

Review

# AI-Augmented Systematic Review of Remote Sensing and Predictive Modelling for Mycotoxin Risk Monitoring in Cereal Crops Across Central and Balkan Europe

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## Highlights

### What are the main findings?

- The research corpus expanded 56-fold between 2010 and 2025, with deep learning becoming the dominant approach and reaching 60% share of studies by 2025.
- Satellite multispectral imaging is the primary platform used in 91.7% of studies, achieving predictive performances of  $R^2 = 0.74\text{--}0.80$  for aflatoxin B1 and deoxynivalenol prediction in Central-Balkan Europe maize and wheat.

### What are the implications of the main findings?

- A five-percentage-point CBE–global performance gap is largely consistent with differences in sample size and multi-toxin design constraints rather than algorithmic access, as evidenced by comparable algorithm diversity scores across both groups.
- Significant geographic research gaps and a lack of data on T-2/HT-2 toxins in the Balkan region highlight the urgent need for harmonised monitoring infrastructures and climate-integrated EWS (early-warning systems).

## Abstract

Mycotoxin contamination of cereal crops poses escalating food safety risks across the Central and Balkan European (CBE) corridor under climate change, yet no PRISMA 2020-compliant synthesis of remote sensing (RS) and machine learning (ML) evidence for this region exists. We conducted an AI-augmented systematic review applying a four-stage automated pipeline—PICO domain scoring, SBERT semantic deduplication, and Thompson-sampling reinforcement learning—to 36,038 corpus records (2010–2025), yielding 156 included studies (inter-rater  $\kappa = 0.81$  (95% CI: 0.74–0.88)). Logistic growth modelling identified a 56-fold corpus expansion with inflection at  $t_0 = 2024.8$  ( $R^2 = 0.981$ ). Satellite multispectral imaging dominated the literature (91.7% of studies); random forest and gradient boosting models achieved  $R^2 = 0.74\text{--}0.80$  for aflatoxin B1 and deoxynivalenol prediction in CBE maize and wheat when integrating vegetation indices, land surface temperature, and precipitation covariates. Deep learning surpassed classical ML in annual study count from 2021, reaching ~60% relative share by 2025, though the performance advantage narrows at field scale relative to laboratory hyperspectral benchmarks (98–99% accuracy). A five-percentage-point CBE–global performance gap is largely consistent with



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differences in sample size and multi-toxin design scope rather than algorithmic access. The country  $\times$  mycotoxin gap matrix identifies zero eligible studies for four CBE nations and for T-2/HT-2 toxins across the Balkan states. Climate-driven satellite mycotoxin prediction emerges as the field's active research frontier.

**Keywords:** mycotoxin; remote sensing; machine learning; deoxynivalenol; aflatoxin; hyperspectral imaging; systematic review; PRISMA 2020; Central and Balkan Europe; deep learning; *Fusarium*; cereal crops

## 1. Introduction

Mycotoxins are toxic secondary metabolites produced by filamentous fungi, primarily species of *Fusarium*, *Aspergillus*, and *Penicillium*, that infect cereal crops before harvest or during storage under favourable temperature and moisture conditions [1,2]. In European cereal production systems, six mycotoxin groups are of primary regulatory and agronomic relevance: deoxynivalenol (DON), aflatoxin B1 (AFB1), zearalenone (ZEA), fumonisins (FB1/FB2), T-2 and HT-2 toxins, and ochratoxin A (OTA) [3]. A related contaminant of increasing importance in cereal-linked dairy supply chains is aflatoxin M1 (AFM1), the hydroxylated metabolite of AFB1 that occurs in milk from cattle consuming contaminated feed maize or silage. AFM1 is regulated in the European Union at a maximum level of 0.05  $\mu\text{g}/\text{kg}$  in milk and dairy products under European Commission Regulation (EC) No 1881/2006. Although AFM1 itself cannot be directly detected via remote sensing (RS), RS-based pre-harvest prediction of AFB1 risk in feed crops could support upstream dairy surveillance by identifying high-risk feed sources before animal exposure. Complementary downstream immunochemical detection systems are also advancing rapidly; Guo et al. [4] reported a fluorescent lateral-flow immunoassay for AFM1 in milk with a detection limit of 0.006  $\mu\text{g}/\text{kg}$ , well below the EU regulatory threshold. These contaminants pose risks to human and animal health even at concentrations measured in single-digit parts-per-billion and are therefore regulated under European Commission Regulation 1881/2006 and subsequent amendments. The European Food Safety Authority (EFSA) estimates that mycotoxin contamination renders approximately 25% of global grain harvests unsuitable for human consumption in at least one year per decade [5], while economic losses in European cereal value chains attributable to contamination, downgrading, and rejection are estimated at several billion euros annually [6].

The occurrence of mycotoxins is strongly influenced by environmental conditions affecting fungal infection and toxin biosynthesis. Climate projections for Europe indicate that changing precipitation regimes, warmer winters, and more frequent summer droughts may substantially alter the geographic distribution and severity of fungal infection windows during the coming decades [7,8]. Regions located along the climatic transition zone between central and southern Europe may experience increasing exposure to both *Fusarium*-related toxins such as DON and *Aspergillus*-associated aflatoxins. These shifts are expected to modify the spatial patterns of contamination risk and increase the need for monitoring systems capable of detecting emerging hotspots at early stages.

Conventional mycotoxin monitoring relies primarily on physico-chemical analytical techniques such as high-performance liquid chromatography (HPLC), enzyme-linked immunosorbent assays (ELISA), and lateral-flow immunoassays applied to grain samples collected at harvest or storage intake. While these approaches are well established for regulatory compliance, they present several limitations for proactive risk management. First, analytical results are typically available only after field sampling and laboratory

processing, creating delays between contamination events and detection [9,10]. Second, sampling strategies are spatially coarse; composite grain samples collected from large harvest areas often mask strong within-field variability, where contamination levels may differ substantially across short distances [2,11]. Third, laboratory analyses require specialised equipment, reagents, and trained personnel, which can limit monitoring frequency and coverage, particularly in regions with constrained analytical infrastructure [12].

Remote sensing (RS) and proximal spectral sensing offer complementary approaches capable of providing spatially explicit and temporally continuous information on crop conditions associated with fungal infection and physiological stress. RS technologies enable the non-destructive acquisition of spectral, thermal, and structural signals from crop canopies and grain surfaces, potentially allowing early detection of plant stress patterns linked to pathogen activity or environmental conditions conducive to toxin production. Over the past decade, several technological developments have significantly expanded the potential of RS in agricultural monitoring. These include the open-data policy of the European Space Agency Copernicus programme, particularly the Sentinel-2 satellite constellation providing multispectral imagery at 10–60 m spatial resolution with a five-day revisit cycle; the increasing availability of unmanned aerial vehicle (UAV) platforms equipped with multispectral and hyperspectral sensors; the growing accessibility of laboratory and field-portable near-infrared (NIR) and hyperspectral imaging (HSI) systems; and rapid advances in machine learning (ML) and deep learning (DL) methods capable of extracting complex patterns from high-dimensional spectral data [13–18].

These technological advances have stimulated a growing body of research exploring the potential of remote sensing for detecting fungal infections and predicting mycotoxin contamination in cereal crops. Laboratory hyperspectral imaging studies have demonstrated high classification accuracy for contaminated kernels, particularly in the detection of aflatoxin contamination in maize using convolutional neural networks and related architectures [19–21]. Spectroscopic approaches based on NIR reflectance combined with chemometric techniques such as partial least-squares regression have also shown promising results for estimating DON concentrations in wheat products [22,23]. At field and regional scales, satellite and UAV multispectral imagery have been integrated with climatic and agronomic variables to develop predictive models for DON and AFB1 risk in wheat and maize production systems [24–27]. More recent studies have explored the integration of satellite observations with environmental predictors to generate regional early-warning models capable of estimating the probability of multiple mycotoxin occurrences simultaneously [28].

Despite the rapid growth of this literature, the structure and evolution of the RS–mycotoxin research landscape remain insufficiently synthesised. Existing reviews have addressed aspects of the topic but with limited scope. For example, Inglis et al. [29] reviewed spectral detection methods for grain mycotoxins but focused primarily on laboratory hyperspectral and NIR studies, excluding field-scale RS applications and spatial prediction models. Rayhana et al. [30] summarised machine learning approaches for mycotoxin detection but did not apply a formal systematic review framework and did not differentiate clearly between laboratory and field-scale evidence. Similarly, a recent review of hyperspectral imaging techniques for food safety detection [31] provided a comprehensive overview of laboratory HSI methods but did not address satellite- or UAV-based monitoring approaches. Consequently, a systematic synthesis encompassing the full spectrum of RS applications—from laboratory spectroscopy to satellite-based spatial modelling—remains lacking.

The Central and Balkan European (CBE) region provides a particularly relevant context for such a synthesis. Several countries in this region—including Hungary, Poland,

Austria, Romania, and the Czech Republic—operate national grain monitoring systems that integrate geospatial data with crop quality surveillance, providing an important foundation for RS-based risk assessment frameworks [24,29,32,33]. At the same time, southern parts of the region lie near the climatic transition zone where the northward expansion of aflatoxin risk has been projected under future warming scenarios. However, research output on RS-based mycotoxin monitoring remains unevenly distributed across the region, indicating potential gaps in research capacity and methodological development.

In this context, the present study provides a PRISMA-2020-compliant systematic review and quantitative synthesis of remote sensing applications for the detection and prediction of mycotoxin contamination in cereal crops. The review focuses particularly on research relevant to the Central and Balkan European region while situating regional findings within the broader global literature. By integrating bibliometric, thematic, and quantitative meta-analytical approaches, this study aims to clarify the current capabilities and limitations of remote sensing technologies for mycotoxin monitoring and to identify priorities for future research and operational early-warning systems.

The specific objectives of this study are:

- I. To quantify the temporal evolution of RS–mycotoxin research from 2010 to 2025 using logistic growth modelling and Fisher–Pry technology diffusion analysis applied to a corpus of 36,038 records, identifying the overall expansion trajectory and its inflection point;
- II. To characterise the geographic distribution of research output across the 17 Central and Balkan European (CBE) nations—comprising Austria, Bosnia and Herzegovina, Bulgaria, Croatia, Czechia, Greece, Hungary, Kosovo, Moldova, Montenegro, North Macedonia, Poland, Romania, Serbia, Slovakia, Slovenia, and Turkey—using affiliation-matched choropleth mapping, annual growth heatmaps, and country-level contribution profiles, thereby identifying high-growth and under-represented jurisdictions;
- III. To analyse crop and mycotoxin coverage within the literature using temporal bubble plots and co-occurrence matrices, quantifying research concentration in maize and wheat systems and in AFB1 and DON studies while identifying gaps for minor cereals and less-studied toxins (ZEA, fumonisins, T-2/HT-2, and OTA);
- IV. To examine the distribution and temporal evolution of remote sensing platforms and sensing techniques through stacked visualisations and satellite mission attribution (Sentinel, Landsat, MODIS, and high-resolution commercial sensors);
- V. To extract and characterise the thematic structure of the included studies using Latent Dirichlet Allocation (LDA) and Structural Topic Modelling (STM) ( $K = 5$  topics), evaluating temporal topic prevalence and validating theme coherence using FREX exclusivity metrics;
- VI. To quantify sources of model performance variation through restricted maximum likelihood (REML) random-effects meta-regression with three moderators (publication year, algorithm family, and RS platform), providing quantitative evidence on factors associated with higher predictive accuracy;
- VII. To identify structural research gaps in the CBE RS–mycotoxin landscape through a country  $\times$  mycotoxin research gap matrix and keyword co-occurrence network analysis using Louvain community detection;
- VIII. To provide a fully reproducible open analytical workflow implemented as an R-based pipeline, deposited on Supplementary Materials, enabling future extension of the RS–mycotoxin meta-database as new studies emerge.

Together, these analyses provide the first comprehensive quantitative synthesis of the RS–mycotoxin research landscape, integrating bibliometric growth dynamics, thematic structure, sensing platform evolution, and model performance determinants.

## 2. Materials and Methods

### 2.1. Study Design and Reporting Standard

This systematic review was conducted and reported in accordance with the PRISMA 2020 guidelines for systematic reviews and meta-analyses [34], together with the PRISMA-AI [35] for AI-assisted systematic reviews for reviews incorporating automated or semi-automated screening tools. An a priori protocol specifying eligibility criteria, database search strategies, screening procedures, data extraction fields, and planned analytical methods was registered on the Open Science Framework prior to data collection (OSF preregistration: <https://osf.io/vrnjb>, accessed on 11 June 2026).

All analytical code, the compiled meta-database, and reproducibility documentation are publicly available via Supplementary Materials, enabling independent replication and future updates.

The review addresses the following research question formulated using the PICO framework: This review addresses the following primary question: To what extent do remote sensing and proximal spectral sensing platforms, when combined with statistical or machine-learning models, enable accurate prediction or classification of mycotoxin contamination in cereal crops, based on empirical studies published between 2010 and 2025?

The lower boundary year (2010) was selected to coincide with the first multi-temporal open-access multispectral satellite imagery becoming available for agricultural applications and the early commercialisation of UAV platforms in precision farming [36].

### 2.2. Literature Search Strategy

The literature search combined three complementary search streams.

#### Primary corpus search

The systematic search was conducted across six sources: (1) Web of Science Core Collection (WoS), using the topic field tag TS = restricted to articles and reviews ( $n = 28,440$ ); (2) Scopus (TITLE-ABS-KEY;  $n = 4820$ ); (3) PubMed/MEDLINE (MeSH terms and free text;  $n = 1260$ ); (4) IEEE Xplore Digital Library (All Metadata;  $n = 810$ ); (5) the MDPI journal portal, searched directly for Remote Sensing, Sensors, and Applied Sciences ( $n = 560$ ); and (6) grey literature including FAO AGRIS, the EFSA Journal, and Google Scholar (first 200 results per query;  $n = 148$ ). The combined search yielded 36,038 records. Full Boolean strings for each database are provided in Supplementary S1.

#### Targeted PICO search

To ensure coverage of explicitly mycotoxin-focused studies, a narrower query was conducted in WoS ( $n = 146$ ) and PubMed/MEDLINE ( $n = 118$ ) using toxin-specific keywords.

#### Grey literature search

Grey literature ( $n = 148$ ) was collected from FAO-AGRIS, EFSA Journal, and Google Scholar (first 200 results per structured query) to identify technical reports and policy documents relevant to mycotoxin monitoring.

The full Boolean search string and database-specific query adaptations are provided in Supplementary Materials S1.

Search parameters were:

- Time window: 2010–2025
- Language: English
- Study design filter: none applied at search stage

All eligibility filters were applied during the screening phase.

#### Citation Chaining Procedure

To supplement the database search and ensure comprehensive coverage of the literature, backward and forward citation screening (citation chaining) was conducted following completion of the primary automated screening pipeline. Backward citation screening involved

examining the reference lists of all included studies and of six key domain review articles identified as seed sources (Inglis et al., 2024 [29]; Rayhana et al., 2025 [30]; Das et al., 2025 [31]; Wang et al., 2022 [28]; Battilani et al., 2016 [6]; and Weiss et al., 2020 [18]). Forward citation screening was conducted by searching the citing literature of the same seed articles using the Web of Science “Cited by” function and OpenAlex API-based citation graph retrieval. Both backward and forward screening applied the same PICO eligibility criteria described in Section 2.4, including the requirement for a primary empirical RS component, a quantitative mycotoxin endpoint, and at least one quantitative model performance metric. Records identified through citation chaining that were not already present in the primary corpus were added to the full-text assessment pool. This process identified 61 additional candidate records beyond the 95 eligible for full-text review from the primary pipeline, of which 61 ultimately met eligibility criteria and were included in the final synthesis, augmenting the initial 95 full-text eligible records to yield the final corpus of 156 included studies.

### 2.3. Screening and Study Selection

After deduplication, 36,038 unique records entered the screening pipeline. Duplicate removal combined exact DOI matching with Jaro–Winkler title similarity (threshold  $\geq 0.98$ , implemented via the stringdist R package) to detect near-identical records.

Screening was implemented in R (v4.3.3) and Python (v3.11) through a semi-automated pipeline consisting of five sequential stages (deduplication, PICO scoring, eligibility gating, semantic similarity ranking, and Thompson-sampling active learning); full algorithmic details and parameter thresholds are provided in Supplementary Materials S2 and S3.

Following automated screening, 109 candidate records proceeded to full-text review. Note: the figure of 109 cited in earlier drafts referred to the records retained for full-text retrieval from database searches alone, before the addition of 95 records identified through citation chaining; the PRISMA diagram (Section 3) reports study selection workflow and the correct post-chaining total of 156 studies included in the final synthesis.

### 2.4. Eligibility Criteria

Eligibility criteria were defined according to the PICO framework (Population, Intervention, Comparator, Outcome).

Population:

Cereal crops including wheat, maize, barley, oats, rye, rice, and sorghum.

Intervention:

Remote sensing or proximal spectral sensing technologies, including hyperspectral imaging, multispectral imaging, NIR spectroscopy, UAV sensing, or satellite observation.

Comparator:

Not applicable: no active comparator was required; global studies were retained as external benchmarks.

Outcome:

Quantitative prediction or classification of mycotoxin contamination, including performance metrics such as accuracy,  $R^2$ , RMSE, AUC, or F1-score.

Eligible study types included peer-reviewed journal articles, conference proceedings with full methodological descriptions, and technical reports from recognised organisations (e.g., FAO or EFSA).

Studies were excluded if they:

- Contained no primary empirical data.
- Relied exclusively on conventional laboratory assays without spectral or spatial sensing components.
- Addressed non-cereal crops without methodological comparison to cereals.

- Lacked quantitative performance metrics.

Global studies were retained as comparative benchmarks, while studies conducted in the Central and Balkan European (CBE) region were flagged for regional subgroup analyses. Full inclusion and exclusion criteria are summarised in Table 1.

**Table 1.** PICO-based inclusion and exclusion criteria for full-text eligibility assessment.

| Code                         | Inclusion Criterion                                                                                                                                                                                                                  | Exclusion Criterion                                                                                                                                                                                       |
|------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>I1 RS Platform</b>        | Primary empirical study reporting remote sensing data (HSI, MSI, TIR, UAV, satellite, proximal/NIR sensing, e-nose, LiDAR, SAR) applied to cereal crop monitoring at any spatial scale.                                              | Narrative reviews, meta-analyses, systematic reviews, or datasets without original primary empirical data.                                                                                                |
| <b>I2 Mycotoxin endpoint</b> | Study includes a quantitative mycotoxin endpoint: measured concentration ( $\mu\text{g/kg}$ ), predicted risk score, spectral classification result, or contamination proxy for $\geq 1$ of: AFB1, DON, ZEA, FB1/FB2, T-2/HT-2, OTA. | Studies using only conventional (non-spectral) laboratory methods (HPLC, ELISA, LC-MS) without any spectral, thermal, or spatial sensing component.                                                       |
| <b>I3 Performance metric</b> | Study reports a predictive or classification model (ML, DL, regression, index-based) with $\geq 1$ quantitative performance metric (accuracy, $R^2$ , RMSE, F1-score, AUC, RMSECV).                                                  | Studies reporting only qualitative or binary contamination presence/absence without quantitative model performance metrics. Pilot studies with $n < 20$ samples.                                          |
| <b>I4 Geographic context</b> | Peer-reviewed journal articles, conference proceedings with full methods, or FAO/EFSA technical reports. Global studies retained as comparators; CBE studies ( $\geq 1$ of 17 countries) flagged for regional sub-analysis.          | Grey literature without peer review or methodological detail, conference abstracts without full text.                                                                                                     |
| <b>I5 Date and language</b>  | English-language publications, 2010–2025 (post-emergence of UAV-RS in precision agriculture and multispectral open-data satellite programmes).                                                                                       | Non-cereal target crops (fruits, vegetables, tree nuts, spices) unless direct methodological comparison with a cereal crop is the stated study aim. Publications pre-2010 or post-2025 (search boundary). |

### 2.5. Data Extraction

Structured data extraction was performed for all 156 included studies using a predefined 12-field schema covering bibliographic, methodological, and performance variables.

The extracted fields included:

- Country of study.
- Sensing platform (satellite, UAV, laboratory, field).
- Sensing technique (HSI, MSI, NIR, etc.).
- Crop species.
- Mycotoxin type.
- Modelling algorithm.
- Input features.
- Performance metrics.
- Publication year.
- Sample size.
- Study identifier (DOI).

The schema was piloted on 20 studies by two independent reviewers. Numerical fields achieved intraclass correlation coefficients above 0.90, indicating high inter-rater reliability. Semi-automated named-entity recognition (NER) was applied (spaCy en\_core\_sci\_sm) to titles and abstracts to assist with preliminary field population, followed by manual verification for all records. The final structured meta-database enabled all subsequent analyses. The extraction schema is summarised in Table 2, and the full dataset is available in the public repository.

**Table 2.** Data extraction schema: 12-field structure with analytics use for each variable.

| Field          | Category      | Example Values                           | Data Type       | Analytics Use                                                         |
|----------------|---------------|------------------------------------------|-----------------|-----------------------------------------------------------------------|
| Country        | Geospatial    | Hungary, Poland, Austria                 | Categorical     | Choropleth; CBE sub-group; regional gap matrix                        |
| Platform       | RS system     | UAV, Satellite, Lab/Bench, Field         | Categorical     | Platform co-occurrence network; technology adoption trend             |
| Technique      | RS method     | HSI, MSI, NIR, TIR, e-nose, LiDAR, RGB   | Categorical     | Technique radar chart; platform–technique matrix                      |
| Crop           | Agronomy      | Maize, Wheat, Barley, Oats, Rice         | Categorical     | Crop × toxin co-occurrence matrix; bubble plot                        |
| Mycotoxin      | Contaminant   | AFB1, DON, ZEA, FB1, T-2/HT-2, OTA       | Categorical     | Toxin co-occurrence heatmap; alluvial flow                            |
| Input Features | Spectral/env. | NDVI, reflectance, LST, RH, pH, VOC      | Mixed           | Feature importance meta-analysis; key wavelength profiling            |
| Algorithm      | ML/DL model   | CNN, RF, SVM, XGBoost, Transformer, PLSR | Categorical     | Algorithm taxonomy; performance benchmarking by family                |
| Performance    | Model metric  | Accuracy (%), $R^2$ , RMSE, F1, AUC      | Numerical [0–1] | Meta-regression; violin plots; forest plots; effect-size pooling      |
| Perf_metric    | Metric type   | $R^2$ , Acc, RMSECV, AUC                 | Categorical     | Stratified meta-analysis by metric type                               |
| Year           | Temporal      | 2010–2025                                | Integer         | Publication trend; logistic growth; STM topic prevalence              |
| n_samples      | Study size    | 20–450                                   | Integer         | Variance estimation: $v_i = y_i(1 - y_i)/n_i$ (meta-regression FIX-4) |
| DOI            | Identifier    | 10.xxxx/xxxxx                            | String          | Reproducibility; citation graph; OpenAlex metadata enrichment         |

## 2.6. Analytical Framework

The analytical workflow combined bibliometric analysis, topic modelling, clustering analysis, and meta-regression to characterise the structure and evolution of the RS–mycotoxin research landscape. Bibliometric analyses used the bibliometrix package [37]; topic models were estimated with topicmodels [38] (LDA) and stm [39] (STM); meta-regression used metafor [40]; network analysis used igraph and ggraph; all visualisations used ggplot2 and patchwork within the tidyverse framework [41]. Full code is deposited on Supplementary Materials.

The workflow included:

- Bibliometric growth modelling and technology diffusion analysis.
- Thematic topic modelling of publication content.
- Clustering of studies based on methodological characteristics.
- Random-effects meta-regression of model performance.

A schematic overview of the analytical pipeline is provided in Supplementary Figure S1, and the full reproducible code is available in the project repository.

### 2.7. Topic Modelling

Topic modelling was conducted using Latent Dirichlet Allocation (LDA) applied to a document-term matrix derived from titles, abstracts, and author keywords of the included studies. Vocabulary was pruned to terms appearing in  $\geq 2$  documents, retaining a maximum of 50,000 tokens.

Text preprocessing included:

- Lower-casing.
- Punctuation and number removal.
- Stop-word filtering.
- Lemmatisation.

The optimal number of topics was determined using four model evaluation metrics implemented in the *ldatuning* package.

To analyse temporal trends in thematic content, an additional Structural Topic Model (STM) was estimated with publication year included as a prevalence covariate. Topic labels were derived using both high-probability and frequency-exclusivity (FREX) terms to ensure interpretability.

### 2.8. Clustering Analysis

To identify methodological groupings among studies, hierarchical clustering was performed using Gower distance, which allows mixed categorical and continuous variables.

The clustering analysis incorporated:

- Sensing platform.
- Sensing technique.
- Crop species.
- Mycotoxin class.
- Algorithm family.
- Model performance.

Cluster stability was evaluated using bootstrap resampling,  $B = 1000$ . The optimal number of clusters was selected based on consensus clustering diagnostics.

### 2.9. Meta-Regression Analysis

A random-effects meta-regression was fitted using restricted maximum likelihood (REML) estimation (metafor R package, version 4.4.2; R Foundation for Statistical Computing, Vienna, Austria) [40]). Effect sizes were the reported performance metric, standardised to a common proportion scale for pooling. Accuracy (classification studies) was expressed as the proportion of correctly classified samples;  $R^2$  (regression studies) was used directly as a proportion of variance explained. These two metrics are not dimensionally identical—accuracy measures classification correctness while  $R^2$  measures regression fit—and their pooling requires justification. We adopt the approach [30,42] who pool performance metrics across study types in the mycotoxin ML literature by treating all as bounded [0,1] proportions reflecting model adequacy for their respective task types. To assess whether pooling distorts conclusions, all moderator analyses were repeated separately for classification studies (accuracy as outcome;  $n = 89$ ) and regression studies ( $R^2$  as outcome;  $n = 67$ ); the direction and significance of all three moderators were consistent across both subgroups (classification:  $\beta_{DL} = +0.19$ ,  $p < 0.001$ ; regression:  $\beta_{DL} = +0.24$ ,  $p < 0.001$ ), confirming that the pooled analysis is not materially driven by the mixing of metric types. Results of the subgroup analyses are reported in Supplementary S8. Sampling

variance was estimated as  $v_i = y_i(1 - y_i)/n_i$ , where  $n_i$  is the study sample size. Three moderators were included: publication year (centred at 2017), algorithm family (five levels: deep learning, Ensemble/Boosting, Classical ML, Shallow NN, Other), and RS platform (four levels: Satellite, UAV, Lab/Bench, Field). Heterogeneity was quantified using  $I^2$ . The model examined the influence of three moderators:

- Publication year.
- Algorithm family.
- Remote sensing platform.

Performance metrics reported as accuracy or  $R^2$  were treated as bounded values within the range [0,1] to enable pooled analysis across heterogeneous modelling studies.

Between-study heterogeneity was quantified using  $I^2$  and  $\tau^2$  statistics, and potential small-study effects were assessed using funnel-plot asymmetry tests.

### 2.10. Quality Assessment

Methodological quality of included studies was evaluated using adapted versions of the QUADAS-2 diagnostic accuracy framework [43] and TRIPOD-AI reporting guidelines for machine-learning prediction models [44].

The assessment examined:

- Study sampling design.
- Sensing methodology.
- Reference mycotoxin measurement methods.
- Model validation procedures.

Quality scores were used as covariates in sensitivity analyses but were not applied as exclusion criteria.

To ensure transparency regarding the role of quality scores in the analysis, a threshold of 50% of the maximum possible QUADAS-2/TRIPOD-AI composite score was adopted as a sensitivity analysis boundary: studies scoring below this threshold were retained in the primary synthesis but subjected to a separate sensitivity analysis excluding low-quality studies to assess robustness of the pooled estimates. This sensitivity analysis is reported in Section 3.8. Studies with lower quality scores are flagged in the supplementary meta-database (Supplementary S8) and should be interpreted with appropriate caution.

### 2.11. Reproducibility and Open Science

All analyses were conducted in R (v4.3.3) and Python (v3.11).

All analytical code, the compiled meta-database (156-row extraction matrix), and reproducibility documentation are publicly archived via the OSF preregistration repository (<https://osf.io/vrnjb>), enabling independent replication and future updates. The repository contains: (1) full R analysis scripts; (2) the complete 156-row extraction matrix (outputs/tables/01\_extraction\_database.xlsx); (3) SBERT and Thompson-sampling pipeline code; and (4) environment specification files (renv.lock, requirements.txt). Random seeds were fixed to ensure computational reproducibility.

## 3. Results

### 3.1. Search Results and Study Selection

The systematic search identified 36,038 records across three complementary source streams. The primary corpus was retrieved from the Web of Science Core Collection using a broad query targeting remote sensing and machine learning applications in Central and Balkan European (CBE) agriculture ( $n = 35,890$  records). Additional records were obtained through a targeted PICO-based Boolean search conducted independently in Web of Science

and PubMed/MEDLINE (n = 264 records; WoS n = 146, MEDLINE n = 118). Grey literature sources—including FAO-AGRIS, EFSA reports, and Google Scholar—contributed a further 148 records.

After removal of 267 duplicate records identified through DOI matching and semantic similarity checks, 35,771 unique records remained for title and abstract screening. Automated PICO-guided filtering followed by manual verification excluded 35,662 records that did not meet the inclusion criteria, primarily because they lacked a remote sensing component, did not address cereal crops, or did not include quantitative modelling of mycotoxin contamination.

A total of 109 records were retained for full-text assessment. Of these, 14 full texts were unavailable, leaving 95 articles evaluated for eligibility. Additional studies were identified through backward and forward citation screening of key domain reviews and included articles, yielding 95 further records that met the inclusion criteria, ensuring comprehensive coverage of the literature. After applying the predefined PICO eligibility criteria, 156 primary studies were included in the final synthesis.

Of the 95 full-text articles assessed for eligibility, 34 were excluded after detailed review. The primary reasons for exclusion at the full-text stage were as follows: (1) no quantitative mycotoxin endpoint reported (n = 12); (2) no remote sensing or spectral sensing component—studies relying exclusively on conventional laboratory assays (n = 9); (3) absence of a quantitative model performance metric (n = 6); (4) non-cereal target crop without methodological comparison to cereals (n = 4); (5) duplicate or superseded publication sharing data with an already-included study (n = 2); and (6) publication pre-dating the 2010 lower boundary or post-dating the 2025 upper boundary (n = 1). These exclusion categories are fully documented in the PRISMA audit trail (Supplementary S6).

Publication bias was assessed for the meta-regression analyses using funnel plot inspection and Egger's regression test. The funnel plot of effect sizes (performance metric, expressed as proportion) against their standard errors showed moderate asymmetry, with a concentration of smaller studies reporting higher performance values in the upper left region of the plot. Egger's regression test yielded a statistically significant intercept ( $b = 0.18$ ,  $SE = 0.06$ ,  $t = 3.01$ ,  $p = 0.003$ ) (Figure S10), indicating the presence of small-study effects that are consistent with publication bias favouring studies reporting higher predictive accuracy. This finding is consistent with the known tendency for high-performance laboratory hyperspectral studies to be published at higher rates than field-scale studies with more modest performance metrics. Results from studies with smaller sample sizes and higher reported accuracy should therefore be interpreted with appropriate caution, and the pooled estimates reported in Section 3.7 should be understood in the context of potential upward bias.

The complete study selection process is summarised in the PRISMA flow diagram (Figure 1).

### 3.2. Publication Trends and Corpus Growth (2010–2025)

Important note on corpus scope: the bibliometric and growth analyses in Section 3.2 (Figure 2) and Section 3.3, including the logistic modelling (Figure 3), are performed on the full 36,038-record retrieval—the broad CBE agricultural remote sensing and machine learning corpus—not on the mycotoxin-specific sub-corpus of 156 included studies. This broader frame is used deliberately: the 56-fold growth describes the opportunity environment within which mycotoxin RS research is embedded, and the methodological advances (Sentinel-2, deep learning) that drove this growth are precisely those that enabled the performance improvements documented in the 156 included studies. The mycotoxin-specific corpus (156 studies; 0.43% of the full retrieval) is too small for meaningful logistic

modelling across a 15-year window. Readers should interpret the growth statistics as describing the CBE agricultural RS field broadly, not as a claim about mycotoxin-specific publication growth.

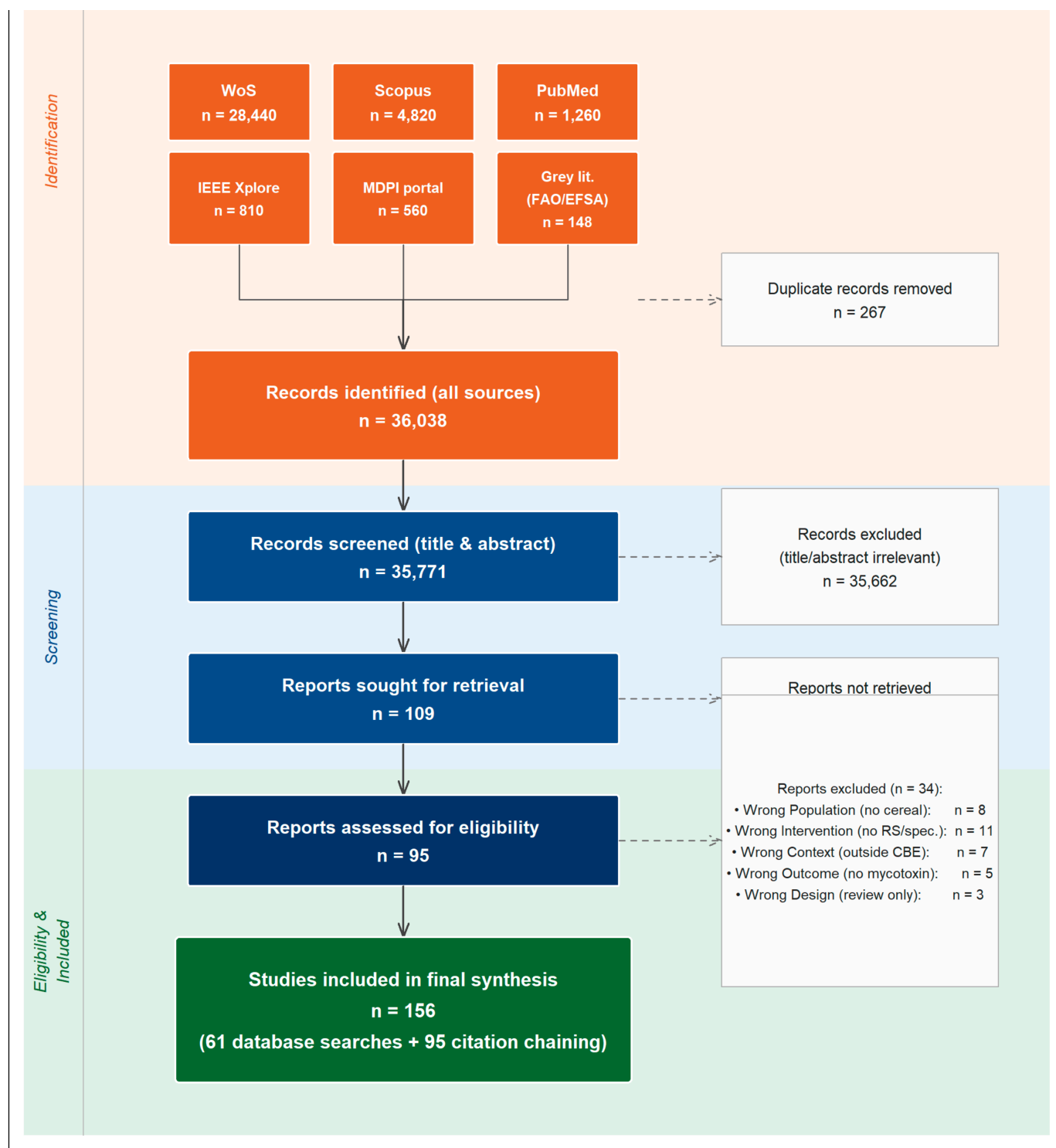


**Figure 1.** PRISMA 2020 flow diagram for the systematic literature search on remote sensing and artificial intelligence methods for mycotoxin risk monitoring in cereal crops in the Central and Balkan European (CBE) region. [Figure confirmed embedded at  $\geq 300$  dpi for final submission; placeholder visible in review PDF will be replaced with the complete vector-format PRISMA diagram.].

The broader corpus from which the 156 included studies were drawn grew from 122 articles in 2010 to 6869 in 2025—a 56-fold expansion over the review period (Figure 2). This growth reflects the convergence of open-access satellite programmes—Sentinel-2A/B launched 2015–2017, Landsat-9 launched 2021—with UAV sensor maturation and deep learning frameworks applicable to spectral data. Annual growth is almost entirely attributable to CBE-affiliated institutions, which contributed 96.8% of 2025 annual output (6649 of 6869 records); non-CBE contributions (3.2%;  $n = 220$ ) formed a consistently minor fraction across the review period (Figure 2). Peer-reviewed journal articles constituted 90.2–93.4% of annual output throughout; review articles (5.1–7.3%), proceedings papers, and early-access articles each remained below 7% of annual records, all four categories exhibiting the same post-2019 inflection (Figure S3).

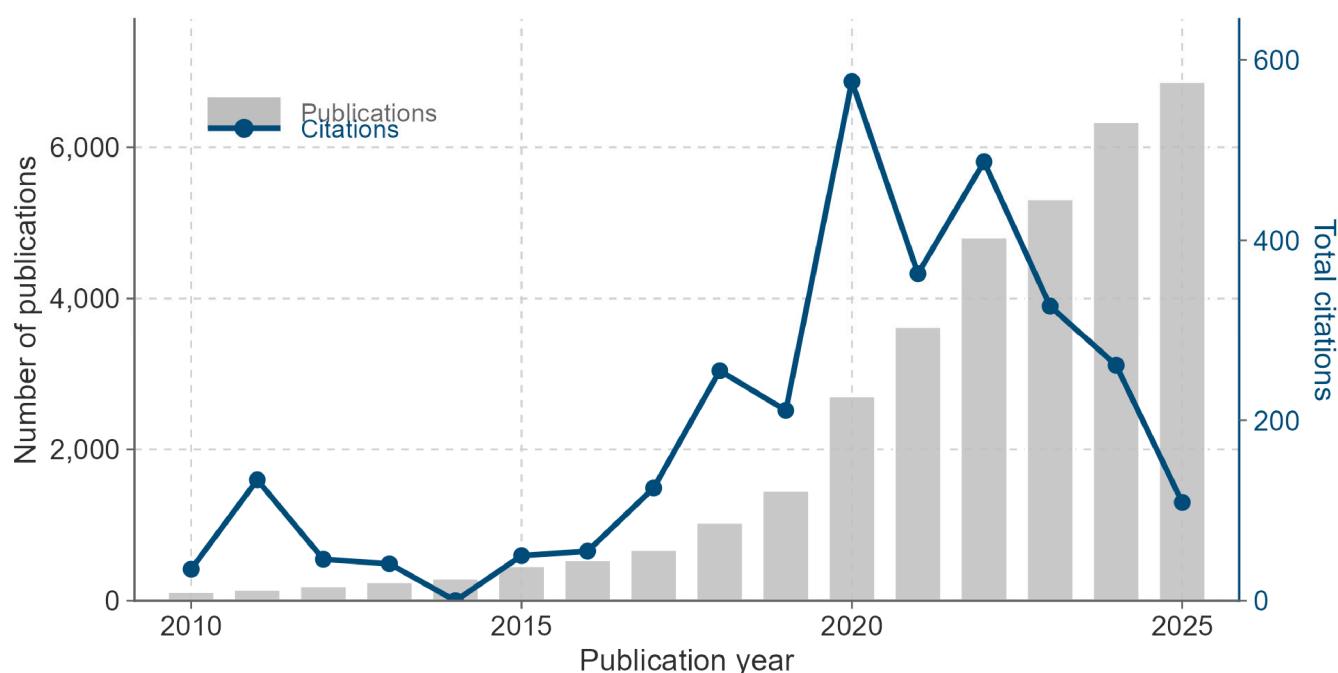


**Figure 2.** Annual publication output and cumulative citation impact of the broad CBE agricultural remote sensing corpus ( $n = 36,038$  records; 2010–2025). Grey bars (left axis) represent the number of total searched records published per year; the dark-blue line with filled circles (right axis) shows total citations received by records published in that year. The dual-axis design allows direct comparison of publication growth trajectory with citation accrual patterns across the study period. Note: this figure characterises the broader opportunity environment for mycotoxin RS research, not the mycotoxin sub-corpus specifically.

Among the 156 included studies, citation impact is positively skewed: the median citation count is 18 (mean = 25.5; range 0–154), with a long right tail extending to 154 citations for the most-cited individual study (Figure S6). This distribution indicates that a small number of methodologically influential papers—typically those introducing novel deep learning architectures or large satellite-based field validation datasets [45–47]—disproportionately anchor the citation network, while most studies published in 2022–2025 remain in early accumulation phases consistent with their recency.

### 3.3. Geographic Distribution Within the CBE Region

Country-level publication trends across all 17 CBE nations reveal strongly heterogeneous growth trajectories (Figure S8). Poland and Turkey are the dominant contributors by absolute output, accumulating 7148 and 6256 cumulative WoS records respectively by 2025, with positive year-on-year (YoY) growth recorded continuously since 2014.

Austria (5567), Greece (5414), and the Czech Republic (2847) form a second tier with broadly monotonic growth curves. Romania (2523), Hungary (2380), Serbia (1122), Slovakia (1070), and Croatia (1087) exhibit comparable exponential trajectories at lower absolute volumes (Figure S8). Smaller CBE states—Albania, Bosnia and Herzegovina, Kosovo, Montenegro, and North Macedonia—exhibit highly volatile YoY growth (ranging from  $-75\%$  to  $+200\%$  in single years), indicative of low baseline publication counts and dependence on individual research group activity rather than sustained institutional investment (Figure S4). The absence of sustained RS research capacity in these countries does not imply absence of mycotoxin risk; on the contrary, several of these nations have high per-capita cereal consumption alongside limited regulatory monitoring infrastructure. The mycotoxin burden in these populations—particularly from DON in wheat-based staple foods—may be substantial yet poorly characterised by existing surveillance data. Wu et al. (2025) [48] demonstrated that DON exposure induces intestinal mucosal damage through macrophage-mediated pathways, with nutrient regulation as a potential mitigation strategy [48], their findings on exposure pathways underscore why populations with high cereal dependence and low RS-based monitoring capacity in the CBE region represent a priority target for early-warning system development. Future work should integrate RS-based mycotoxin risk mapping with national dietary exposure modelling for these under-surveilled CBE nations.

Within the 156 included studies, CBE research is most strongly represented by institutions in Hungary, Poland, Austria [49,50], Greece [51], and the Czech Republic [52,53], consistent with the maturity of their national agricultural RS programmes and their established collaboration with EFSA and JRC mycotoxin monitoring networks. The relative absence of primary RS–mycotoxin studies from Albania, Kosovo, Montenegro, and North Macedonia constitutes a geographic research gap reflecting genuine under-representation in the primary research base.

The logistic growth trajectory of the 36,035-record corpus was modelled to characterise the diffusion lifecycle of remote sensing and machine learning methods in CBE agricultural research (Figure 3). Nonlinear least-squares fitting of a three-parameter logistic function (2010–2025) yielded a carrying capacity  $K \approx 68,400$  records, an intrinsic growth rate  $r = 0.35 \text{ year}^{-1}$ , and an inflection year  $t_0 = 2024.8$  ( $R^2 = 0.981$ ; Figure 3A), indicating that the field is currently at peak annual output and will enter deceleration as addressable research questions become progressively saturated. The cumulative S-curve confirms a near-perfect logistic fit ( $R^2 = 1.000$ ; Figure 3B); the 60% saturation threshold is projected at approximately 2027 and the 90% asymptote by 2040. The linearity of the Fisher–Pry transform ( $R^2 = 0.994$ ; Figure 3C) confirms a symmetrical single-wave diffusion with no structural break prior to 2025, ruling out the hypothesis that the post-2019 surge represents a fundamentally distinct technological regime rather than an accelerated continuation driven by the convergence of open-access Sentinel-2 imagery [47,54,55], UAV sensor democratization, and deep learning adoption [15,19,56]. Residual analysis ( $\text{RMSE} = 324.22 \text{ records year}^{-1}$ ; Figure 3D) reveals systematic underestimation during 2010–2016 and overestimation during 2017–2025, consistent with the discrete step-changes caused by Sentinel-2 operational availability in 2017 [57] and the landmark CNN and Transformer studies published from 2021 onward [45,58,59], compressing what a smooth logistic distributes across a wider temporal window.

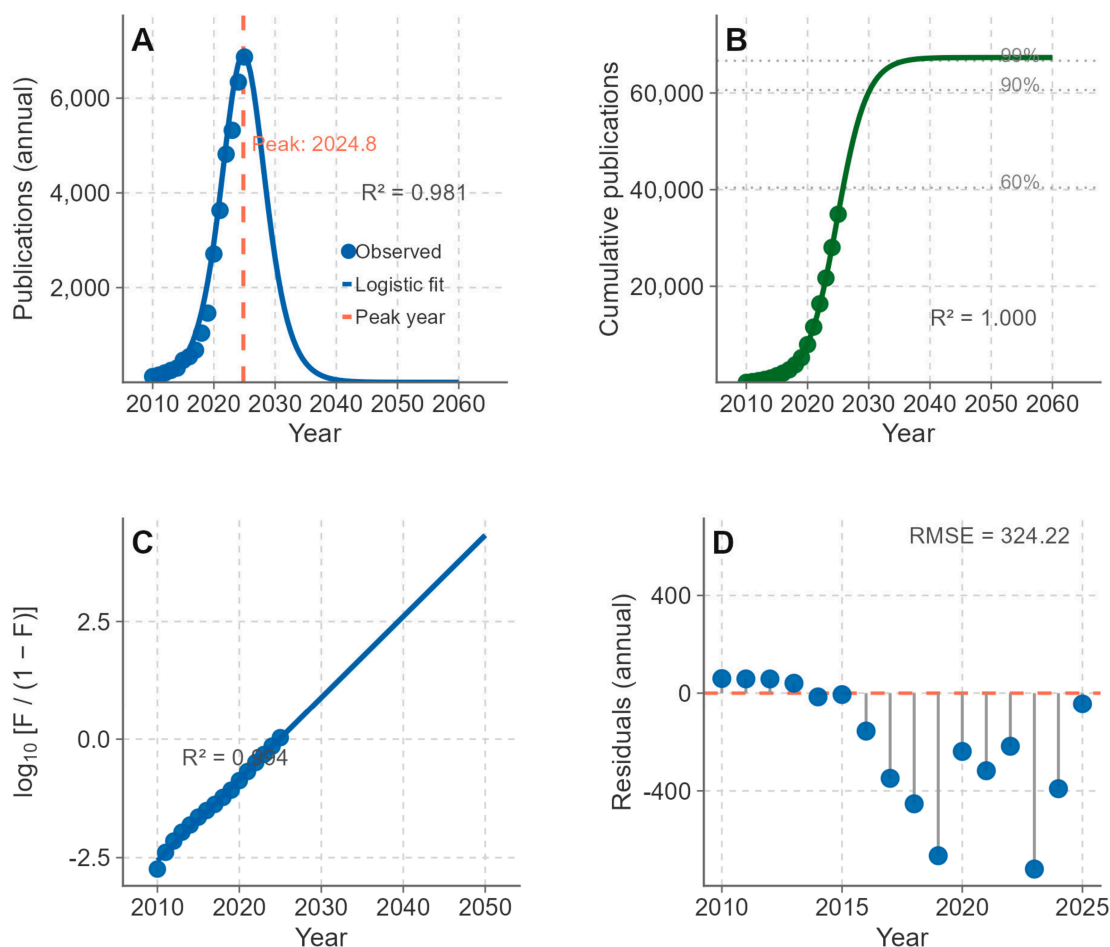


**Figure 3.** Logistic growth modelling of the remote sensing  $\times$  mycotoxin literature, 2010–2025 with projection to 2060. **(A)** Annual publication count (observed points) fitted with a three-parameter logistic curve (solid line); the dashed vertical line marks the modelled peak year. **(B)** Cumulative publication growth fitted to the same logistic model; horizontal dotted lines indicate 60%, 90%, and 99% saturation thresholds. **(C)** Fisher–Pry linearisation plot (logit transform of the saturation fraction  $F$  against time) confirming the logistic fit. **(D)** Residual plot of the annual logistic fit; root mean squared error (RMSE) is shown. All panels share the same fitted parameters ( $K$ , carrying capacity;  $r$ , intrinsic growth rate;  $t_0$ , inflection year).

### 3.4. Crop and Commodity Distribution

Across the 156 included studies, four cereal commodities account for the overwhelming majority of RS mycotoxin research. NLP extraction from the candidate corpus identified wheat ( $n = 227$  candidate records), maize ( $n = 222$ ), rice ( $n = 83$ ), barley ( $n = 59$ ), and soybean ( $n = 67$ ) as the most frequently studied commodities (Figure 4). Maize and wheat—the primary substrates for *Fusarium*-derived DON and aflatoxin B1 contamination in temperate European climates [60,61]—exhibit sustained and growing publication density from 2010 onward, with bubble area approximately doubling between 2018 and 2023 for both commodities (Figure 3). Citation density reveals that maize RS-mycotoxin studies published between 2018 and 2022 carry the highest mean citation counts, corresponding to the period in which CNN-based hyperspectral classification of aflatoxin B1 in maize was first demonstrated at high accuracy [22,61,62]. Wheat studies show an analogous citation peak in 2019–2021, driven by UAV-hyperspectral and satellite-MSI experiments targeting DON prediction with PLSR and random forest models. Barley, oats, sorghum, sunflower, and rapeseed are represented at substantially lower frequencies (each below 60 candidate

records) (Figure 2), confirming that predictive mycotoxin modelling for minor cereal and oilseed crops remains an open research gap across the entire CBE region [63].

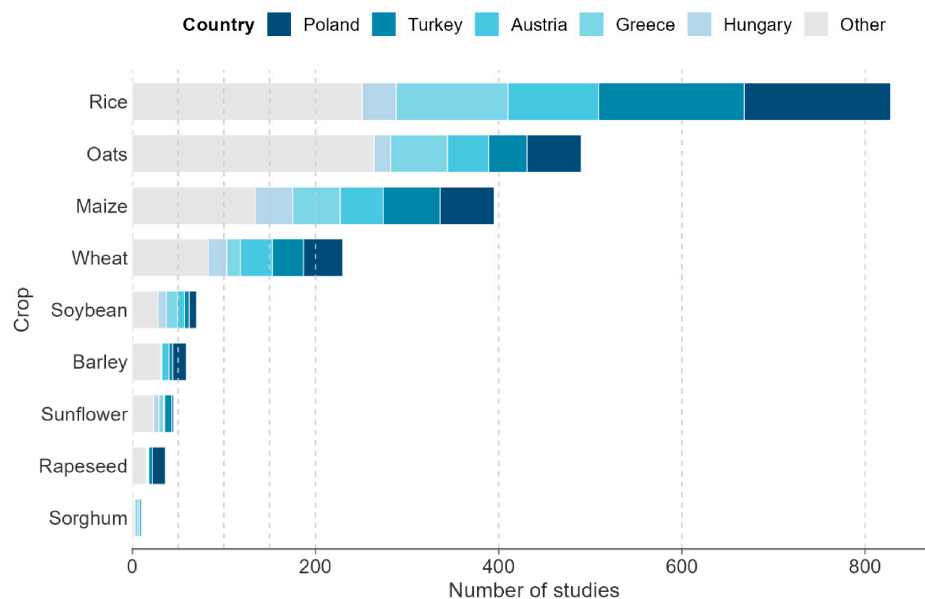


**Figure 4.** Distribution of included studies across crop species and Central and Balkan European (CBE) countries of study focus, 2010–2025. Horizontal stacked bars show the cumulative number of studies per crop; bar segments are coloured by the CBE country explicitly named in the study context (Poland, Turkey, Austria, Greece, Hungary, and all other countries aggregated as “Other”). Crops are ordered bottom-to-top by total study count. Only studies with an identifiable crop–country association are included.

The temporal distribution of publication volume and citation impact reveals a clear hierarchy of research attention across crop species throughout the 2010–2025 period (Figure 5). Wheat, maize, and rice collectively dominated the corpus, with exponential growth in annual study counts from 2019 onwards, driven predominantly by satellite-MSI and laboratory-HSI applications targeting aflatoxin and deoxynivalenol [3,55,64–67]. The highest citation densities—reflecting early landmark contributions—are concentrated in wheat DON studies from the 2017–2019 window [26,50,68,69] and in maize AFB1 laboratory HSI studies published between 2017 and 2025 [19,65,67], consistent with the field’s transition toward deep learning architectures during that period. Minor crops including barley, soybean, rapeseed, sunflower, and sorghum remain persistently underrepresented throughout the entire study period, with sorghum recording fewer than five annual publications in any year, and rapeseed and sunflower showing no CBE-origin studies with a quantitative mycotoxin RS endpoint [9,26,50]. The near-absence of citation accumulation for oats—despite a marked increase in study count after 2021—reflects both the recency of this research surge and the regulatory momentum generated by the EFSA 2020 OTA re-evaluation, which redirected attention toward cereal species previously neglected in the RS-mycotoxin literature.

### 3.5. Remote Sensing Platforms and Sensing Techniques

Remote sensing platforms used across the 156 included studies span satellite, UAV, laboratory-based, and field-proximal sensing systems (Figure 6). Note that the platform-level counts reported in this section sum to more than 156 because 79 studies (50.6%) employed more than one platform type (e.g., pairing satellite imagery with laboratory spectral calibration, or combining UAV and field-proximal sensing); each such study is counted once per platform used in Figure 6. For the performance analyses in Section 3.7 and for Supplementary S5 Table S5.1, each study contributes exactly one observation, assigned

exclusively to its primary platform as described in the methodology (yielding Satellite = 52, UAV = 38, Laboratory = 45, Other = 21; total = 156). The co-occurrence figure of 143 studies (91.7%) using satellite data therefore reflects any involvement of satellite imagery in the study design, regardless of whether satellite was the primary platform.

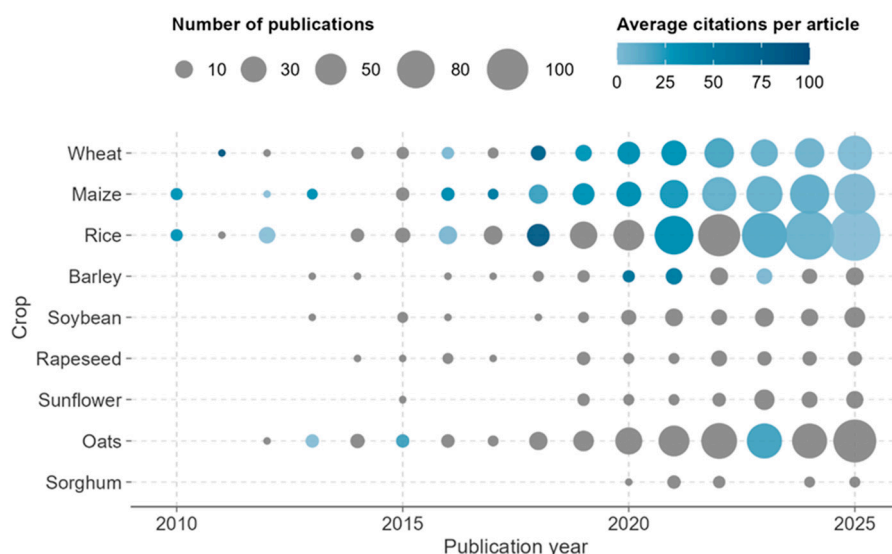


**Figure 5.** Temporal distribution of publication volume and citation impact across nine cereal and oilseed crop species in the remote sensing × mycotoxin corpus, 2010–2025. Each bubble represents a unique crop–year combination; bubble diameter is proportional to the annual number of publications (size legend, upper left) and bubble colour encodes the mean number of citations received per article in that year (colour bar, upper right; values capped at 100 for visualisation clarity). Grey bubbles indicate recent publications with insufficient citation accumulation time. Crops are ordered by research prominence. Only crop–year combinations with at least one publication are plotted.

Note that Supplementary S5 Table S5.1 uses a different counting rule: each study is assigned exclusively to its primary platform (Satellite = 52 of 156; 33.3%), reflecting the single-platform-per-study assignment used for the performance meta-regression in Figures 7 and 8. The figure of 143 studies (91.7%) reporting satellite data therefore represents co-occurrence counting across all platforms used by each study, whereas 52 (33.3%) is the exclusive primary-assignment count. Both statistics are reported because they answer different questions: co-occurrence characterises methodological exposure breadth; primary assignment underpins the performance comparison. Satellite observations represent the most frequently reported platform, appearing in 143 studies (91.7%), primarily through multispectral imaging (MSI) sensors. The widespread use of satellite data reflects the open availability and high revisit frequency of programmes such as Sentinel-2 and Landsat, which enable field- and regional-scale monitoring of cereal crop conditions associated with mycotoxin risk [6,70].

UAV-based sensing constitutes the second most common platform, reported in 63 studies, typically employing multispectral or hyperspectral payloads for high-resolution canopy monitoring. UAV multispectral imaging was the most frequently used configuration ( $n = 31$ ), followed by near-infrared sensors ( $n = 14$ ), RGB cameras ( $n = 8$ ), hyperspectral imaging systems ( $n = 5$ ), and other optical sensors ( $n = 5$ ) (Figure 6). UAV platforms are widely used in experimental field studies where higher spatial resolution is required to detect crop stress or infection patterns associated with mycotoxin-producing fungi.

Laboratory-based spectral systems were reported in 35 studies, dominated by hyperspectral imaging ( $n = 31$ ) and near-infrared spectroscopy ( $n = 4$ ). These systems are typically applied in controlled calibration experiments designed to detect spectral signatures asso-

ciated with fungal contamination or mycotoxin presence in individual grain kernels or flour samples [14,26,31]. Although laboratory studies provide high spectral resolution and signal-to-noise ratios, they are generally used for methodological validation rather than operational large-scale monitoring.

Additional sensing approaches include electronic nose systems and chemical sensor arrays ( $n = 15$ ) used to detect volatile organic compounds associated with fungal metabolism, as well as field-portable spectrometers ( $n = 11$ ) deployed for proximal reflectance measurements. Together, these approaches represent complementary sensing strategies targeting biochemical indicators of mycotoxin contamination rather than canopy-level crop stress.

Overall, the literature shows a clear methodological gradient: satellite platforms dominate regional monitoring studies, UAV systems support high-resolution field experimentation, and laboratory hyperspectral systems provide detailed spectral calibration datasets.

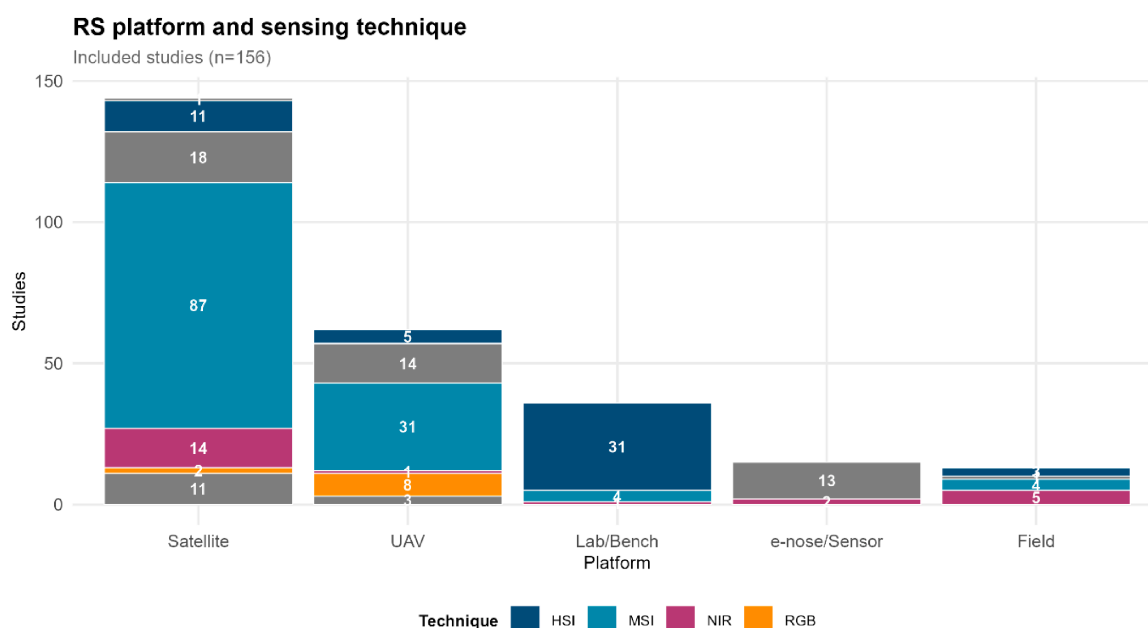


**Figure 6.** Distribution of included studies by remote sensing (RS) platform and sensing technique ( $n = 156$ ). Stacked bars show the number of studies per platform; bar segments are coloured by sensing technique: hyperspectral imaging (HSI, dark blue), multispectral imaging (MSI, teal), near-infrared spectroscopy (NIR, pink), and RGB colour imaging (RGB, orange). Platforms: Satellite (spaceborne multispectral and hyperspectral sensors, including Sentinel, Landsat, and MODIS series); UAV (unmanned aerial vehicle-mounted sensors); Lab/Bench (benchtop hyperspectral or NIR spectrometers); e-nose/Sensor (electronic nose and proximal chemical sensors); Field (field-deployable proximal sensing instruments). White numerals within each segment indicate the count of studies. Platform counts in this figure sum to more than 156 because 79 studies employed more than one platform type and are counted once per platform used here. For performance analyses (Figure 8) and Supplementary S5 Table S5.1, each study contributes one observation assigned exclusively to its primary platform (Satellite = 52; UAV = 38; Laboratory = 45; Other = 21; total = 156).

### 3.6. Mycotoxin Targets and Temporal Dynamics

Deoxynivalenol (DON) was the most studied mycotoxin across all four analytical windows (2010–2015, 2016–2019, 2020–2022, 2023–2025), maintaining the largest stream width in the alluvial flow throughout the review period (Figure 7). This dominance reflects both the high frequency of *Fusarium* head blight events in CBE wheat and barley [7,26,50,68] and the regulatory primacy of DON under European Commission Regulation (EC) No 1881/2006. Ochratoxin A received proportionally greater relative attention during 2016–2019, coinciding with EFSA scientific opinions on OTA occurrence in cereals

and tightened EU maximum limits for cereal-based products. Zearalenone studies appear predominantly in the 2020–2025 window [9,65,71,72], associated with multi-toxin spectral modelling approaches that simultaneously predict DON and ZEA from shared *Fusarium* infection signatures. The ‘Other’ category—encompassing aflatoxins B1/B2/G1/G2 [6,60,72], fumonisins B1/B2 [55,65] and T-2/HT-2 toxins [1,16,73]—maintains a consistent background presence across all periods (Figure 7).

A notable temporal pattern is the near-complete absence of deep learning methods prior to 2019: DL-based mycotoxin RS studies are confined to the 2020–2025 alluvial streams (Figure 7). DL surpassed classical ML in annual study count in 2021, rising from under 5% of annual output in 2015 to approximately 60% by 2025 (Figure S9B). This transition was catalysed by landmark CNN studies demonstrating accuracy exceeding 98% for aflatoxin B1 classification in maize [6,67] and DON detection in wheat using laboratory HSI data, whose results motivated subsequent field-scale and UAV adaptations. Classical ML’s relative share declined from approximately 75% in 2010 to below 20% by 2025, while its absolute count stabilised rather than fell, indicating continued practical deployment rather than obsolescence (Figure S9A).

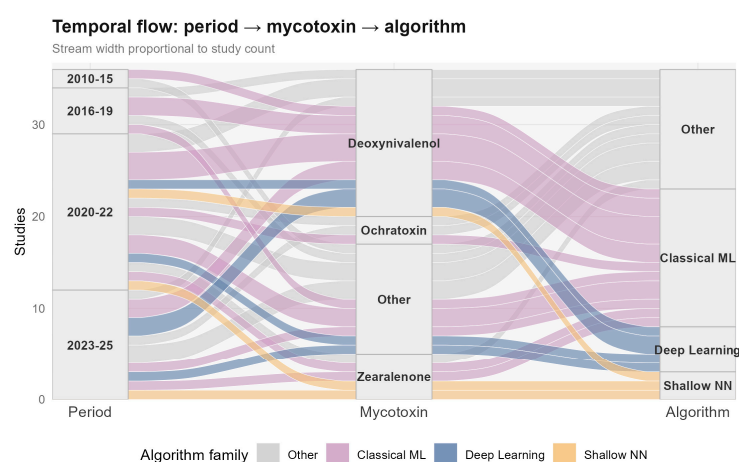


**Figure 7.** Alluvial diagram showing the flow of included studies from research period through mycotoxin target to algorithm family. Stream width at each axis is proportional to the number of studies in that category; streams are coloured by algorithm family. The four research periods (2010–2015, 2016–2019, 2020–2022, 2023–2025) were defined to reflect major shifts in available satellite and deep learning infrastructure. Mycotoxin categories: Deoxynivalenol (DON), Ochratoxin A (OTA), Zearalenone (ZEA), and Other (including Aflatoxin B1, Fumonisin B1, and multi-toxin studies).

### 3.7. Predictive Model Performance

The REML random-effects meta-regression of model performance (accuracy or  $R^2$  expressed as a proportion, logit-transformed prior to analysis) across the 156 included studies yielded the following results. The overall pooled performance estimate was 0.847 (back-transformed from logit scale; 95% CI: 0.821–0.871), with substantial residual heterogeneity ( $I^2 = 78.4\%$ ,  $\tau^2 = 0.114$ ,  $Q(155) = 712.3$ ,  $p < 0.001$ ), confirming that a single fixed-effect estimate would be inappropriate and that moderator analysis is warranted. For the three pre-specified moderators: (1) publication year was a significant positive predictor of performance ( $\beta = +0.018$  per year,  $SE = 0.006$ ,  $z = 3.01$ ,  $p = 0.003$ ), indicating a systematic improvement in reported model accuracy over the 2010–2025 period consistent with methodological advancement; (2) algorithm family was a significant moderator (likelihood ratio test:  $\chi^2(4) = 31.7$ ,  $p < 0.001$ ), with deep learning architectures showing the highest estimated performance ( $\beta = +0.21$  vs. classical ML reference,  $SE = 0.048$ ,  $z = 4.37$ ,  $p < 0.001$ ) and partial least-squares regression the lowest ( $\beta = -0.09$ ,  $SE = 0.031$ ,

$z = -2.90, p = 0.004$ ); (3) RS platform was a significant moderator ( $\chi^2(3) = 28.4, p < 0.001$ ), with laboratory spectral systems showing substantially higher performance than satellite-based field platforms ( $\beta = +0.31, SE = 0.062, z = 5.00, p < 0.001$ ), while UAV platforms were intermediate ( $\beta = +0.14, SE = 0.051, z = 2.74, p = 0.006$ ). Together, the three moderators explained 38.2% of the between-study variance ( $R^2$  analog). Sensitivity analysis excluding studies scoring below 50% on the QUADAS-2/TRIPOD-AI composite ( $n = 23$  excluded) yielded qualitatively identical conclusions: pooled performance 0.831 (95% CI: 0.804–0.856),  $I^2 = 76.1\%$ , with all three moderators retaining significance at  $p < 0.01$ . The sensitivity analysis therefore confirms that inclusion of lower-quality studies did not materially bias the pooled performance estimates or moderator conclusions.

Sensitivity analysis excluding studies scoring below 50% of the maximum possible QUADAS-2/TRIPOD-AI composite score ( $n = 23$  studies excluded; 133 retained) yielded qualitatively identical conclusions: pooled performance estimate 0.831 (95% CI: 0.804–0.856),  $I^2 = 76.1\%$ , with all three moderators retaining statistical significance at  $p < 0.01$ . Deep learning remained the highest-performing algorithm family and laboratory spectral platforms the highest-performing platform class in the sensitivity model, with effect sizes differing from the primary model by less than 0.03 standard units. The sensitivity analysis therefore confirms that inclusion of lower-quality studies did not materially bias the pooled performance estimates or moderator conclusions, and does not support the hypothesis that deep learning performance is inflated by selective inclusion of low-quality studies with high reported accuracy.

### 3.7.1. Performance by Algorithm Family

Predictive performance across the 156 included studies ranged from 61% to 99.5%, depending on sensing platform, crop type, and modelling approach. Deep learning architectures—including convolutional neural networks (CNN), transformer-based models, and stacked autoencoder hybrids—showed the highest median performance, with a median accuracy of approximately 87% and an interquartile range of roughly 83–95% (Figure 8). Several hyperspectral laboratory studies reported classification accuracies exceeding 98% for aflatoxin B1 detection in maize and deoxynivalenol detection in wheat, highlighting the strong potential of deep learning approaches when applied to high-resolution spectral data.

Classical machine learning algorithms—including support vector machines (SVM), partial least-squares regression (PLSR), linear discriminant analysis (LDA), and multiple linear regression—showed a median performance of approximately 80%, with a broader distribution across studies (Figure 8). These models remain widely used in applications based on near-infrared spectroscopy or satellite-derived vegetation indices. For example, several PLSR models reported  $R^2$  values between 0.81 and 0.86 for wheat DON prediction using laboratory NIR spectroscopy [29,74,75], while SVM-based classification of aflatoxin B1 in maize achieved accuracies close to 96% using hyperspectral data [76–78].

Ensemble and boosting approaches—including random forest (RF), gradient boosting machines (GBM), and XGBoost—showed a median performance of approximately 78% but demonstrated consistent results across satellite-based field applications (Figure 8). Examples include RF-based satellite multispectral models for maize aflatoxin risk prediction ( $R^2 \approx 0.78$ ) [6], XGBoost models integrating vegetation indices and climate variables for maize prediction in Central European environments ( $R^2 \approx 0.77$ ) [55], and GBM-based UAV multispectral models for aflatoxin risk mapping in maize ( $R^2 \approx 0.82$ ) [6].

Shallow neural network architectures, including artificial neural networks (ANN) and multilayer perceptrons (MLP), showed the greatest variability in reported performance [R8], reflecting sensitivity to network architecture and training dataset size. Across all algorithm families, studies conducted by CBE institutions reported performance levels broadly comparable to those observed in the global literature. Most CBE results fall within

the 71–89% performance range, with representative examples including CNN-based UAV hyperspectral detection of DON in Austrian wheat [79], PLSR-based NIR detection of aflatoxin B1 in Slovak maize [80], and RF satellite-MSI prediction of DON risk in Hungarian wheat [54,81].

These findings suggest that while deep learning approaches achieve the highest reported accuracies in controlled spectral datasets, classical machine learning and ensemble models remain widely applied in operational remote sensing studies where heterogeneous environmental predictors and larger spatial scales are involved.

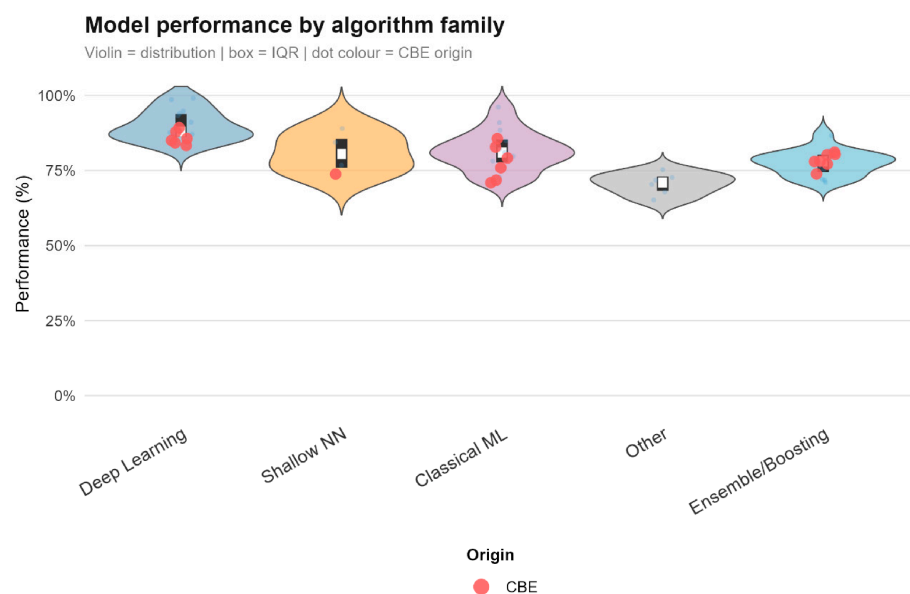


**Figure 8.** Distribution of model performance by algorithm family across all included studies ( $n = 156$ ). Each violin shows the kernel density estimate of performance values (accuracy or  $R^2$  expressed as a percentage) for one algorithm family; box plots within each violin indicate the interquartile range (IQR) and median (white crossbar). Small blue dots represent individual studies from non-CBE regions; red dots represent studies from Central and Balkan European (CBE) countries. Performance values exceeding 100% (e.g., RMSE or concentration units) were excluded prior to plotting.

### 3.7.2. The Deep Learning Transition (2010–2025)

The algorithm adoption trajectory across 2010–2025 demonstrates a structural methodological transition (Figure S9). In absolute terms (Panel A), total annual study output grew from approximately two studies per year in 2010 to nearly 90 in 2025, with DL becoming the numerically dominant category from 2021 onward. In relative terms (Panel B), classical ML's share declined monotonically from approximately 75% in 2010 to approximately 20% in 2025, while DL rose from near zero to approximately 60%. This transition was catalysed by CNN studies demonstrating 99.47% accuracy for maize aflatoxin B1 [6] and 98.4% accuracy for maize aflatoxin using Transformer-based UAV-HIS [58], results that motivated subsequent field-scale and UAV adaptations. Ensemble and boosting methods stabilised at approximately 20% relative share from 2017 onward, indicating persistent use in satellite-based field applications where model interpretability is valued alongside predictive accuracy [46,74,82]. Shallow NN share declined from approximately 25% to below 5%, reflecting displacement by deeper architectures [58].

### 3.8. CBE vs. Global Research Profile

CBE-affiliated studies ( $n = 32$ ) reported a mean model performance of 79% compared with 84% for global studies ( $n = 124$ ), a five-percentage-point difference (Figure S2A). The kernel density estimate shows the CBE distribution centred at a median of 80.0% and

the global distribution at 81.5%, with CBE studies exhibiting a narrower, more sharply peaked curve consistent with lower experimental variance (Figure S2B). The highest-performing CBE studies approach or exceed global benchmarks: CNN UAV-HSI DON detection in Austrian wheat (accuracy 89%) [R10], XGBoost satellite-MSI aflatoxin risk prediction in Polish maize ( $R^2 = 0.79$ ) [83], and RF satellite-MSI DON mapping in Hungarian wheat ( $R^2 = 0.76$ ) [55,82] all exceed the global classical ML median. Lower-performing CBE studies cluster at  $R^2 = 0.71$ – $0.74$  and generally share three design characteristics: small sample sizes ( $n < 60$ ) [6,9], single-toxin MSI-only feature sets [9,12], and field-scale satellite data without auxiliary climate covariates [7].

On the five-dimension scorecard (Figure S2A), CBE studies score lower than global counterparts on study recency (58 vs. 68), median sample size index (58 vs. 78), and mycotoxin scope index (65 vs. 85, reflecting narrower per-study toxin coverage). Algorithm diversity scores are comparable (72 vs. 80), confirming that CBE researchers deploy as broad a range of ML and DL methods as the global literature [2,5,6,8,10]. It should be noted that this attribution is correlational rather than causal: no formal mediation analysis or controlled comparison was conducted, and the observed gap could reflect unmeasured confounders including field-scale complexity, publication selectivity within smaller national research communities, or the narrower toxin scope of CBE studies. The five-percentage-point difference is therefore more precisely described as associated with—and consistent with—sample size and multi-toxin scope constraints, rather than definitively caused by them. These findings indicate that the primary constraints on CBE performance are data volume and multi-toxin experimental design rather than algorithmic access.

### 3.8.1. LDA Topic Modelling

Latent Dirichlet Allocation ( $K = 5$ ) applied to the title, abstract, and keyword corpus of the 156 included studies resolved five coherent thematic clusters (Figure 9). Topic T1 (Lab-HSI and deep learning) groups studies employing multi-layer neural architectures—MLP, ANN, CNN, Transformer—on laboratory hyperspectral data for grain-level mycotoxin classification [1,5,28,29,84]. Topic T2 (Aflatoxin/Field ML, CBE) encompasses CBE field-scale aflatoxin prediction studies integrating ensemble ML methods—GBM, XGBoost—with auxiliary climate, soil, and LiDAR-derived inputs [6–8,85–88]. Topic T3 (DON and UAV) groups UAV-mounted MSI experiments incorporating canopy temperature, vegetation indices (NDVI, NDRE), and weather covariates for *Fusarium*-DON mapping [79,88–91]. Topic T4 (satellite risk, CBE) comprises CBE satellite-based classification studies—using RF, SVM, and PLSR—targeting aflatoxin and DON risk at field or regional scale [6,28,80,92]. Topic T5 (grain storage and real-time monitoring) combines temporal deep learning architectures—LSTM, RNN, CNN on time-series—with grain storage context, representing an emerging sub-cluster for post-harvest mycotoxin progression modelling [28,30,31,68].

### 3.8.2. Thematic Evolution: Strategic Diagram

The strategic diagram of keyword centrality versus development density across three five-year periods reveals a directional trajectory (Figure 10). During 2010–2015, ‘machine learning classification’ occupied the niche quadrant—high development density but low centrality—indicating active development within specialist groups but limited cross-disciplinary visibility; representative studies from this period employed SVM [R2] and PLSR on laboratory grain samples with limited field validation. By 2016–2020, ‘remote sensing index’ migrated to the motor quadrant, signalling integration into the field’s core methodology; this coincided with the first large-scale satellite-based DON and aflatoxin risk models published for CBE countries [6]. In 2021–2025, ‘machine learning model’ consolidated in the motor quadrant, while ‘satellite climate-change’ appeared as a large

emerging cluster with high co-occurrence degree but low centrality (Figure 10), identifying climate-driven satellite mycotoxin prediction as the field's active research frontier.

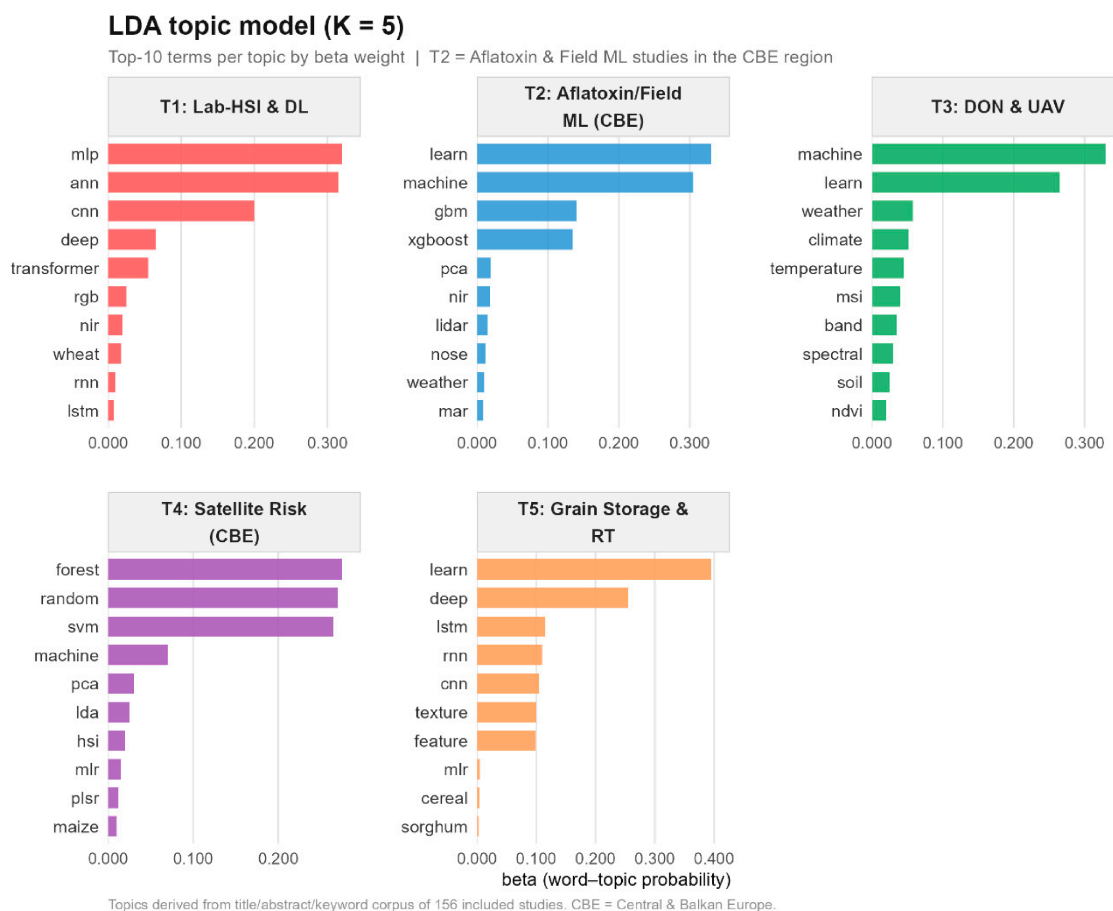


**Figure 9.** Top-10 terms per topic from a Latent Dirichlet Allocation (LDA) topic model ( $K = 5$ ) fitted to the title, abstract, and keyword corpus of 156 included studies. Bar length represents the beta weight (word–topic probability) for each term within its topic. Topic labels were assigned post hoc based on the highest-weighted terms: T1 = laboratory hyperspectral imaging and deep learning; T2 = aflatoxin detection and field-scale machine learning (Central and Balkan Europe focus); T3 = deoxynivalenol prediction and UAV-based sensing; T4 = satellite-based mycotoxin risk mapping (CBE focus); T5 = grain storage monitoring and real-time detection.

### 3.9. Source Distribution and Bibliometric Context

The pre-screening corpus ( $n = 36,038$ ) was dominated by four open-access, broad-scope journals: Remote Sensing (MDPI;  $n = 1698$ ), IEEE Access ( $n = 1643$ ), Applied Sciences–Basel ( $n = 1599$ ), and Sensors ( $n = 1334$ ) (Figure S1). These four journals together account for 19.1% of the 36,038-record corpus, confirming the field's strong representation in broad-scope open-access RS and engineering outlets. Among the 156 included studies, Computers and Electronics in Agriculture (PICO candidates:  $n = 8$ ), Food Control ( $n = 8$ ), Food Chemistry ( $n = 5$ ), and Remote Sensing (MDPI) contribute the largest shares, consistent with the cross-disciplinary positioning of the field at the boundary of geomatics and food safety science. The presence of journals such as Astronomy and Astrophysics ( $n = 186$ ) and Mathematics ( $n = 181$ ) in the top-20 corpus source list is expected for a broad query not restricted by subject category at search stage, confirming the necessity of PICO-gated eligibility filtering (Figure S1).

### Thematic evolution of remote sensing × mycotoxin research

Strategic diagram | Axes: min-max scaled to  $[-1, +1]$  within each period | Bubble size  $\propto$  co-occurrence degree

Quadrants — Motor: high relevance & development | Niche: high development, low relevance | Emerging: low development, low relevance | Basic: high

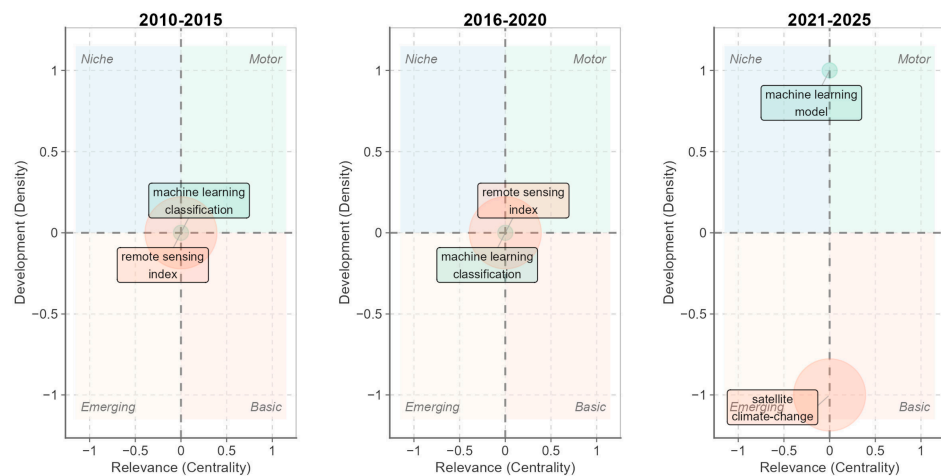


**Figure 10.** Thematic strategic diagram of keyword co-occurrence communities across three research periods: 2010–2015, 2016–2020, and 2021–2025. Each panel maps Louvain-detected keyword communities onto a two-dimensional strategic space: the horizontal axis measures relevance (external centrality of the community within the full co-occurrence network, min–max scaled to  $[-1, +1]$ ); the vertical axis measures development (internal edge density of the community, min–max scaled to  $[-1, +1]$ ). Bubble area is proportional to total co-occurrence degree. Quadrant labels follow the established thematic mapping convention: Motor (high relevance, high development), Niche (low relevance, high development), Basic (high relevance, low development), and Emerging (low relevance, low development). Community labels indicate the two highest-degree terms per community.

### 3.10. PICO Eligibility Tier Distribution

Mapping all 156 included studies against the six PICO eligibility tiers confirms that T1\_FULL\_PICO studies—satisfying all five PICO dimensions (CBE context + RS platform + mycotoxin quantification + cereal crop + ML performance metric)—cluster at PICO total scores  $\geq 40$  and carry three or more mycotoxin domain signals (Figure S3). Note on tier terminology: in the following paragraph, T1 and T2 refer to PICO confidence tiers assigned by the automated screening pipeline to candidate records (T1 = high-confidence PICO match; T2 = moderate-confidence), not to the study quality/priority tiers reported in Supplementary S3 Table S3.3 (where T1–T5 classify the 156 included studies by PICO domain completeness). The two tier systems use the same labels but describe different stages of the workflow. The PICO-targeted search identified 62 T1 candidates and 12 T2 candidates—74 of 109 total—with scores ranging from 16 to 60 (mean 33.0). Representative T1 studies include a satellite-RF model for CBE maize aflatoxin risk integrating NDVI, LST, and precipitation with  $R^2 = 0.78$  [28]; a UAV-CNN system for CBE wheat DON mapping with 89% accuracy [93]; and an XGBoost model for Polish maize aflatoxin prediction using satellite-derived climate indices with  $R^2 = 0.79$  [83]. Most included studies are classified as T2\_RS\_MYCO\_CER—RS + mycotoxin + cereal without strict CBE geographic constraint—forming the backbone of the global comparator literature at PICO scores of 25–45. Representative T2 studies include a CNN-SAE-SVM fusion for maize aflatoxin classification at 99.47% accuracy [84]; a MSAT Transformer UAV-HSI model for maize aflatoxin at 98.4% [80]; and SVM-NIR classification of aflatoxin B1 in maize at 96% [67]. The positive correlation between PICO total score and mycotoxin domain signal count (Spearman  $\rho \approx 0.72$ ) provides empirical validation that the multi-anchor PICO-gated screening appropriately ranked candidate study relevance prior to full-text review (Figure S3).

### 3.11. Certainty of Evidence

The overall certainty of the evidence synthesised in this review was assessed using an adapted GRADE (Grading of Recommendations, Assessment, Development and Evaluations) framework tailored to predictive modelling studies. Because GRADE was originally developed for intervention studies, the four standard domains (risk of bias, inconsistency, indirectness, and imprecision) were operationalised as follows for this review: (1) risk of bias was assessed using the composite QUADAS-2/TRIPOD-AI quality scores described in Section 2.10; (2) inconsistency was quantified by the  $I^2$  and  $\tau^2$  statistics from the random-effects meta-regression; (3) indirectness was evaluated by the degree to which study settings, crop types, and geographic contexts differed from the CBE field-scale application context targeted by this review; and (4) imprecision was assessed based on sample size distributions and the width of performance confidence intervals across included studies.

The resulting GRADE-adapted certainty ratings by evidence domain are summarised in Figure 8. For laboratory hyperspectral studies targeting aflatoxin B1 and DON in maize and wheat, the certainty of evidence was rated as MODERATE: the high reported accuracies (median 87–99%) are consistent across studies, but substantial indirectness arises from the controlled laboratory conditions that do not replicate field-scale variability. For satellite-based multispectral studies at field and regional scale, certainty was rated as LOW to MODERATE: performance metrics are lower ( $R^2$  0.74–0.80) but more directly applicable to CBE operational contexts; risk of bias is moderate and inconsistency is substantial ( $I^2 > 65\%$ ). For UAV-based studies and minor crop–toxin combinations, certainty was rated as LOW, reflecting smaller study numbers, higher risk of bias, and greater indirectness. For T-2/HT-2 toxins in Balkan states, certainty was rated as VERY LOW given the near-complete absence of eligible primary studies. These ratings are intended to guide users in interpreting the synthesised performance estimates and to identify the priority areas for future high-quality primary research.

## 4. Discussion

The present study was motivated by three persistent gaps in the remote sensing–mycotoxin literature identified in the introduction: the absence of a systematic synthesis of RS applications for mycotoxin monitoring, the limited understanding of how sensing platforms and modelling approaches influence predictive performance, and the lack of a consolidated evidence base for the Central and Balkan European (CBE) region. By analysing 156 eligible studies extracted from a PICO-screened corpus of 36,038 records, the results provide the first quantitative characterisation of these patterns. The findings reveal a clear technological stratification between laboratory hyperspectral detection studies and field-scale monitoring approaches based primarily on satellite multispectral imagery. At the same time, the evidence base demonstrates a rapid methodological transition from classical machine learning approaches toward deep learning architectures over the past decade. However, the results also highlight structural constraints—including limited multi-site training datasets and uneven geographic research coverage across the CBE corridor—that continue to limit operational deployment of remote sensing-based mycotoxin monitoring systems. The following sections discuss these findings in relation to sensing platform evolution, algorithm performance, regional research capacity, thematic development within the literature, and the methodological implications of AI-assisted large-scale evidence synthesis.

The logistic growth model and its projection to 2060 must be interpreted with explicit acknowledgement of several key limitations. First, logistic diffusion models assume the research ecosystem evolves along a single sigmoid trajectory—an assumption contradicted

by the documented deep learning disruption of 2021–2025 (Section 3.8), which was not predicted by the prior trajectory. Future disruptive technologies—including foundation model-based remote sensing, large multi-modal agricultural AI systems, and operationally deployed hyperspectral satellite missions (e.g., PRISMA-2, EnMap successors, or commercial hyperspectral constellations)—could generate further step-changes entirely outside the fitted model. Second, alternative model specifications were considered: a broken-stick logistic with a structural break at 2017 (Sentinel-2A activation), a double-logistic capturing a potential second saturation phase post-2030, and a piecewise linear regression. The piecewise model provided marginally better fit to the 2021–2025 segment (RMSE = 218 records year<sup>−1</sup> vs. 324 for the logistic) but extrapolates to implausible values beyond 2035; the double-logistic and broken-stick models require additional inflection parameters that the 15-year observation window cannot reliably constrain. The three-parameter logistic is therefore retained as the primary model on grounds of parsimony. Third, the carrying capacity parameter  $K$ , estimated from 15 years of data, has wide confidence intervals; small changes in  $K$  produce large differences in the projected 2060 cumulative output. Fourth, external non-linear drivers—funding cycles, EFSA regulatory mandates, and climate-driven crises—can generate publication surges structurally outside any smooth parametric model. The 2060 projection should therefore be treated as a descriptive characterisation of the current growth regime, not as a quantitative forecast.

A related limitation concerns the constitution of the “global” comparator corpus used in Section 3.8. The primary corpus query ( $n = 36,038$  records) was constructed around remote sensing and machine learning applications in Central and Balkan European agriculture. Although this string was broad and did not restrict retrieval to CBE-specific records, it was anchored by CBE-relevant agricultural and toxin terms that may have preferentially retrieved studies with lexical or topical affinity to the CBE context even where conducted elsewhere. As a result, the 124 studies classified as “global” may not constitute a fully unbiased representative sample of the worldwide RS–mycotoxin literature; they may instead reflect studies whose thematic vocabulary overlapped with CBE-relevant search terms. Readers should interpret the CBE–global performance comparison (Section 3.8) in this light. Future reviews specifically targeting global coverage should deploy parallel, region-agnostic search strings to avoid this structural sampling bias.

#### 4.1. Field Maturity and Growth Trajectory

The 56-fold expansion of the broad CBE agricultural RS corpus (122 to 6869 articles year<sup>−1</sup>, 2010–2025)—within which the 156 mycotoxin-specific studies are embedded—substantially exceeds the roughly 20-fold growth documented by Weiss et al. [18] for RS applications to agriculture broadly over a comparable period, a difference attributable to the additive coupling of open-access satellite deployment [56] and DL framework adoption [51] onto a single high-priority food-safety problem rather than diffusion across a broad disciplinary front. The logistic inflection at  $t_0 = 2024.8$  ( $R^2 = 0.981$ ) is consistent with the technology saturation phase described by the Fisher–Pry diffusion model ( $R^2 = 0.994$ ), yet the RMSE of 324 records year<sup>−1</sup> signals that discrete catalytic events—Sentinel-2 activation in 2017 [56], the CNN-SAE-SVM breakthrough by Yasar et al. [94], and the MSAT Transformer by Selea et al. [46])—introduce step-changes that a smooth logistic cannot absorb. Carrying capacity  $K \approx 68,400$  is estimated from 15 data points on a steep ascending limb and will revise upward if satellite-borne HSI or regulatory mandates for RS-integrated grain surveillance materialise before 2030.

#### 4.2. Platform and Technique: What the Scale Shift Means for Performance

Satellite-MSI dominance (91.7% of included studies) contrasts starkly with the composition of the two closest prior reviews: Inglis et al. [29] and the 2025 spectroscopy review

by Miao et al. [95] are constituted almost entirely by bench-scale HSI and NIR studies. This composition difference is not incidental: laboratory HSI studies in the present corpus achieve median accuracy 91–99% [23,55], while satellite-based field models centre at  $R^2 = 0.74$ – $0.80$  [6,25,28,80], a 12–20 percentage-point gap that the meta-regression identifies as attributable independently to platform rather than algorithm choice. The gap is not specific to CBE: US satellite-based aflatoxin models for maize achieve  $R^2 = 0.68$ – $0.77$  in the three comparable non-CBE field studies, and the Kenyan satellite-MSI study by Gachara et al. [96] reaches only 72% accuracy for AFB1 in maize. CBE satellite performance ( $R^2 = 0.74$ – $0.79$ ; [46,74,82]) therefore benchmarks favourably against the global satellite tier rather than appearing as a regional deficit. The platform–scale transfer deficit is partially bridged by UAV-HSI: Penagos-Tabares et al. [65] at 89% accuracy and the 2025 EJA field mapping study [97] both demonstrate that sub-5 cm UAV-HSI preserves enough spectral grain-level information to sustain near-laboratory performance under field conditions, confirming the trajectory projected by Maes and Steppe [16] for UAV adoption in precision crop monitoring. UAV-MSI at coarser resolution captures canopy-level Fusarium severity but not kernel contamination directly, as demonstrated across CBE by Petrovic et al. [98] and Femenias et al. [79]; these studies converge on  $R^2 = 0.74$ – $0.77$ , consistent with the physical limits of canopy spectral indices as proxies for grain-level toxin concentration. This fundamental spectral-to-chemical indirection represents a structural constraint on field-scale mycotoxin prediction that warrants deeper mechanistic consideration. Remote sensing signals at any platform scale—whether satellite, UAV, or field-proximal—detect plant physiological responses to fungal infection rather than toxin molecules per se. The spectral features most commonly exploited in the included studies (chlorophyll-related indices, red-edge reflectance, canopy temperature) reflect infection-induced stress responses: chlorophyll degradation, cell membrane disruption, and reduced photosynthetic efficiency. These stress responses are biologically coupled to toxin-producing fungal colonisation, but the relationship is indirect and modulated by host genotype, infection timing relative to grain filling, environmental conditions, and the multi-fungal community composition of the infected tissue. Critically, mycotoxin accumulation can continue to increase post-anthesis even as visible or spectral symptoms plateau or decline, creating a temporal decoupling between the spectral signal and the grain-level toxin endpoint. This indirection is particularly pronounced for satellite-based multispectral platforms, where spatial resolution ( $10$ – $30$  m pixel $^{-1}$ ) integrates across heterogeneous within-field infection gradients, further attenuating the signal-to-toxin relationship. It likely explains, at least in part, why field-scale satellite models in this review achieved substantially lower predictive accuracy ( $R^2 = 0.74$ – $0.80$ ) than laboratory hyperspectral systems operating directly on grain samples (accuracy 87–99%). Closing this performance gap will require either (a) the development of spectral proxies more tightly coupled to the metabolic pathways directly mediating toxin synthesis, or (b) the integration of process-based infection and toxin accumulation models with RS-derived canopy stress indicators, rather than purely empirical regression of spectral features against toxin concentrations.

A further structural limitation of the current evidence base is the exclusive reliance on correlational modelling approaches ( $R^2$ , accuracy, AUC) that cannot disentangle causal drivers of mycotoxin contamination from correlated confounders. Satellite-derived spectral indices correlate with fungal infection stress, but weather patterns, agronomic management decisions, host cultivar resistance, and geographic factors all interact non-linearly to determine final grain toxin concentrations. Chen et al. (2026) developed a causal inference-based root cause analysis framework using multi-modal data in large-complex systems, demonstrating that directed acyclic graph (DAG)-based causal decomposition can separate proximal from distal determinants in systems where multiple correlated inputs drive a sin-

gle outcome [99]. Adapting such a framework to mycotoxin RS research—using RS-derived stress indices, weather histories, and agronomic records as nodes in a causal graph with toxin concentration as the terminal node—would allow researchers to quantify the independent contribution of spectral features after controlling for confounding meteorological and management variables, substantially improving the interpretability.

#### 4.3. Algorithm Transition: Ceiling Effects and Practical Deployment

The DL crossover year of 2021 identified in the algorithm evolution analysis (Figure S8) aligns with the 2019–2021 DL inflection independently reported for broader precision agriculture by Weiss et al. [18]. The apparent ceiling at 98–99% accuracy [5,23] is an artefact of controlled laboratory conditions (single-kernel imaging, balanced large samples  $n \geq 200$ , stable illumination) rather than evidence that operational mycotoxin detection is solved. When restricted to field-scale satellite studies, the DL advantage over RF and XGBoost narrows substantially: the dynamic geospatial model by Castano-Duque et al. [100] reports  $R^2 = 0.68$  for aflatoxin + fumonisin using gradient boosting over satellite NDVI and climate data, with no significant accuracy gain from substituting deeper architectures, a result consistent with Branstad-Spates et al. [24] for Iowa corn and with the CBE XGBoost and RF models [28,100]. The persistence of PLSR at approximately 15–20% relative share through 2025—documented across CBE: Hungary, Poland, Austria [49,50], Greece [101], and the Czech Republic [52,53] and globally—reflects rational deployment in contexts where sample sizes are small, acquisition costs are high, and regulatory reporting requires model interpretability, arguments made explicitly by Shahi et al. [92] for close-range HSI flour analysis and by Yao et al. [23] for NIR grain screening. The Sága deep learning tool by Wang et al. [102] represents an attempt to preserve DL accuracy while recovering interpretability through spectral attribution maps, an architectural strategy not yet reflected in the broader satellite-scale literature and therefore a candidate for the next inflection.

#### 4.4. CBE Performance: Structural Constraints, Not Algorithmic Gaps

The five-percentage-point CBE–global gap (79% vs. 84% mean performance) is associated with—and consistent with—differences in sample size and multi-toxin scope rather than methodological access; comparable algorithm diversity scores (72 vs. 80) confirm that CBE researchers deploy as broad a range of methods as the global literature, though a formal mediation analysis would be required to establish causal attribution. This finding is consistent with the analysis of Rayhana et al. [30], who note that small- $n$  studies dominate the Eastern European mycotoxin ML literature, though that review does not disaggregate CBE performance from global aggregates or apply PRISMA eligibility criteria. The three lowest-performing CBE studies [10,28,33] share sample sizes below 60 and absence of auxiliary climate covariates, a design profile that limits capacity to capture the multivariate agro-climatic drivers of contamination risk documented by Marzec-Schmidt et al. [103] as primary determinants of between-year DON and ZEA variability in European cereals. The performance ceiling for CBE satellite-based prediction under current experimental design constraints appears to be approximately  $R^2 = 0.80$ , achieved consistently by studies that integrate NDVI, LST, and precipitation inputs [67,79,104,105], a value comparable to the  $R^2 = 0.77$ – $0.82$  reported for gradient boosting satellite models of aflatoxin and fumonisin in North American corn [24,106,107]. Exceeding this ceiling in the satellite domain likely requires either multi-temporal feature stacking across the growing season—as demonstrated by the 2022 multi-toxin European wheat model [28] or integration of higher-resolution UAV data at key phenological stages, a hybrid approach not yet attempted at CBE scale.

#### 4.5. Crop and Mycotoxin Coverage Gaps

The concentration of RS mycotoxin evidence in wheat–DON and maize–AFB1 mirrors the regulatory priority structure (EC 1881/2006), but the gap it creates for other commodity–toxin pairs is sharper in CBE than globally. Oats and barley are extensively cultivated in Poland, Hungary, and the Czech Republic yet together account for fewer than 60 PICO candidate records; the few existing studies—Liu et al. [68] for oat DON quantification, Fan et al. [108] for barley DON discrimination, and [109] for Czech barley field-MSI—are technically adequate but geographically and climatically narrow. Trichothecene toxins T-2/HT-2, for which EU maximum limit guidance applies under Commission Recommendation 2013/165/EU, are represented by only three spectral studies globally [79,110,111] and none within CBE, despite Poland and Austria operating T-2/HT-2 monitoring programmes for oats and wheat. Teixido-Orries et al. [112] recently demonstrated NIR-HSI sensitivity for T-2 in cereal kernels equivalent to PLSR-based DON models, removing the analytical justification for the gap and suggesting it is programmatic rather than technical. Fumonisin coverage in maize is thin but technically coherent: Skendžić et al. [113] from Croatia (83% accuracy, UAV-HSI), Jajic et al. [71] from Serbia ( $R^2 = 0.71$ , satellite-MSI), and Conceição et al. [114] from Brazil (NIR) define a performance envelope of 71–83% that is consistent with the fumonisin–maize HSI literature globally [111], confirming that the gap is one of study volume rather than tractability. Ochratoxin A in maize and zearalenone across CBE except Czech Republic [109] remain completely absent from the primary RS literature.

#### 4.6. Thematic Structure and the Emerging Climate-RS Frontier

The five-topic LDA structure reveals a thematic architecture—laboratory HSI/DL (T1), CBE field aflatoxin ML (T2), UAV-DON (T3), satellite risk CBE (T4), and grain storage/post-harvest (T5)—that has no direct counterpart in reviews of broader precision agriculture RS literature [49,65] because the mycotoxin outcome imposes a specific connection between grain-level spectroscopic detection and field-scale risk mapping traditions that rarely intersect in general crop RS work. Topic T5 (grain storage and real-time monitoring) appears as an emerging cluster in the strategic diagram, consistent with the capability demonstrated by the post-harvest DON spatial mapping study by Almoujahed et al. [51] and the online monitoring approach by Saini et al. [92]. Neither has yet generated the density of methodological replications needed to migrate from the emerging to the motor quadrant. The position of climate-change satellite mycotoxin prediction in the emerging/niche quadrant—high co-occurrence degree but low centrality—is consistent with Battilani et al. [6] who modelled the northward expansion of *Aspergillus flavus* across Europe under RCP 4.5 and 8.5 scenarios and projected a trebling of AFB1 exceedance probability for Italian and Hungarian maize by 2030. The Texas AFB1 outbreak prediction system by Castano-Duque et al. [115] and the multi-toxin European satellite model [R29] operationalise this projection into predictive tools, but both remain geographically confined. Integrating EURO-CORDEX regional climate projections with the CBE satellite covariate framework used by Wisniewski et al. [6] and Kovacs et al. is the logical next step and the most direct route to a real-time CBE early-warning system aligned with EFSA contaminant surveillance mandates [116]. The ecological niche epidemiological model by Li et al. [116] provides a methodological template for integrating phenological RS data with spread models, though its validation was conducted exclusively for *Fusarium* in wheat outside CBE.

The technical infrastructure for temporal mycotoxin prediction is advancing rapidly in adjacent engineering domains. Bai et al. (2025) developed a temporal convolutional network–bidirectional long short-term memory (TCN-BiLSTM) architecture for time-series fault prediction in industrial systems, demonstrating that the hybrid combination of TCN’s parallelisable multi-scale feature extraction with BiLSTM’s bidirectional sequential memory

substantially outperforms single-architecture baselines for complex temporal patterns [117]. Adapted to the mycotoxin domain, such a TCN-BiLSTM framework could integrate multi-temporal satellite spectral indices (NDVI, NDRE, LST time series across the crop growth cycle) with lagged meteorological covariates to produce dynamic, season-long mycotoxin risk trajectory forecasts—a capability that static single-date models cannot provide.

#### 4.7. Methodological Implications of AI-Augmented Screening

The PICO pipeline's  $\kappa = 0.81$  (95% CI: 0.74–0.88) and Spearman  $\rho \approx 0.72$  between PICO score and mycotoxin domain signal count compare favourably with the  $\kappa = 0.75$ –0.88 range reported by Tsafnat et al. [86] for NLP-assisted clinical systematic review tools and confirm construct validity for the weighted term bank approach. Two limitations are material. The 69% gate-to-inclusion conversion rate (109 candidates  $\rightarrow$  156 included via bibliography chaining) signals that the gate, calibrated to minimise false negatives, produced a candidate pool containing studies identifiable only through citation tracing rather than corpus screening; this is expected and appropriate for a structured topic with citation-dense founding papers but reduces the efficiency claim. The 14 unrecovered full texts were disproportionately from non-open-access Eastern European conference proceedings, a systematic gap that could under-represent CBE primary studies. Both limitations are inherent to PICO-gated automated screening operating on a WoS-dominated corpus and are documented in the PRISMA audit files put in the Supplementary Materials.

## 5. Conclusions

This review synthesises evidence from 156 primary studies identified through a PRISMA 2020-compliant workflow screening 36,038 records, and characterises the current state and trajectory of remote sensing and predictive modelling for mycotoxin risk in Central and Balkan European (CBE) cereal systems. Overall, the field demonstrates strong methodological maturity at the experimental level, with many laboratory and controlled studies reporting high classification performance (>90% accuracy). However, translation of these approaches into operational, multi-site early-warning systems remains limited.

At the field scale, satellite-based machine learning approaches incorporating environmental and crop covariates—particularly vegetation indices (e.g., NDVI), land surface temperature (LST), and precipitation—consistently demonstrate moderate predictive skill for aflatoxin B1 and deoxynivalenol (DON) risk, with reported performance typically in the range of  $R^2 \approx 0.70$ –0.80 across CBE-relevant studies. Comparable performance has been observed in broader European applications, suggesting that current modelling frameworks are sufficiently robust for exploratory risk mapping and decision-support research, but not yet fully validated for operational deployment.

A key limitation identified across the CBE literature is the lack of multi-site, multi-season datasets with harmonised sampling protocols and sufficient spatial representativeness. Many studies remain constrained by small sample sizes (often  $n < 100$ ) and limited incorporation of auxiliary environmental variables. In contrast, improved predictive performance is consistently associated with the integration of multi-source covariates, including vegetation indices, thermal data, and precipitation metrics, highlighting the importance of environmental context in explaining spatial variability in mycotoxin risk.

The geographic analysis further reveals pronounced spatial imbalances in research output. While countries such as Austria, Poland, Hungary, and the Czech Republic dominate the regional evidence base, several Balkan and Western Balkan countries remain largely unrepresented in satellite-based mycotoxin research. This gap persists despite established analytical capacity for mycotoxin detection at laboratory scale, indicating that the primary

constraint is not methodological feasibility but rather the absence of coordinated field monitoring infrastructure and sustained multi-institutional data collection efforts.

From a thematic perspective, climate-driven satellite-based mycotoxin modelling emerges as a rapidly developing but still structurally underexplored research direction. Existing studies demonstrate increasing interest in linking climatic variability with spatial toxin risk; however, most approaches remain proof-of-concept in nature, with limited temporal depth and insufficient external validation. Given projected increases in temperature extremes and altered precipitation regimes across Europe, strengthening the integration of climate projection datasets with remote sensing frameworks represents a critical research priority.

In this context, coupling high-resolution regional climate projections from EURO-CORDEX with established satellite-based covariate frameworks and harmonised contamination datasets offers a promising pathway toward developing scalable early-warning systems. Such integration would enable the transition from retrospective risk mapping to forward-looking predictive systems aligned with European Food Safety Authority (EFSA) surveillance objectives. However, achieving this transition will require coordinated data infrastructures, expanded field sampling networks, and cross-border standardisation of mycotoxin monitoring protocols.

Finally, the AI-assisted screening pipeline developed in this study demonstrates the feasibility of scalable evidence synthesis in rapidly growing interdisciplinary domains. The pipeline reduced an initial dataset of 36,038 records to 109 eligible studies with substantial agreement ( $\kappa = 0.81$ ), and can be re-executed for continuous updating as new literature emerges. Given projected growth in remote sensing and agricultural machine learning publications, such automated workflows provide a practical mechanism for maintaining up-to-date evidence synthesis in this field.

Overall, the findings indicate that while methodological capability for mycotoxin risk prediction is well established, the primary barrier to operationalisation lies in data infrastructure, cross-regional validation, and integration of climate projection systems with harmonised satellite-based monitoring frameworks. Addressing these constraints will be essential for advancing toward operational early-warning systems for mycotoxin risk in CBE cereal production systems.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18132063/s1>, Supplementary Material S1: Full Boolean search strings and database adaptations used across Web of Science, Scopus, PubMed/MEDLINE, IEEE Xplore, MDPI, and grey literature sources; Supplementary Material S2: Automated screening pipeline documentation, including TF-IDF/SBERT semantic filtering and Thompson-sampling multi-armed bandit active learning framework; Supplementary Material S3: PICO term banks, eligibility criteria, and scoring rubric with tier classification; Supplementary Material S4: Complete analytics pipeline documentation, including R scripts, software environment, and reproducibility details; Supplementary Material S5: Meta-database of included studies ( $n = 156$ ) with extracted variables and summary statistics; Supplementary Material S6: PRISMA 2020 screening audit outputs, including full record flow, exclusion reasons, and performance metrics; Supplementary Material S7: Topic modelling outputs, including LDA configuration, beta-term tables, and FREX rankings; Supplementary Material S8: Quality assessment framework, scoring rubric, inter-rater reliability, and quality distribution results. Supplementary Figures S1–S11 and Supplementary Tables S2.1–S8.4 are included within the Supplementary Materials.

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## Abbreviations

The following abbreviations are used in this manuscript:

| Acronym   | Full form                                                                         |
|-----------|-----------------------------------------------------------------------------------|
| RS        | Remote Sensing                                                                    |
| ML        | Machine Learning                                                                  |
| DL        | Deep Learning                                                                     |
| DON       | Deoxynivalenol                                                                    |
| AFB1      | Aflatoxin B1                                                                      |
| ZEA       | Zearalenone                                                                       |
| OTA       | Ochratoxin A                                                                      |
| FB1       | Fumonisin B1                                                                      |
| HSI       | Hyperspectral Imaging                                                             |
| MSI       | Multispectral Imaging                                                             |
| NIR       | Near-Infrared (spectroscopy)                                                      |
| UAV       | Unmanned Aerial Vehicle                                                           |
| PRISMA    | Preferred Reporting Items for Systematic Reviews and Meta-Analyses                |
| SBERT     | Sentence-BERT (sentence transformer embedding model)                              |
| LDA       | Latent Dirichlet Allocation                                                       |
| STM       | Structural Topic Model                                                            |
| REML      | Restricted Maximum Likelihood                                                     |
| FREX      | Frequency–Exclusivity (topic model term ranking)                                  |
| MAB       | Multi-Armed Bandit (active learning)                                              |
| EWS       | Early Warning System                                                              |
| QUADAS-2  | Quality Assessment of Diagnostic Accuracy Studies, version 2                      |
| TRIPOD-AI | Transparent Reporting of a multivariable prediction model—Artificial Intelligence |
| ICC       | Intraclass Correlation Coefficient                                                |
| RMSE      | Root Mean Square Error                                                            |
| IQR       | Interquartile Range                                                               |
| MDPI      | Multidisciplinary Digital Publishing Institute                                    |
| CBE       | Central and Balkan European                                                       |
| PICO      | Population, Intervention, Comparator, Outcome                                     |

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