolution; simplified disease dynamics; reduced robustness under climate variability.

Improvement opportunities: Spatial downscaling through GIS; hybridization with data-driven models; incorporation of microclimate variability.

Machine Learning and Artificial Intelligence Approaches

Machine learning (ML) and artificial intelligence (AI) approaches have gained increasing prominence in crop disease forecasting due to their capacity to capture complex, non-linear relationships among environmental variables, crop conditions, and pathogen dynamics (Tammina et al., 2024;

Basu & Narayan, 2025). Supervised learning techniques - such as random forests, support vector machines, artificial neural networks, and gradient boosting algorithms - are commonly employed to predict disease occurrence, severity, or risk classes using labeled datasets (González-Rodríguez et al., 2024; Ajaharuddin et al., 2025).

Unsupervised learning methods, including clustering and dimensionality reduction techniques, are used to identify latent patterns in multi-source datasets, enabling the detection of emerging disease hotspots or anomalous crop stress signals without requiring extensive ground truth data. These approaches are particularly valuable in exploratory analyses and in large-scale monitoring contexts.

A major strength of ML-based models lies in their ability to integrate high-dimensional inputs derived from UAV-based remote sensing and GIS layers. Spectral features extracted from multispectral and hyperspectral imagery, vegetation indices, canopy texture metrics, topographic attributes, soil parameters, and agro-meteorological variables can be jointly analyzed within unified modeling frameworks. This integration enables spatially explicit disease risk predictions that reflect both biophysical crop status and environmental constraints. Despite their strong predictive performance, ML and AI approaches face challenges related to data dependency, interpretability, and generalization. Model robustness is highly sensitive to data quality, temporal coverage, and representativeness, while limited transparency may hinder trust and adoption by end users. As a result, hybrid modeling paradigms that combine epidemiological knowledge with machine learning techniques are increasingly advocated as a means to balance interpretability and predictive accuracy.

Critical assessment:

Advantages: High predictive accuracy; effective integration of multi-source datasets; fine spatial resolution.

Limitations: Data-intensive; limited interpretability; risk of overfitting and reduced transferability.

Improvement opportunities: Explainable AI methods; hybrid epidemiological–ML frameworks; standardized datasets for model training and validation.

Real-Time Decision Support Systems

Real-time decision support systems (DSS) represent the operational layer of smart forecasting architectures, translating model outputs into actionable recommendations for agricultural risk management. In cereal cropping systems, these platforms increasingly rely on cloud-based infrastructures that enable continuous data ingestion, processing, and visualization from UAVs, ground sensors, meteorological services, and GIS databases.

A relevant operational reference for such architectures is provided by the decision support systems developed for Romanian national anti-hail protection networks. These systems were designed to support rapid operational decisions by integrating real-time meteorological observations, radar data, numerical weather prediction outputs, and spatial zoning information within centralized informatic platforms. Their primary objective was to assess the spatio-temporal evolution of convective hazards and to assist intervention decisions under strict temporal constraints (Șulea et al., 2010; 2011).

The core principles underpinning these anti-hail DSS - continuous data acquisition, real-time spatial analysis, threshold-based and probabilistic risk evaluation, and operator-oriented visualization - are directly applicable to pathogen risk management in agriculture. Similar to hail hazards, disease outbreaks are strongly influenced by short-term atmospheric dynamics, microclimatic variability, and spatial heterogeneity in land and crop conditions. When embedded within GIS environments, DSS can generate dynamic disease risk maps that evolve in response to changing environmental drivers.

Furthermore, the integration of Internet of Things (IoT) technologies enhances the temporal resolution of DSS by providing near-real-time measurements of microclimate parameters, soil moisture, and canopy conditions. When combined with UAV-derived indicators and forecasting models - whether epidemiological or machine learning-based - these systems enable adaptive risk assessments and early warning alerts tailored to specific

fields or management units. GIS acts as the spatial integration backbone, ensuring data consistency and enabling intuitive, map-based communication of risk levels.

Experience gained from operational anti-hail DSS demonstrates the feasibility and robustness of real-time, spatially explicit decision support under complex environmental conditions. However, extending these systems to crop disease management requires addressing challenges related to system scalability, data interoperability, and user accessibility. Simplified interfaces and automated workflows are essential to facilitate adoption by farmers and land managers while preserving the analytical rigor of the underlying models.

Critical assessment:

Advantages: Proven real-time operational capability; integration of meteorological forecasting and spatial analysis; transferable architecture for early warning systems.

Limitations: High system complexity; reliance on dense monitoring networks; need for specialized technical expertise.

Improvement opportunities: User-oriented DSS interfaces; tighter integration with UAV-based disease indicators; linkage with regional and national agricultural monitoring platforms.

Implications for Policy and Precision Agriculture

GIS-based pathogen risk mapping has substantial implications for agricultural policy formulation and the adoption of precision agriculture practices. By delivering spatially explicit, risk-based assessments, integrated UAV-GIS systems support evidence-driven decision-making at both farm and policy levels. These tools enable optimized input allocation, reduced pesticide use, and the implementation of more sustainable crop protection strategies consistent with environmental engineering principles (Wolfert et al., 2017; Ahmed & Yadav, 2023).

At the policy level, spatial disease risk mapping aligns closely with European and global environmental monitoring initiatives, including the Common Agricultural Policy (CAP) and the Copernicus Earth Observation Programme. These frameworks prioritize digitalization, climate resilience, and data-driven land management as central pillars of modern agriculture. GIS-supported disease monitoring contributes directly to these objectives by providing scalable solutions for surveillance, early warning, and compliance monitoring across agricultural landscapes (European Commission, 2022; 2024).

Moreover, the integration of Earth Observation, GIS, and smart forecasting tools facilitates a shift toward risk-based land management, where interventions are guided by probabilistic spatial assessments rather than uniform prescriptions. This paradigm strengthens the role of geospatial intelligence as a critical interface between scientific innovation, environmental engineering, and agricultural governance in addressing challenges related to climate change, food security, and sustainable intensification.

Critical assessment:

Advantages: Enables risk-based management; enhances policy transparency; supports scalable and replicable monitoring frameworks.

Limitations: High technical complexity and implementation costs; lag between technological development and policy uptake; lack of standardized risk indicators.

Improvement opportunities: Development of policy-oriented GIS dashboards; incentives through CAP eco-schemes; harmonization of risk indicators aligned with EU and global standards (Table 2).

Table 2. Advantages, Limitations and Directions for Improvement

Section	Key Advantages	Main Limitations	Future Directions / Improvements
5.1 GIS as Core Tool	Multi-source data integration; high-resolution mapping; continuous risk surfaces	Data density & quality dependent; static datasets; limited temporal representation	Near-real-time data streams; spatio-temporal GIS models; standardized workflows
5.2 Risk Mapping Techniques	Intuitive outputs; MCDA integrates multiple factors; hotspot analysis identifies clusters	Context-specific thresholds; subjective MCDA weighting; relies on historical data	Hybrid MCDA + ML weighting; dynamic risk classification; uncertainty quantification
5.3 Integration with Surveying Data	Alignment with farm units; better soil–water–disease understanding; supports precision interventions	Outdated/inconsistent data; limited interoperability; non-uniform high-res data	Digital cadastral modernization; open geospatial standards; UAV micro-topography coupling
9.3 Policy & Precision Ag	Supports risk-based management; policy transparency; scalable monitoring	Technical complexity; policy adoption lag; lack of standardized indicators	GIS dashboards for policy; CAP eco-scheme incentives; harmonized EU/global risk indicators

Challenges, Limitations, and Research Gaps

Technical and Operational Constraints

Despite the promising experimental results surveyed above, several constraints limit the transition to large-scale deployment.

Data throughput: high-resolution UAV missions generate datasets of hundreds of GB per season; the sequential processing pipeline introduces substantial latency that may erode decision advantage during fast-spreading outbreaks.

Acquisition consistency: wind, illumination shifts, and battery limits introduce variability between campaigns unless strict QA/QC protocols and standardized SOPs are enforced (Su et al., 2018).

Model transferability: ML classifiers exhibit vulnerability to domain shift - a model trained on specific cultivar-climate conditions frequently degrades in new contexts without recalibration, requiring continuous local ground-truth annotation that restricts scalability (Kamilaris and Prenafeta-Boldú, 2018; Su et al., 2018).

Economic barriers: while standard RGB systems are cost-effective, transitioning to high-performance hyperspectral systems for early pre-symptomatic detection incurs substantially higher capital expenditure, creating accessibility barriers for smallholder operations (Agrawal and Arafat 2024, Xing et al., 2026).

Regulatory constraints: BVLOS operations essential for large-area coverage require special authorization, and fragmented frameworks across jurisdictions create planning uncertainty (Tsouros et al., 2019, Joshi et al., 2024).

Interoperability: proprietary formats, platform-specific tools, and non-standardized metadata schemas hinder integration with GIS and FMIS, constraining landscape-level environmental governance. The primary bottleneck is not sensing technology per se, but the absence of mature, standardized, low-friction operational pipelines.

Future Perspectives and Opportunities

Recent Earth observation advances are strengthening pathogen risk mapping along three convergent axes. **Sensor miniaturization:** compact multispectral, hyperspectral, and thermal payloads with improved signal-to-noise ratios are enabling increasingly capable multi-modal sensor stacks on low-cost commercial platforms (Su et al., 2018; Agrawal & Arafat, 2024). Emerging modalities include fluorescence imaging sensors detecting chlorophyll fluorescence emission linked to photosystem II efficiency, which has demonstrated pre-symptomatic detection capability in high-value pathosystems (Mahlein, 2016; Zarco-Tejada et al., 2018).

Temporal resolution: autonomous mission scheduling, waypoint-based operations, and multi-UAV coordination enable more frequent revisits for tracking disease trajectories rather than relying on isolated snapshots. Integration with high-revisit satellite constellations (Sentinel-2, PlanetScope) and ground IoT networks creates multi-scale observation stacks improving monitoring continuity and gap-filling resilience (Xing et al., 2026).

Processing architectures: the shift to cloud-native and edge computing dramatically reduces acquisition-to-output latency. Edge processing on or near the UAV delivers preliminary risk assessments during or immediately after acquisition (Agrawal & Arafat, 2024).

Methodologically, the field is transitioning from static risk maps toward **dynamic risk-state estimation** using Bayesian updating, ensemble modeling, and data assimilation, providing uncertainty-aware probabilistic outputs that communicate confidence levels to decision-makers (Wolfert et al., 2017). Deep learning architectures (CNNs, vision transformers) demonstrate superior feature extraction from complex UAV imagery, while explainable AI (XAI) methods address interpretability requirements for operational trust and regulatory acceptance (Kamilaris & Prenafeta-Boldu, 2018). An emerging frontier is **digital twin systems** in which real-time observations continuously calibrate virtual crop models simulating disease dynamics under current and projected conditions, enabling scenario analysis and adaptive resource allocation. The convergence of better sensors, smarter processing, and more sophisticated analytics positions integrated UAV–GIS–forecasting systems for a qualitative leap in operational readiness over the coming decade.

CONCLUSIONS

Major cereal pathogens remain highly responsive to environmental conditions, and their importance is expected to grow under ongoing climatic and agronomic change. Rusts, Fusarium diseases, residue-borne leaf blights, powdery mildew, and emerging threats such as wheat blast each respond to specific combinations of temperature, moisture, and management factors. A deeper understanding of these drivers is therefore essential for building resilient cereal production systems and designing next-generation phytosanitary strategies based on prevention, prediction, and precision management.

The spread of diseases in cereals is shaped by complex spatial and temporal processes that operate from leaf to landscape scales. Environmental monitoring provides a critical foundation for understanding and anticipating these processes, particularly when integrated with remote sensing, GIS, and predictive epidemiological models. Future phytosanitary strategies should therefore prioritize spatiotemporal intelligence and real-time decision support to improve sustainability, reduce unnecessary chemical inputs, and enhance resilience in cereal production systems.

The present study demonstrates that the integration of unmanned aerial vehicle (UAV) sensing, geographic information systems (GIS), and smart forecasting tools provides an effective framework for real-time pathogen risk mapping in cereal production systems. By combining high-resolution spatial observations with environmental monitoring and predictive epidemiological analytics, this approach enables earlier identification of disease-prone zones than conventionalm scouting methods and supports a more precise understanding of within-field disease dynamics.

The results highlight that pathogen risk in cereal fields is inherently heterogeneous and strongly influenced by interactions among crop status, microclimate, field variability, and short-term weather conditions. Consequently, static or calendar-based protection strategies are often insufficient to capture the rapidly changing nature of disease development. In contrast, dynamic risk maps generated from integrated digital datasets can improve the timing and spatial targeting of interventions, thereby increasing management efficiency and reducing unnecessary phytosanitary inputs.

The study also confirms that the value of UAV imagery is substantially enhanced when remote sensing outputs are interpreted together with GIS-based spatial layers and forecasting models rather than used as isolated diagnostic tools. This integrated perspective transforms crop observations into actionable intelligence, allowing farmers and advisors to move from reactive disease control toward anticipatory and preventive management. Despite these advances, several challenges remain for large-scale implementation. Model transferability across environments, sensor standardization, data interoperability, economic accessibility, and user-friendly interfaces will be critical for wider adoption. Future research should therefore focus on multi-season validation, incorporation of machine learning and pathogen-specific biological parameters, and the development of scalable platforms capable of operating across diverse cereal-growing regions.

Overall, real-time pathogen risk mapping represents a significant step toward next-generation cereal health management. The convergence of UAV technologies, geospatial analytics, and smart forecasting systems offers a practical pathway to more resilient, data-driven, and sustainable cereal production under current and future disease pressures.

AKNOWLEDGEMENTS

The authors would like to thank all colleagues and collaborators who provided valuable discussions and support during the preparation of this review.We also thank colleagues from the Department of Agricultural and Forestry Technologies (Phytopathology) and the Department of Automatics and Electronics from University of Craiova for their valuable comments and discussions during the preparation of this review.

USE OF GENERATIVE ARTIFICIAL INTELLIGENCE (GenAI)

The authors declare the use of Generative Artificial Intelligence (GenAI) tools in the preparation of this manuscript. GenAI was used exclusively for language editing and text refinement in the Introduction and Conclusions sections. All scientific content, data analysis, and interpretations were developed and verified by the authors.

REFERENCES

Agrawal, J., & Arafat, M. Y. (2024). Transforming farming: A review of AI-powered UAV technologies in precision agriculture. *Drones*, 8(11), 664. https://doi.org/10.3390/drones8110664

Ahmad, W., Bibi, N., Sanwal, M., Ahmed, R., Jamil, M., Kalsoom, R., Arif, M., & Fahad, S. (2024). Cereal crops in the era of climate change: An overview. In S. Fahad, S. Saud, T. Nawaz, L. Gu, M. Ahmad, & R. Zhou (Eds.), *Environment, climate, plant and vegetation growth* (pp. 609–630). Springer. https://doi.org/10.1007/978-3-031-69417-2_21

Ahmed, I., & Yadav, P. K. (2023). Plant disease detection using machine learning approaches. *Expert Systems*, *40*(5), e13136.

Ajaharuddin, S. K. M. D., Das, K. K., Kar, P., Goswami, S., Bhattacharya, S., & Maharana, C. (2025). Harnessing AI and Machine Learning for Effective Pest and Disease Control. In *Ecologically Mediated Development: Promoting Biodiversity Conservation and Food Security* (pp. 461-485). Singapore: Springer Nature Singapore.

Ali, N., Ullah, M., Mohammed, A., Bais, A., Berraies, S., Ruan, Y., Cuthbert, R. D., & Sangha, J. S. (2025). Advancing Fusarium Head Blight Detection in Wheat Crop: A Review and Future Directions to Sustainable Agriculture. *IEEE Transactions on Consumer Electronics*, 71(3), 7473–7491. https://doi.org/10.1109/TCE.2025.3549057

Amoghavarsha, C., Pramesh, D., Sridhara, S., Patil, B., Shil, S., Naik, G. R., Naik, M. K., Shokralla, S., El-Sabrout, A. M., Mahmoud, E. A., Elansary, H. O., Nayak, A., & Prasannakumar, M. K. (2022). Spatial distribution and identification of potential risk regions to rice blast disease in different rice ecosystems of Karnataka. *Scientific Reports*, 12, 7403. https://doi.org/10.1038/s41598-022-11453-9

Asfew, M., & Bedemo, A. (2022). Impact of climate change on cereal crops production in Ethiopia. *Advances in Agriculture*, 2022, 2208694. https://doi.org/10.1155/2022/2208694

Atkinson, N. J., & Urwin, P. E. (2012). The interaction of plant biotic and abiotic stresses: From genes to the field. *Journal of Experimental Botany*, 63(10), 3523–3543. https://doi.org/10.1093/jxb/ers100

Barbedo, J. G. A. (2019). A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. *Drones*, 3(2), Article 40. https://doi.org/10.3390/drones3020040

Basu, A., & Narayan, A. (2025). The role of machine learning in transforming agricultural practices: insights into crop yield optimization and disease detection. *Iran Journal of Computer Science*, *8*(4), 1199-1217.

Bielecka, E., & Burek, E. (2019). Spatial data quality and uncertainty publication patterns and trends by bibliometric analysis. *Open Geosciences*, 11(1), 219–235. https://doi.org/10.1515/geo-2019-0018

Bonciu, E. (2022). Trends in the evolution of organic agriculture at the global level – A brief review. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, 22(3), 81–86.

Bouguettaya, A., Zarzour, H., Kechida, A., & Taberkit, A. M. (2023). A survey on deep learning-based identification of plant and crop diseases from UAV-based aerial images. *Cluster Computing*, 26(2), 1297–1317. https://doi.org/10.1007/s10586-022-03627-x

Chai, Y., Senay, S., Horvath, D., & Pardey, P. (2022). Multi-peril pathogen risks to global wheat production: A probabilistic loss and investment assessment. *Frontiers in Plant Science*, 13, Article 1034600. https://doi.org/10.3389/fpls.2022.1034600

Chaloner, T. M., Gurr, S. J., & Bebber, D. P. (2021). Plant pathogen infection risk tracks global crop yields under climate change. *Nature Climate Change*, 11(8), 710–715. https://doi.org/10.1038/s41558-021-01104-8

Chandel, A. S. (2025). Mapping drought risks in agriculture: a GIS and remote sensing study of Nagele Arsi district, Ethiopia. *Cogent Food & Agriculture*, *11*(1), 2525319.

Chandran, J., Gopinath, P. P., Pramod, R., & Vijayan, A. (2025). Modeling plant disease epidemics: A comprehensive review of disease progress curves. *Journal of Sustainable Technology in Agriculture*, 1(2). https://doi.org/10.65287/josta.202512.72CB

Cheţan, F., Tărău, A., Vălean, A. M., Şopterean, L., Şimon, A., Urdă, C., Călugăr, R., Cheţan, C., Rusu, T., & Suciu, L. (2025). The influence of tillage systems on the occurrence of diseases and pests on spring cereals, in the Transylvanian Plateau. *Romanian Journal for Plant Protection*, 18, 20–31. https://doi.org/10.54574/RJPP.18.03

Cotuna, O., Sarateanu, V., Durau, C., Paraschivu, M., & Rusalin, G. (2013). Resistance reaction of some winter wheat genotypes to the attack of Fusarium graminearum L. Schw. in the climatic conditions of Banat Plain. *Research Journal of Agricultural Science*, 45(1), 117–122.

Cotuna, O., Paraschivu, M., Paraschivu, M., & Olaru, L. (2018). Influence of crop management on the impact of Zymoseptoria tritici in winter wheat in the context of climate change: An overview. *Research Journal of Agricultural Science*, 50(3), 69–74.

Cotuna, O., Paraschivu, M., Bulai, A., Toma, I., Sărăţeanu, V., Horablaga, N. M., & Buzna, C. (2021). Behaviour of some oat lines to the attack of the fungus Blumeria graminis (D. C.) f. sp. avenae

Em. Marchal. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, 21(4), 161–170.

Cotuna, O., Paraschivu, M., Sărățeanu, V., Partal, E., & Durău, C. C. (2022). Impact of fusarium head blight epidemics on the mycotoxins' accumulation in winter wheat grains. *Emirates Journal of Food and Agriculture*, 34(11), 949–962.

Cressie, N. A. C. (1993). *Statistics for spatial data*. John Wiley & Sons. https://doi.org/10.1002/9781119115151

Dhavale, M. C., Patel, D., & Khangarot, J. S., (2025). Plant disease epidemiology. In R. Yuvarani, U. Shankar, S.B. Gowdar, S. Kumar, S.S. Hiremath (Eds.), *Plant health and disease management: A modern approach* (p. 94-114). Textify Publishers

Downie, R. C., Lin, M., Corsi, B., Ficke, A., Lillemo, M., Oliver, R. P., Phan, T. T., Tan, K. C., & Cockram, J. (2021). Septoria nodorum blotch of wheat: Disease management and resistance breeding in the face of shifting disease dynamics and a changing environment. *Phytopathology*, 111(6), 906–920.

Elen, O. (2003). Long-term experiments with reduced tillage in spring cereals. III. Development of leaf diseases. *Crop Protection*, 22(1), 65–71. https://doi.org/10.1016/S0261-2194(02)00112-6

European Commission. (2022). Commission Implementing Regulation (EU) 2022/1173 of 31 May 2022 laying down rules for the application of Regulation (EU) 2021/2116 of the European Parliament and of the Council with regard to the integrated administration and control system in the common agricultural policy. *Official Journal of the European Union*, L 183, 23–34.
https://eur-lex.europa.eu/eli/reg_impl/2022/1173/oj/eng

European Commission. (2024). The Commission continues to simplify the common agricultural policy for EU farmers. *Agriculture and Rural Development*, 11 July 2024.
https://agriculture.ec.europa.eu/media/news/commission-continues-simplify-common-agricultural-policy-eu-farmers-2024-07-11_en

FAO. (2007). *Land Evaluation towards a Revised Framework*. FAO.

Farda, B., Sabbi, E., Fares, R., Djebaili, R., Mignini, A., Mitra, D., & Pellegrini, M. (2026). Shifting disease dynamics: Effect of climate change on plant pathogens and their management in field crops. *Journal of Plant Biochemistry and Biotechnology*, 35(1), 57–79. https://doi.org/10.1007/s13562-026-01042-6

Feng, L., Chen, S., Zhang, C., Zhang, Y., & He, Y. (2021). A comprehensive review on recent applications of unmanned aerial vehicle remote sensing with various sensors for high-throughput plant phenotyping. *Computers and Electronics in Agriculture*, *182*, 106033.

Fernandes, L. D., Mata, A. S., Godoy, W. A. C., & Reigada, C. (2022). Refuge distributions and landscape connectivity affect host-parasitoid dynamics: Motivations for biological control in agroecosystems. *PLOS ONE*, 17(4), e0267037. https://doi.org/10.1371/journal.pone.0267037

Fu, Y., Zhu, Z., Liu, L., Zhan, W., He, T., Shen, H., Zhao, J., Liu, Y., Zhang, H., Liu, Z., Xue, Y., & Ao, Z. (2024). Remote sensing time series analysis: A review of data and applications. *Journal of Remote Sensing*, 4, 0285. https://doi.org/10.34133/remotesensing.0285

Geldsetzer, T., Yackel, J., Tomar, K. S., Mahmud, M., Nandan, V., & Kumar, S. (2023). Melt pond detection on landfast sea ice using dual co-polarized Ku-band backscatter. *Remote Sensing of Environment*, 296, 113725. https://doi.org/10.1016/j.rse.2023.113725

Getis, A., & Ord, J. K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24(3), 189–206. https://doi.org/10.1111/j.1538-4632.1992.tb00261.x

Goluguri, N. V. R., & Baik, O. D. (2026). Revolutionizing wheat plant disease detection: A review of imaging, AI, and innovations. *Archives of Computational Methods in Engineering*, 33(5), 6883–6914. https://doi.org/10.1007/s11831-026-10502-0

González-Domínguez, E., Caffi, T., Rossi, V., Salotti, I., Fedele, G. (2023). Plant disease models and forecasting: changes in principles and applications over the last 50 years. *Phytopathology®*, *113*(4), 678-693.

González-Rodríguez, V. E., Izquierdo-Bueno, I., Cantoral, J. M., Carbú, M., Garrido, C. (2024). Artificial intelligence: a promising tool for application in phytopathology. *Horticulturae*, *10*(3), 197.

Gutaker, R. M., & Purugganan, M. D. (2024). Adaptation and the geographic spread of crop species. *Annual Review of Plant Biology*, 75, 679–706. https://doi.org/10.1146/annurev-arplant-060223-030954

Haggag, W. M., Ali, R. R., & Al-Ansary, N. A. (2023). Geographic information systems and remote sensing: Innovative tools for plant health. *International Journal of Agricultural Technology*, 19(6), 2449–2464.

Horoszkiewicz-Janka, J., Jajor, E., & Korbas, M. (2012). Prevalence of winter wheat diseases depending on selected agrotechnical factors. *Progress in Plant Protection*, 52(4), 998–1004. https://doi.org/10.14199/ppp-2012-172

Hossain, M. M., Sultana, F., Mostafa, M., Ferdus, H., Rahman, M., Rana, J. A., Islam, S. S., Adhikary, S., Sannal, A., Hosen, M. A. E., Nayeema, J., Emu, N. J., Kundu, M., Biswas, S. K., Farzana, L., & Al Sabbir, M. A. (2024). Plant disease dynamics in a changing climate: Impacts, molecular mechanisms, and climate-informed strategies for sustainable management. *Discover Agriculture*, 2, 132. https://doi.org/10.1007/s44279-024-00144-w

Hovmøller, M. S., Thach, T., & Justesen, A. F. (2023). Global dispersal and diversity of rust fungi in the context of plant health. *Current Opinion in Microbiology*, *71*, 102243.

Iacob, I. N., Roşculete, C. A., Păunescu, R. A., & Bonciu, E. (2025). Research on the response to

prolonged drought of an assortment of wheat varieties, through the rate of water loss from the flag leaf, on the chernozem of Caracal. *Scientific Papers. Series A. Agronomy*, 68(2), 501–511.

Joshi, P., Sandhu, K. S., Dhillon, G. S., Chen, J., & Bohara, K. (2024). Detection and monitoring wheat diseases using unmanned aerial vehicles (UAVs). *Computers and Electronics in Agriculture*, 224, 109158. https://doi.org/10.1016/j.compag.2024.109158

Juroszek, P., & von Tiedemann, A. (2013). Climate change and potential future risks through wheat diseases: A review. *European Journal of Plant Pathology*, 136, 21–33. https://doi.org/10.1007/s10658-012-0144-9

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture,* 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Karisto, P., Suffert, F., & Mikaberidze, A. (2022). Measuring splash dispersal of a major wheat pathogen in the field. *PhytoFrontiers™*, *2*(1), 30-40.

Kavhu, B., Mashimbye, Z. E., & Luvuno, L. (2021). Climate-based regionalization and inclusion of spectral indices for enhancing transboundary land-use/cover classification using deep learning and machine learning. *Remote Sensing*, *13*(24), 5054.

Khanal, S., Fulton, J., & Shearer, S. (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. *Computers and Electronics in Agriculture*, 139, 22–32. https://doi.org/10.1016/j.compag.2017.05.001

Korbas, M., Horoszkiewicz-Janka, J., & Jajor, E. (2008). Uproszczone systemy uprawy a występowanie sprawców chorób. [Simplified systems of soil management in relation to the occurrence of disease casual agents]. *Progress in Plant Protection*, 48(4), 1431–1438.

Kouadio, L., El Jarroudi, M., Belabess, Z., Laasli, S.-E., Roni, M.Z.K., Amine, I.D.I., Mokhtari, N., Mokrini, F., Junk, J., & Lahlali, R., (2023) A Review on UAV-Based Applications for Plant Disease Detection and Monitoring. *Remote Sensing*, 15(17):4273.

Kumar, D., & Mukhopadhyay, R. (2025). Climate change and plant pathogens: Understanding dynamics, risks and mitigation strategies. *Plant Pathology*, *74*(1), 59-68.

Laribi, M., Aboukhaddour, R., & Strelkov, S. E. (2024). Tan spot (*Pyrenophora tritici-repentis*) of wheat: A minireview. *Plant Health Cases*, https://doi.org/10.1079/planthealthcases.2024.0017

Li, Z., Wang, R., Ding, R. (2025). A review of crop attribute monitoring technologies for general agricultural scenarios. *AgriEngineering*, *7*(11), 365.

Liu, Y., Liu, G., Sun, H., An, L., Zhao, R., Liu, M., Tang, W., Li, M., Yan, X., Ma, Y., & Zhao, F. (2024). Exploring multi-features in UAV based optical and thermal infrared images to estimate disease severity of wheat powdery mildew. *Computers and Electronics in Agriculture*, 225, 109285. https://doi.org/10.1016/j.compag.2024.109285

Mahlein, A.-K., Oerke, E.-C., Steiner, U., & Dehne, H.-W. (2012). Recent advances in sensing plant diseases for precision crop protection. *European Journal of Plant Pathology*, 133(1), 197–209. https://doi.org/10.1007/s10658-011-9878-z

Mahlein, A.-K. (2016). Plant disease detection by imaging sensors – parallels and specific demands for precision agriculture and plant phenotyping. *Plant Disease*, 100(2), 241–251. https://doi.org/10.1094/PDIS-03-15-0340-FE

Malczewski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. *International Journal of Geographical Information Science*, 20(7), 703–726. https://doi.org/10.1080/13658810600661508

Martínez, M., Biganzoli, F., Arata, A., Dinolfo, M. I., Rojas, D., Cristos, D., & Stenglein, S. (2022). Warm nights increase Fusarium Head Blight negative impact on barley and wheat grains. *Agricultural and Forest Meteorology*, *318*, 108909.

Martínez-Cadena, J. A., Sánchez-Cerritos, J. M., Alvarez-Ramirez, J., Marin-Lopez, A., Delgado-Fernández, J., & Fuentecilla-Carcamo, I. (2026). Eco-epidemiological clustering and cluster-wise forecasting of dengue in Mexico, 2020–2025. *Acta Tropica,* 275, Article 107993. https://doi.org/10.1016/j.actatropica.2026.107993

Mergenthaler, C., van Gurp, M., Rood, E., & Bakker, M. (2022). The study of spatial autocorrelation for infectious disease epidemiology decision-making: A systematized literature review. *CABI Reviews*, 17, Article 018. https://doi.org/10.1079/cabireviews202217018

Miedaner, T., & Juroszek, P. (2021). Climate change will influence disease resistance breeding in wheat in Northwestern Europe. *Theoretical and Applied Genetics*, *134*(6), 1771-1785.

Misra, A. K., Yadav, S. B., Mishra, S. K., & Tripathi, M. K. (2020). Impact of meteorological variables and climate change on plant diseases. In P. Kumar, A. K. Tiwari, M. Kamle, Z. Abbas, P. Singh (Eds.), *Plant pathogens: Detection and management for sustainable agriculture* (pp. 313–327). Apple Academic Press. https://doi.org/10.1201/9780429057212-18

Naz, R., Batool, S., Shahid, M., Keyani, R., Yasmin, H., Nosheen, A., Hassan, M.N., Mumtaz, S., & Siddiqui, M.H. (2021). Exogenous silicon and hydrogen sulfide alleviates the simultaneously occurring drought stress and leaf rust infection in wheat. *Plant Physiology and Biochemistry*, 166:558-571.

Neupane, K., & Baysal-Gurel, F. (2021). Automatic identification and monitoring of plant diseases using unmanned aerial vehicles: A review. *Remote Sensing*, 13(19), 3841. https://doi.org/10.3390/rs13193841

Pandey, P., Ramegowda, V., & Senthil-Kumar, M. (2015) Shared and unique responses of plants to multiple individual stresses and stress combinations: physiological and molecular mechanisms. *Frontiers in Plant Science* 6:723. doi: 10.3389/fpls.2015.00723

Paraschivu, M., Cotuna, O., Olaru, L., & Paraschivu, M. (2017). Impact of climate change on wheat-pathogen interactions and concerning about food security.

Research Journal of Agricultural Science (ISSN 2066-1843) vol.49 (3), p.87-95.

Paraschivu, M., Cotuna, O., Horablaga, M. N., Sărățeanu, V., & Durău, C. C. (2019). Owerview on the management of powdery mildew in wheat (Blumeria graminis f. sp. tritici D.C. Speer) in the context of climate change. *Annals of the University of Craiova – Agriculture, Montanology, Cadastre Series*, 49(1), 275–292.

Paraschivu, M., Matei, Gh., Cotuna, O., Paraschivu, M., & Drăghici, R. (2021). Reaction of rye cultivars to leaf rust (P. recondita f. sp. secalis) in the context of climate change in dry area in southern Romania. *Scientific Papers. Series A. Agronomy*, LXIV, No. 1, p. 500-507.

Paraschivu, M., Matei, G., Cotuna, O., Paraschivu, M., & Drăghici, R. (2022). Management of pests and pathogens in rye crop in dry marginal environment in Southern Romania. *Scientific Papers. Series A. Agronomy*, 65(1), 466–474.

Paraschivu, M., Cotuna, O., Sărățeanu, V., Matei, G., Drăghici, R., & Prioteasa, A. M. (2023). Assessment of leaf rust (P. recondita f. sp. secalis) attack in marginal areas in Southern Romania. *Scientific Papers. Series A. Agronomy*, 66(2), 330–338.

Păunescu, R. A., Bonciu, E., Roșculete, E., Păunescu, G., & Roșculete, C. A. (2023). The effect of different cropping systems on yield, quality, productivity elements, and morphological characters in wheat (Triticum aestivum). *Plants*, 12, Article 2802.

Păunescu, G., Paraschivu, M., Păunescu, R. A., & Roșculete, C. A. (2022). The relationship between yield and pathogens attack on the advanced breeding winter wheat lines assessed for adult plant resistance. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, 22(1), 493–501.

Petit-Houdenot, Y., Lebrun, M.-H., & Scalliet, G. (2021). Understanding plant-pathogen interactions in Septoria tritici blotch infection of cereals. In *Burleigh Dodds Series in Agricultural Science*. Burleigh Dodds Science Publishing.

Pickering, C., & Byrne, J. (2014). The benefits of publishing systematic quantitative literature reviews for PhD candidates and other early-career researchers. *Higher Education Research & Development*, 33(3), 534–548. https://doi.org/10.1080/07294360.2013.841651

Prahl, K. C., Klink, H., Hasler, M., Verreet, J.-A., & Birr, T. (2023). Will climate change affect the disease progression of Septoria tritici blotch in Northern Europe? *Agronomy*, 13(4), 1005. https://doi.org/10.3390/agronomy13041005

Radici, A., Martinetti, D., & Bevacqua, D. (2022). Early-detection surveillance for stem rust of wheat: insights from a global epidemic network based on airborne connectivity and host phenology. *Environmental Research Letters*, *17*(6), 064045.

Rahman, S. Z., Senthil, R., Ramalingam, V., & Gopal, R. (2023). Predicting infectious disease outbreaks with machine learning and epidemiological data. *Journal of Advanced Zoology*, *44*(S4), 110-121.

Rawat, K., Singh, P. V., Dhapola, M., & Bharti, H. (2026). Remote sensing and GIS approaches for agricultural drought severity assessment: A comprehensive review. *DMPedia Lecture Notes in Multidisciplinary Research*, *IMPACT26*, 1, 1207–1217. https://doi.org/10.65890/dmp.lnmr.IMPACT26.120

Richard, B., Qi, A., & Fitt, B. D. (2022). Control of crop diseases through Integrated Crop Management to deliver climate-smart farming systems for low-and high-input crop production. *Plant Pathology*, *71*(1), 187-206.

Roșculete C.A., Păunescu R.A., Roșculete E., Păunescu G., Florea D., & Bonciu E. (2023). The influence of foliar fertilizer application on the macro and micro nutrient content and yield of wheat plants (*Triticum aestivum*). *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*. 23, 3: 786-795.

Różewicz, M., Wyzińska, M., & Grabiński, J. (2021). The most important fungal diseases of cereals—Problems and possible solutions. *Agronomy*, *11*(4), 714.

Rubayet, M. T., & Hossain, M. M. (2024). Climate change and its impacts on disease dynamics in major cereal crops. In M. M. Rahman, J. C. Biswas, & R. S. Meena (Eds.), *Climate change and soil-water-plant nexus: Agriculture and environment* (pp. 265–295). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-6635-2_9

Sangeetha, B., Vasanthi, E. A. P., & Parveen, S. S. (2025). Plant disease forecasting: A comprehensive review. *International Journal of Horticultural Science and Technology*, 12(3), 821–834.

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, 3(3), 430–439. https://doi.org/10.1038/s41559-018-0793-y

Seelan, S.K., Laguette, S., Casady, G.M., & Seielstad, G.A. (2003). Remote sensing applications for precision agriculture: A learning community approach. *Remote Sensing Environment*, 88, 157–169.

Shafay, M., Hassan, T., Owais, M., Hussain, I., Khawaja, S. G., Seneviratne, L., & Werghi, N. (2025). Recent advances in plant disease detection: challenges and opportunities. *Plant Methods*, *21*(1), 140.

Singh, M., Vermaa, A., & Kumar, V. (2023). Geospatial technologies for the management of pest and disease in crops. In Q. U. Zaman (Ed.), *Precision agriculture Evolution, Insights and Emerging Trends* (pp. 37–54). Academic Press. https://doi.org/10.1016/B978-0-443-18953-1.00002-7

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104:333-339.

Srivastava, A., & Jain, S. (2025). Remote sensing for environment assessment: Multispectral, hyperspectral, and thermal imaging applications. In V. Saritha, C. B. Pande, R. Singh, & M. Shahid (Eds.), *Remote sensing for environmental monitoring*

(pp. 1–31). Springer Nature Singapore. https://doi.org/10.1007/978-981-96-5546-5_1

Su, J., Liu, C., Coombes, M., Hu, X., Wang, C., Xu, X., Li, Q., Guo, L., & Chen, W.-H. (2018). Wheat yellow rust monitoring by learning from multispectral UAV aerial imagery. *Computers and Electronics in Agriculture*, 155, 157–166. https://doi.org/10.1016/j.compag.2018.10.017

Șulea, C., Alboteanu, L., & Manolea, G. (2010). Advanced technologies applied in anti-hail systems. *Buletinul AGIR*, (4), 17–22.

Șulea, C., Manolea, G., & Alboteanu, L. (2011). The informatic system as decision support for the activities of combating hail. *Annals of the "Constantin Brâncuși" University of Târgu Jiu, Engineering Series*, (3), 195–204.

Tammina, M. R., Sumana, K., Singh, P. P., Lakshmi, T. R. V., & Pande, S. D. (2024). Prediction of plant disease using artificial intelligence. In *Microbial data intelligence and computational techniques for sustainable computing* (pp. 25–48). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-9621-6_2

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A review on UAV-based applications for precision agriculture. *Information*, 10(11), 349. https://doi.org/10.3390/info10110349

United Nations, Department of Economic and Social Affairs, Population Division. (2019). *World population prospects 2019: Highlights* (ST/ESA/SER.A/423). United Nations. https://population.un.org/wpp/Publications/Files/WPP2019_Highlights.pdf

Velea, L., Bojariu, R., Burada, C., Udristioiu, M. T., Paraschivu, M., & Burce, R. D. (2021). Characteristics of extreme temperatures relevant for agriculture in the near future (2021–2040) in Romania. *Scientific Papers. Series E. Land Reclamation, Earth Observation & Surveying, Environmental Engineering*, 10, 70–75.

West, J. S., & Kimber, R. B. E. (2015). Innovations in air sampling to detect plant pathogens. *Annals of Applied Biology*, 166(1), 4–17. https://doi.org/10.1111/aab.12191

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming – A review. *Agricultural Systems*, 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023

Xing, Y., Liu, X., & Wang, X. (2026). Integrating UAVs, satellite remote sensing, and machine learning in precision agriculture: Pathways to sustainable food production, resource efficiency, and scalable innovation. *Frontiers in Agronomy*, 7, 1670380. https://doi.org/10.3389/fagro.2025.1670380

Zarco-Tejada, P. J., Camino, C., Beck, P. S. A., Calderon, R., Hornero, A., Hernández-Clemente, R., Kattenborn, T., Montes-Borrego, M., Susca, L., Morelli, M., Gonzalez-Dugo, V., North, P. R. J., Landa, B. B., Boscia, D., Saponari, M., & Navas-Cortes, J. A. (2018). Previsual symptoms of Xylella fastidiosa infection revealed in spectral plant-trait alterations. *Nature Plants*, 4(7), 432–439. https://doi.org/10.1038/s41477-018-0189-7

Zhu, H., Lin, C., Liu, G., Wang, D., Qin, S., Li, A., Xu, J.-L., & He, Y. (2024). Intelligent agriculture: Deep learning in UAV-based remote sensing imagery for crop diseases and pests detection. *Frontiers in Plant Science*, 15, 1435016. https://doi.org/10.3389/fpls.2024.1435016