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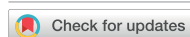
Predicting aflatoxin risk with seasonal meteorological forecast

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Predicting aflatoxin risk with seasonal meteorological forecast

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E-mail: paola.battilani@unicatt.it**Keywords:** agriculture, *Aspergillus flavus*, climate change, food safety, maize, mycotoxins, predictive modelsSupplementary material for this article is available [online](#)

Abstract

Aflatoxin contamination in maize (*Zea mays*), primarily caused by *Aspergillus flavus*, is strongly influenced by meteorological conditions and remains a major food safety concern. Predictive models have been developed to support contamination risk assessment and management strategies, typically relying on meteorological data from local weather stations. While these inputs offer high accuracy, their limited spatial coverage and lack of forecasting capability reduce their application as early warning systems and in-season decision support. This study evaluates the integration of ERA5-Land reanalysis and seasonal climate forecasts into AFLA-maize, a mechanistic model for predicting aflatoxin B1 contamination, to extend its spatial and temporal applicability. Using historical data from the Emilia-Romagna, Italy (2008–2025), we tested bias-adjusted ERA5-Land inputs and developed a hybrid forecasting approach combining reanalysis data for the early-season with adjusted forecasts for the later crop stages. Results show that simulations driven by ERA5-Land reproduced contamination probability in 91% of years compared to station-based results, supporting its use in regions with low quality observations or missing station networks. Hybrid integrations of bias-adjusted forecasts provided contamination risk assessments 3–8 weeks ahead of harvest, showing the trade-off between lead time and accuracy. Forecast initialized later in the season (August) achieved much higher accuracy (up to 91%) but offer less time for action, whereas earlier initializations (June, July) bear larger uncertainty (accuracy of 88%–93%) but extended the decision windows. Furthermore, the availability of ensemble forecasts allows to quantify the uncertainty, providing probability ranges across members that support risk communication and early warning outputs. In summary, the presented approach extends AFLA-maize into a scalable and transferable tool for anticipatory risk management, supporting climate-resilient agriculture and food safety through publicly available meteorological data.

1. Introduction

Aflatoxins (AFs), a group of toxic secondary metabolites produced mainly by *Aspergillus flavus* and *A. parasiticus*, are the most dangerous mycotoxins in food and feed. Aflatoxin B₁ (AFB₁), the most potent among them, is classified as a Group 1 human carcinogen by the International Agency for Research on Cancer (IARC Working Group on the Evaluation of Carcinogenic Risks to Humans 1993). These toxins compromise food safety, limit international trade, and cause severe health and economic

burdens worldwide (Wild and Gong 2010, Wu 2015, Branstad-Spates *et al* 2023).

Maize (*Zea mays*) is one of the main crops affected by AF contamination, especially in warm and drought-prone areas (Cotty and Jaime-Garcia 2007, Kos *et al* 2023). Conditions of high temperature and intermittent drought are known to promote fungal infection and toxin accumulation (Medina *et al* 2015). Given the widespread cultivation of maize and the health risks caused by contaminated grain, anticipating these environmental triggers is essential for effective mitigation.

Climate change is increasingly altering the fungal ecology, influencing both the geographic distribution and the toxigenic potential of mycotoxigenic fungi (Magan *et al* 2011, Battilani *et al* 2016). Once rare in temperate climates, aflatoxin-producing fungi are now common in parts of Southern and even Central Europe (Van Der Fels-Klerx *et al* 2016). Projections in a scenario of + 2 °C suggest a dramatic northward shift in risk zones for AF contamination in maize (Battilani *et al* 2016). Given that global warming has amplified in recent decades (Intergovernmental Panel on Climate Change IPCC), and that the likelihood of breaching the 1.5 °C target set in the Paris Agreement is increasing (Smith *et al* 2018, Bevacqua *et al* 2025), the improvement of predictive models becomes crucial for supporting climate adaptation strategies.

Mechanistic models, such as AFLA-maize (Battilani *et al* 2013), offer a structured approach to simulating the dynamics of *A. flavus* infection and AF accumulation based on environmental conditions. The model consists of two components: one simulating maize phenology, and the other describing the life cycle and toxin production behaviour of *A. flavus*. Hourly meteorological inputs such as temperature (T), relative humidity (RH), precipitation (P), and leaf wetness (LW) duration are used to drive the simulations from plant emergence to harvest. The model has been validated across several European regions and used as a foundation for operational tools in both research and agricultural environments for risk assessment (Camardo Leggieri *et al* 2021). However, the model's dependence on station-based weather data limits its wider application, especially in regions where observational networks are sparse or unreliable (Ceglar *et al* 2016)).

To enable broader geographic use of AFLA-maize, an important methodological improvement involves replacing station observations with gridded data such as meteorological reanalyses. ERA5-Land (Muñoz Sabater *et al* 2021) is the fifth-generation reanalysis of the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5-Land provides high-resolution, hourly atmospheric variables, integrating satellite, radar, and ground observations into a globally consistent dataset. While temperature and humidity data from ERA5-Land have shown to agree well with station data in many studies (Urraca *et al* 2018, Dibi-Anoh *et al* 2023), the adequate representation of precipitation remains a significant challenge. ERA5-Land is understood to have a wet-bias, and shows deficits in representing precipitation extremes while tending to overestimate low-intensity rainfall (Hoerling *et al* 2016, Lavers *et al* Muñoz Sabater *et al* 2021), which can misrepresent fungal development processes in mechanistic models. Therefore, data pre-processing and bias corrections must be applied to ensure realistic inputs (Dhawan *et al* 2024).

In addition to improving spatial applicability, a key motivation is to extend AFLA-maize into predictive space by incorporating seasonal meteorological forecasts. Ensemble-based long-term forecasts from the ECMWF and other systems allow users to estimate a range of possible future weather conditions in advance (Weisheimer and Palmer 2014, Copernicus Climate Change Service 2018). However, their performance remains limited with increasing uncertainty in long lead times and known systematic biases, mainly a cold bias for temperature and a wet bias for precipitation, particularly in European regions (Mishra *et al* 2019, Calí Quaglia *et al* 2021). Hybrid integration approaches, where reanalysis data is used early in the season and forecasts are introduced later, may offer a practical balance between accuracy and foresight. This strategy of progressive forecast integration has been successful in other agricultural management contexts (Phillips and Hansen 2001, Dainelli 2022), and shows potential for extending AFLA-maize.

Therefore, the objectives of this study are: (1) to evaluate ERA5-Land reanalysis as an alternative to station observations for driving AFLA-maize, (2) to assess the feasibility of using seasonal forecasts for early warning of AF risk, and (3) to develop and test bias adjustment methods for the datasets applied to improve model accuracy. We hypothesize that ERA5-Land data, once corrected for known biases, can match the reliability of station data in estimating AF risk, and that progressively introduced forecasts can support the creation of a functional early warning system. The significance of this work lies in its potential to enable global transferability of AFLA-maize model, particularly in regions where AF contamination is expected to increase due to climate change, but where high-quality observational data are lacking.

2. Methods

2.1. Meteorological data

The analysis was carried out in Emilia-Romagna (Northern Italy), a major maize-growing area increasingly exposed to AF contamination. The modelling period spanned growing seasons (April–September) for 2008–2025 (year 2008 represents the earliest availability of harmonised agrometeorological weather observations). Three meteorological datasets were used: station observations, ERA5-Land reanalysis, and long-term seasonal forecasts. Daily station observations (Bottarelli and Zinoni 2002) (sourced from Giasonline.it) were used as a reference value for mean air T, RH, total P, and LW duration. These were used to evaluate and calibrate the gridded datasets. ERA5-Land reanalysis data (Muñoz Sabater *et al* 2021) were obtained from ECMWF, offering hourly meteorological fields at a 0.1° resolution. Seasonal forecasts (Copernicus

Climate Change Service 2018) sourced from ECMWF were acquired at daily resolution on a 1° grid, with 51 ensemble members. Ensemble members are generated through perturbations in initial conditions to represent a spread of plausible future climate scenarios. Forecasts were initialized monthly for April and June, July or August (suitable as early-warning), for each year in the study period. ERA5-Land and forecast datasets were preprocessed and bias-adjusted before use in the AFLA-maize (see section 2.3). Ten representatively distributed test sites were selected for evaluation across different reanalysis and forecast grid cells. The full list is provided in the supplementary material (SM).

2.2. AFLA-maize model

The mechanistic model AFLA-maize (Battilani et al 2013), adapted to operate with daily input data (Battilani et al 2012), was used to simulate the risk of AFB₁ contamination in maize in the present study. Required variables included daily mean T, RH, total P, and LW duration. For the station observations, LW was obtained directly from the agrometeorological network as a sensor derived binary index (wet = 1, dry = 0) aggregated to daily wet hours. For gridded data, LW was approximated by a rule: LW = 1 if daily precipitation > 0 mm or RH > 80%, else 0. Simulations were conducted for the entire growing season for each input dataset. The primary model output is the Aflatoxin index (AFI), a cumulative value representing the potential risk for contamination throughout the growing season (an exemplary figure showing AFLA-maize input and output is included in the Supplementary material). AFI values are translated into contamination probability using a probabilistic function with previously established threshold of AFI > 95 corresponding to a 50% probability of AF contamination exceeding regulatory limits (Battilani et al 2016). For comparative analysis, the maximum AFI value (AFI_{max}) was extracted at a fixed date (September 30th) and used as the key indicator of seasonal contamination risk. AFI_{max} values derived from the station driven simulations were used as a reference proxy for the model performance evaluation due to the lack of harmonized georeferenced contamination data. Although actual harvest dates vary across years, maize harvest in the study area typically occurs from mid August until the end of September (Azar et al 2016). Therefore the September 30th was chosen as a consistent end of season reference point.

2.3. Bias adjustments

Bias adjustments were applied to ERA5-Land and seasonal forecast data to improve their agreement with station observations. For ERA5-Land, daily precipitation values were filtered using a threshold approach to reduce the influence of overestimated low-intensity rainfall events. Thresholds from 0.5

to 5.0 mm (0.5 mm increments) were tested to best reproduce wet-day frequency during the growing season. Based on this evaluation, a 2.0 mm threshold was applied for all subsequent simulations. For seasonal forecasts, temperature values were adjusted for altitude mismatch caused by differences in dataset spatial resolution, using the ERA5-Land orography and a standard lapse rate of $-6.5^\circ\text{C km}^{-1}$, followed by re-aggregation to the original 1° grid. RH was adjusted by applying a constant offset determined using the mean bias (MB) error at each grid point, calculated as the long-term average deviation from station observations (see SM). Precipitation was adjusted using the same approach as for ERA5-Land. Thresholds from 1.0 mm to 10.0 mm (0.5 mm increments) were tested against observed wet-day frequencies, and a 3.0 mm threshold was selected for use in all forecast-driven simulations. These adjustments were applied uniformly across all years in the study period for inputs driving the AFLA-maize simulations.

2.4. Hybrid forecasting strategy

A hybrid input approach was developed using bias-adjusted ERA5-Land (ERA5-Land*) for the early season and bias-adjusted forecasts from a predefined transition date onward (June 1st, July 1st, and August 1st). For each transition configuration, the model was run using 51 ensemble members from the forecast system. Each ensemble member represents a plausible future outcome of ambient meteorological conditions, generated by introducing small perturbations to the initial atmospheric conditions. This allows the model to capture a spread of possible outcomes, supporting a probabilistic interpretation of aflatoxin risk. Hybrid simulations were generated by concatenating ERA5-Land* data up to the end of the month preceding the transition point with forecast data from the corresponding initialization date onward. This allowed comparisons between input integration schemes across seasons and forecast dates.

2.5. Data analysis

Statistical comparison was performed using Pearson correlation coefficients (r), root mean square error, mean absolute error, and mean bias. These metrics were applied to: (1) meteorological variables from ERA5-Land and ECMWF forecasts versus station observations, and (2) AFI_{max} values from AFLA-maize simulations using corrected gridded inputs from ERA5-Land* and ECMWF forecasts (full season and all hybrid combinations) versus station-based simulations. (3) Yearly AFI_{max} exceedance (threshold = 95) was evaluated as a categorical event, with outcomes classified relative to the station-based simulation as True/Negative, False/Negative, and summarized as accuracy. For the seasonal forecast evaluation, only the ensemble mean value was used, to obtain a

single category. In addition, sensitivity (true positive rate), specificity (true negative rate), and $F1$ -score was also calculated. All analyses were conducted using Python (v3.12) and can be found in SM.

3. Results

3.1. Evaluation of ERA5-Land as input for AFLA-maize

Emilia-Romagna region is covered by meteorological network of 391 active stations, providing a wide range of meteorological variables at hourly resolution. To test the feasibility of extending the model's application to areas with less robust station infrastructure, we evaluated the suitability of ERA5-Land reanalysis (0.1° resolution (~ 9 km), corresponding to ~ 485 grid points) as an alternative input source. Daily aggregated ERA5-Land variables (T, RH, P) were compared with station observations at ten representative sites from 2008–2025 (summary statistics in SM). As illustrated in figure 1, where location Mirandola (2019) was selected as an exemplary site, reanalysis showed strong correlation in T ($r = 0.99$) and RH ($r = 0.90$). These variables were therefore used directly as AFLA-maize inputs. In contrast, precipitation data showed a systematic bias, overestimating both the magnitude and frequency of low-intensity rainfall. While the excess in total precipitation has no direct impact on model dynamics, the increased frequency of low intensity rainfall events introduced an artificially persistent 'wet signal'. This suppresses spore dispersal and distorts AFLA-maize simulations, disabling it to assess the contamination risk.

To address the precipitation bias, ERA5-Land data were adjusted using the thresholding approach described in section 2.3. Evaluation against station data indicated that a 2.5 mm daily precipitation cutoff most closely reproduced the observed annual frequency of wet days. However, when testing AFLA-maize simulations with multiple thresholds (2, 2.5, and 3 mm), the 2 mm threshold produced outputs that aligned most closely with station-based $AFI_{\max}$ values. This threshold was therefore adopted for all subsequent simulations. The impact of this adjustment is further illustrated in figure 2, which shows an example from station Mirandola during the 2019 season. The uncorrected ERA5-Land simulation showed negligible contamination risk due to excessive rainfall frequency, while the 2-mm-adjusted (ERA5-Land*) input improved both the timing and magnitude of the risk curve, aligning more closely with the station-based reference.

3.2. Evaluation of the suitability of seasonal forecasts for AFLA-maize

Preliminary comparison of raw forecast variables against station observations revealed systematic

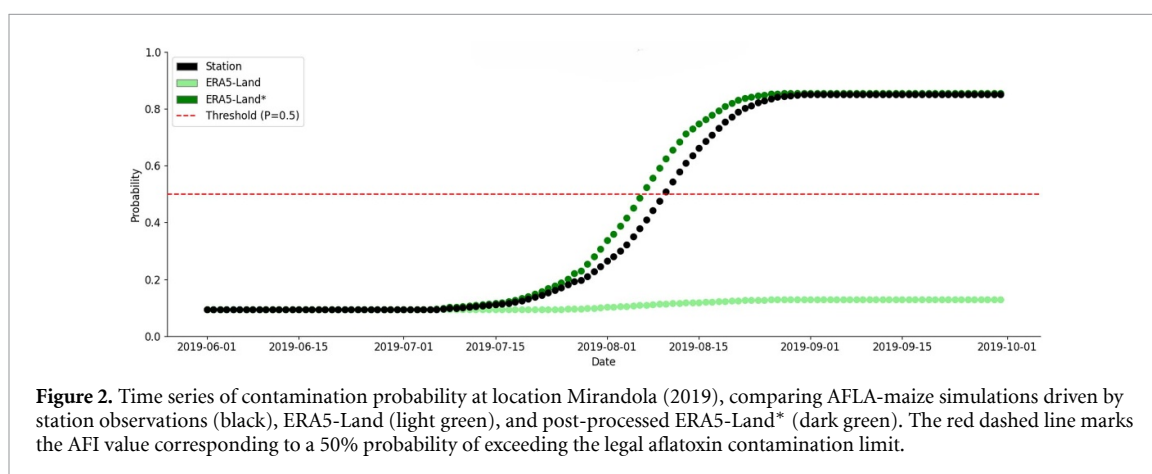
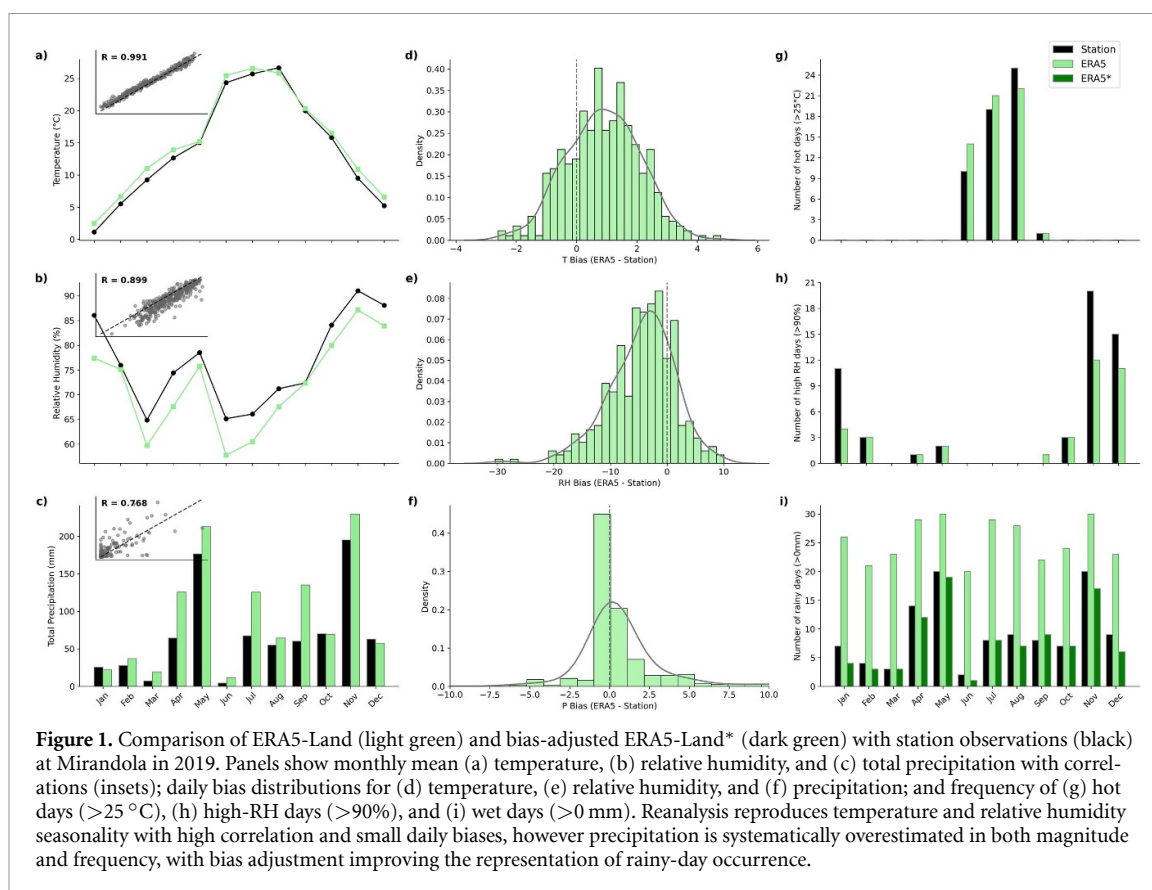
biases: underestimation of T, while RH and P were overestimated (summary statistics in SM). These biases resulted in systematically cool and wet conditions, suppressing spore dispersal, and resulting in unrealistically low AFLA-maize outputs, even in years with known contamination events. After bias adjustment (section 2.3), AFLA-maize simulations were able to produce realistic outputs, as illustrated in figure 3 for location Mirandola (2019). However, a wide spread in predicted AFI values was observed at harvest, with contamination probabilities ranging from 9.5% to 73.5% across ensemble members. This reflects the uncertainty associated with early-season forecasts and limits their standalone applicability for operational decision-making.

3.3. Reducing uncertainty with hybrid reanalysis-forecast integration

To address the limitations associated with the sole application of early-season forecasts, a hybrid strategy combined ERA5-Land* for early-season inputs with bias-adjusted forecasts from June, July, or August onward. Each configuration used all 51 ensemble members across all years and sites. The resulting outputs were compared with simulations driven entirely by station observations and full-season ERA5-Land*. Exemplary site Mirandola (2019) is shown in figure 4. Early integration (June, figure 4(a)) showed the widest ensemble spread and the lowest agreement with the station-based $AFI_{\max}$ values. Mid-season integration (July, figure 4(b)) slightly reduced the variability among ensemble members and improved the correspondence with observed risk. Late integration (August, figure 4(c)) achieved the most accurate outputs relative to the reference data but also limited the forecast lead time to approximately 3–8 weeks before harvest. This indicates that progressive reanalysis-forecast integration can reduce uncertainty in model outputs while maintaining practical forecast windows within the growing season.

3.4. Expanded performance evaluation

Performance of different input sources was evaluated across all sites and seasons ($n = 180$ per dataset), with outcomes classified against station-based results (figure 5). The reference dataset included 63 positive and 117 negative cases. A naive classifier that predicts only the majority class (no contamination) would achieve 65% accuracy but a sensitivity and $F1$ -score of zero. ERA5-Land* correctly reproduced contamination probability outcomes in 91% of cases ($F1$ -score = 0.88), with no false negatives and 17 false positives. Forecast accuracy improved with later integration. April simulations showed the lowest accuracy (69%, $F1$ -score = 0.25), with 54 false negatives and 1 false positive. June reached 88% accuracy ($F1$ -score = 0.80), with 18 false negatives and 4 false positives. July accuracy improved to 93% ($F1$ -score = 0.90),



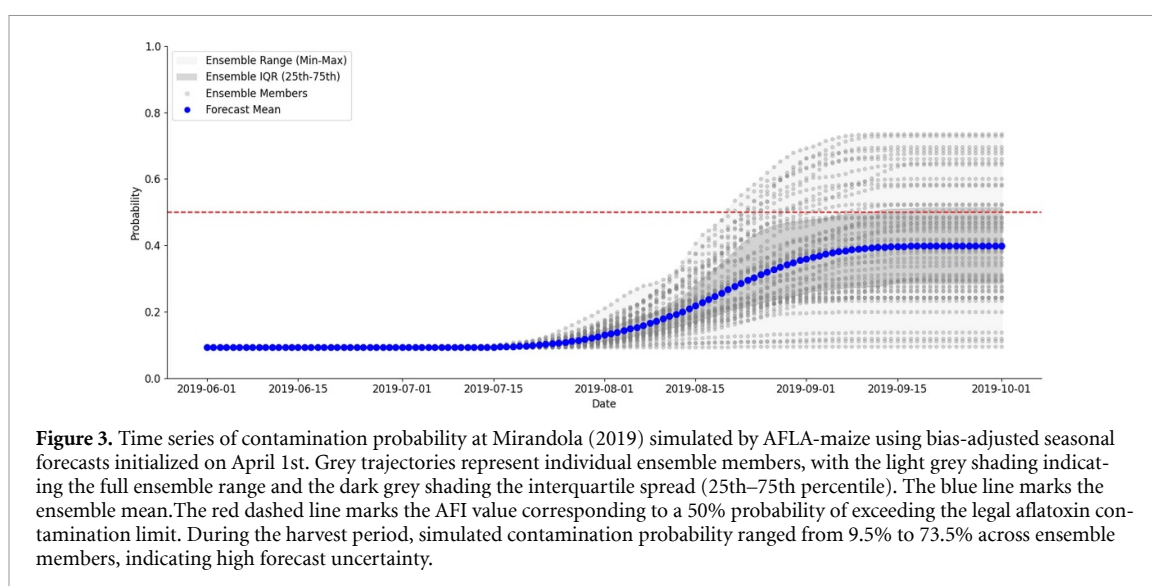
with 3 false negatives and 10 false positives. August achieved 91% accuracy ($F1\text{-score} = 0.88$), matching ERA5-Land* with no false negatives and 17 false positives. Full evaluation counts and metrics are reported in SM.

4. Discussions and conclusions

While meteorological observations remain the ideal input for mycotoxin predictive models to ensure reliable simulations (Battilani 2016), the limited availability and uneven distribution of agrometeorological stations restrict their use in many maize-growing regions, mainly in areas with complex terrain or poor monitoring infrastructure (Hansen

2005, Kępińska-Kasprzak and Struzik 2023). Without spatially consistent sources of input data, such models remain restricted to experimental or well-monitored areas. The growing availability of freely accessible, global meteorological datasets, such as the ERA5-Land reanalysis and seasonal forecasts, provided by ECMWF changes this perspective, as both offer consistent, high-resolution data on fine grids (Copernicus Climate Change Service 2018, Muñoz Sabater *et al* 2021). The question is not if these datasets can be used, but how they are best prepared and adjusted to serve as reliable drivers for contamination risk models.

In Emilia-Romagna, where dense observational networks are available for evaluation, ERA5-Land



closely reproduced T and RH but systematically overestimated low-intensity rainfall. This wet signal, known from reanalysis assessments (Beck *et al* 2017, Hassler and Lauer 2021, Gomis-Cebolla *et al* 2023, Dhawan *et al* 2024), disrupted fungal development in AFLA-maize and suppressed contamination risk. Applying a simple 2 mm precipitation threshold removed this bias and restored agreement with station-based predictions. Similar thresholding have been proven useful in other studies (Kim *et al* 2018, Alexopoulos *et al* 2023, Ansari *et al* 2023). This demonstrated that ERA5-Land, with minimal preprocessing, can function as a reliable alternative for station data, extending the applicability of AFLA-maize to regions without observation data and to areas projected to expand maize production under climate change pressure (Battilani *et al* 2016, Ramirez-Cabral *et al* 2017, Focker *et al* 2023). However, its delayed release of several weeks remains a limitation (Hersbach *et al* 2020), which reduces its applicability for in-season decision support.

Seasonal forecasts offer the complementary advantage of timing, as they are issued in advance and could inform crop management decisions. However, raw forecasts show systematic underestimation of T and overestimation of RH and P, consistent with earlier evaluations over Europe (Weisheimer and Palmer 2014, Mishra *et al* 2019, Calí Quaglia *et al* 2021, Crespi *et al* 2021). As a result, AFLA-maize simulations showed no contamination risk even in high risk years, making the forecasts unsuitable in the original form. After a set of bias adjustments (section 2.3), forecasts became suitable inputs and produced realistic risk trajectories. This aligns with findings by Verkade *et al* (2013) and Adineh *et al* (2021) who emphasized the importance of preprocessing when using operational forecasts. Despite improvement in forecast input, ensemble outputs

displayed a wide variability (figure 3), highlighting persistent uncertainty when using early-season forecasts alone. However, this spread of ensemble forecasting provides a quantified measure of uncertainty, allowing decision-makers to assess risk across a range of plausible scenarios rather than relying on a single deterministic outcome (Ho and Budescu 2019). Our findings also suggest that this uncertainty primarily originates from input variability rather than from the model itself. When meteorological inputs become more accurate with shorter lead times, AFLA-maize simulations align with station-driven outputs which confirms that the model is highly sensitive to meteorological inputs and is capable of producing risk forecasts when driven by accurate data.

To balance accuracy and lead time, a hybrid forecasting strategy was designed combining the reliability of ERA5-Land inputs during early crop stages with the adjusted forecasts later in the season, when predictive skill improves and AF risk becomes more sensitive to weather conditions. This approach aligns with previous work advocating progressive forecast integration in agricultural systems (Hansen 2005, Dainelli 2022). Three integration dates (June 1st, July 1st, and August 1st) were tested. Of these, the August 1st integration achieved the highest overall agreement with station-based risk estimates (91% accuracy), with no false negatives and 17 false positives. While this shows a slight tendency to overestimate risk, it also ensured that no high-risk seasons were missed in the test period, which is a preferable trade-off in food safety contexts. This result confirms that forecast accuracy improves as the target window narrows, consistent with previous evaluations of the seasonal forecast reliability (Weisheimer and Palmer 2014, Crespi *et al* 2021). Although this narrower time window reduces the possibility for preventive field interventions, it remains relevant for decision

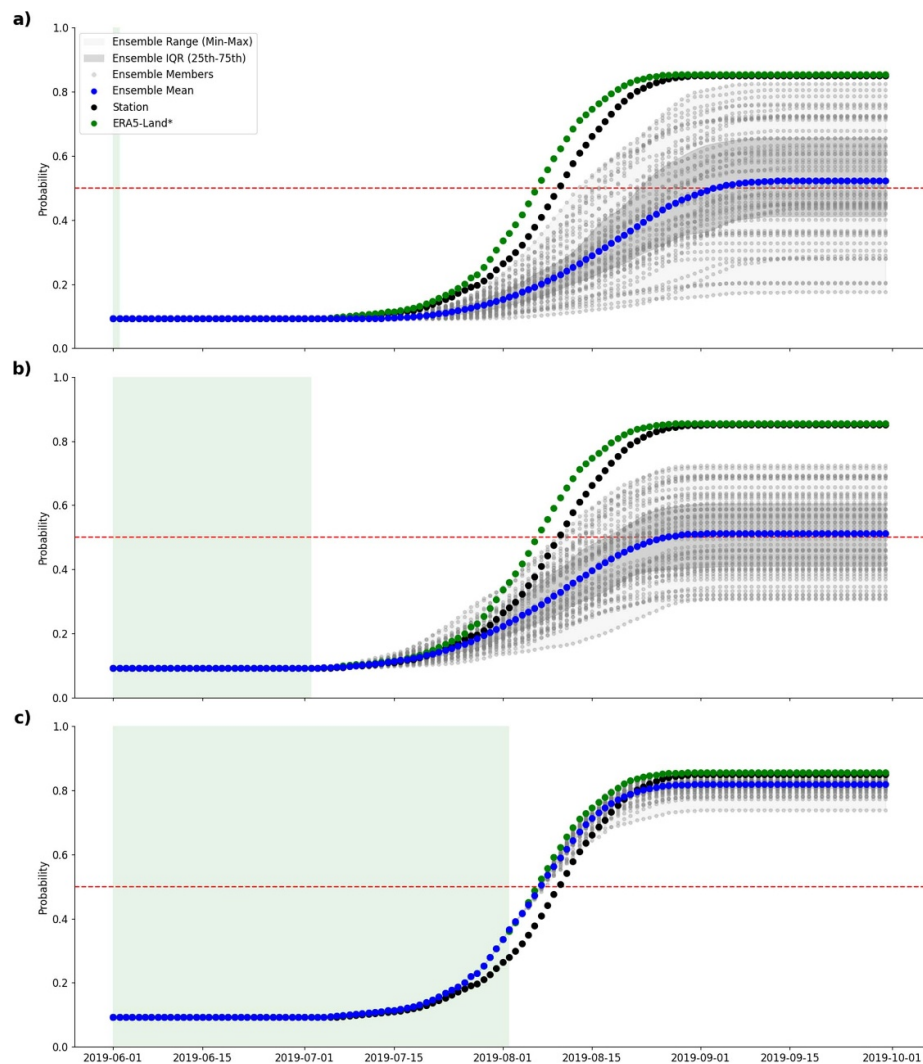


Figure 4. Time series of contamination probability at Mirandola (2019) under three hybrid reanalysis-forecast integration schemes: (a) early (June 1st), (b) mid-season (July 1st), and (c) late (August 1st) with light green background indicating the ERA5-Land* period before transition to seasonal forecast. Grey trajectories represent individual ensemble members of the hybrid forecast, with the light grey shading indicating the full ensemble range and the dark grey shading the interquartile spread (25th–75th percentile). The blue line shows the hybrid forecast ensemble mean. For comparison, simulations using only station observations are shown in black, and those using full-season ERA5-Land* inputs are shown in green. The red dashed line marks the AFI value corresponding to a 50% probability of exceeding the legal aflatoxin contamination limit. Late-season integration shows the best agreement with station-based estimates, capturing both the timing and magnitude of the contamination signal while still offering time for intervention.

support at harvest and during the post-harvest phase. In comparison the July 1st integration emerged as a practical compromise, offering improved accuracy while still providing several weeks for intervention. The June 1st integration, although substantially less precise, could still serve as an early indicator of risk, especially when used to trigger enhanced monitoring. In contrast, April forecasts, while the earliest available, displayed low reliability, with frequent false negative outcomes and should be interpreted cautiously. However, in a few extreme seasons with high contamination risk (e.g. 2015, 2016, and 2024), forecasts already captured elevated risk signal. These indications were not sufficiently accurate for risk prediction, but they could still serve as a trigger for intensified monitoring. From an operational perspective,

early-season forecasts (April–May) could inform preventive decisions such as hybrid selection, sowing dates, or agronomic planning, whereas mid-season updates (June–July) could support irrigation management (Smigic *et al* 2022). Late-season predictions (August) could inform the ideal harvest dates, prioritization of post-harvest drying, and grain testing (Borrás-Vallverdú *et al* 2022, El-Desouky 2025). The results of our analysis of historical forecasts indicated that this framework would have proven useful to identify heightened risk during June and July issued forecast predictions in years when contamination events over the legal AF limit occurred in this area, such as 2009, 2010, 2011 (Bertuzzi *et al* 2015), and 2015, 2016 Ferrari *et al* (2022), confirming its potential value for operational decision-making.

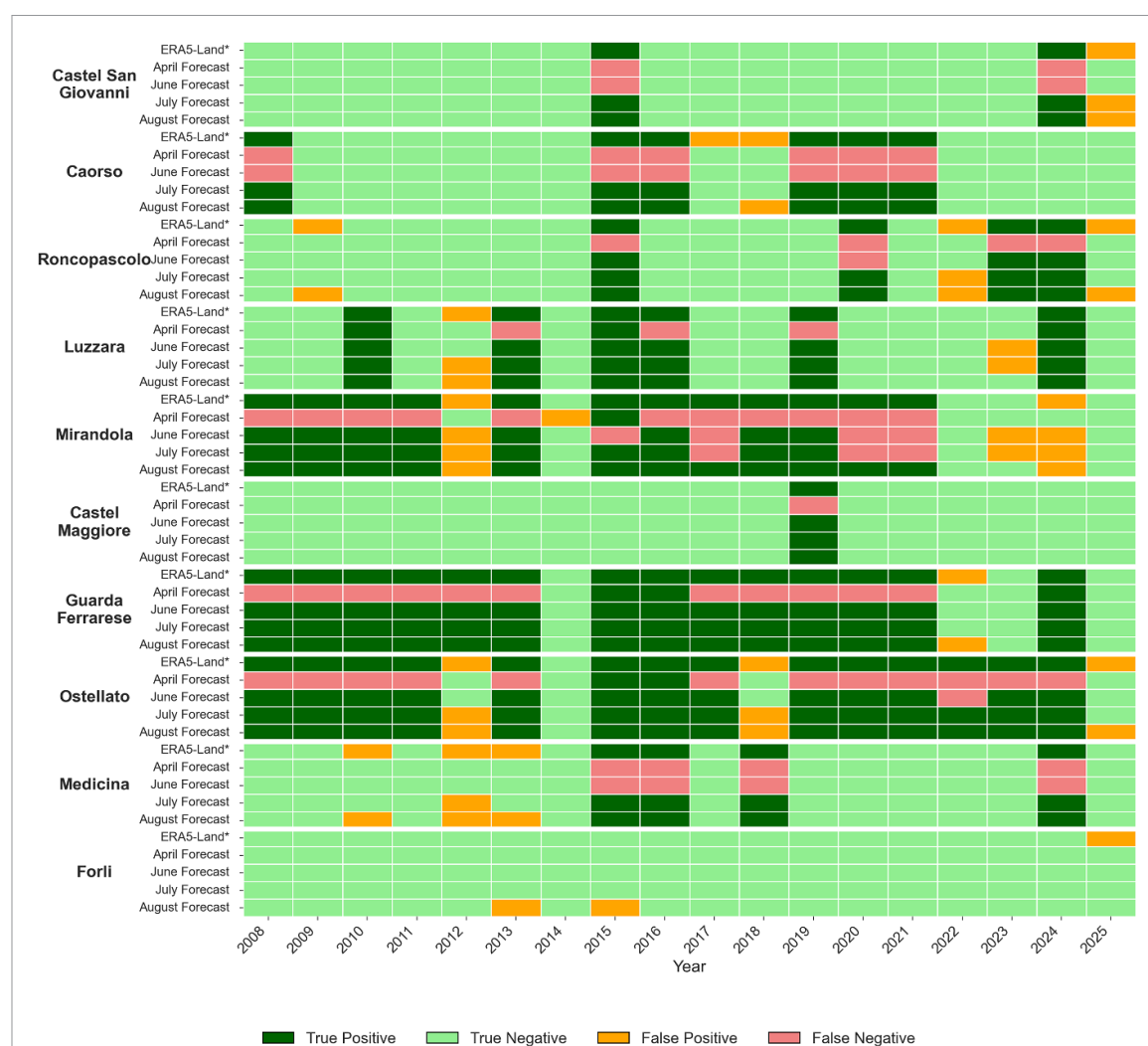


Figure 5. Evaluation of annual contamination probability outcomes (AFI > 95) over 2008–2025 for alternative input sources compared to station-driven AFLA-maize output. ERA5-Land* and seasonal forecasts integrated in April, June, July, and August (ensemble mean) are shown. Colours represent the classification of outcomes as true positives (dark green: contamination probability over 50% correctly predicted), true negatives (light green: contamination probability below 50% correctly predicted), false positives (orange: probability over 50% predicted but not matching the station output), and false negatives (red: probability over 50% present in the station output but not predicted by the alternative input).

The hybrid strategy was designed in a modular and adaptable way. Where observations are available, ERA5-Land inputs can be replaced to increase site specificity, while forecasts can provide broader regional coverage by capturing multiple plausible risk trajectories. This makes the framework suitable for both field-level advice and national surveillance systems (European Environment Agency 2025). Since ERA5-Land and ECMWF forecasts (and similar products) are freely available and globally consistent, the same methodology could be applied to any maize-growing region or extended to other crop-pathogen systems for which risk models exist. In this study, computations were performed both on an institutional server and locally on a standard workstation, confirming that regional simulations can run without high performance infrastructure. Single site ERA5-Land simulations can be completed in under one hour, including data

preparation. Forecasts require 1–2 hours per grid due to ensemble size and adjustments, depending on the time period. Since forecasts are issued monthly, periodic updates are sufficient for most use cases. For larger simulations, automation and parallelization would be necessary, to handle the input preparation, which remain the main computational challenge together with the bias adjustment and quality control.

Main limitation of this workflow remains the high uncertainty associated with forecasts issued at long lead times. While forecast ensembles help, they cannot fully resolve sub-seasonal shifts or extreme event variability. Additionally, bias-adjustment parameters are region specific and should be recalibrated against local observations whenever used in a new regional setting. If observations are unavailable, bias adjustments could be derived by comparison with independent observation-based gridded datasets.

Such cross-correction helps reduce systematic biases, although the resulting predictions carry higher uncertainty that should be communicated explicitly (Abbas *et al* 2025). Second, the AFLA-maize model focuses exclusively on meteorological inputs and currently does not account for agronomic practices, which are known to substantially influence AF contamination (Fountain *et al* 2014, Borrás-Vallverdú *et al* 2022). The integration of agronomic variables has already been shown to improve model performance (Camardo Leggieri *et al* 2021) and should be prioritized in future developments. Third, expanding the model to incorporate additional toxigenic fungi, such as *Fusarium* spp., would further increase its applicability to a broader spectrum of mycotoxin risks (Leggieri *et al* 2021). This is particularly important given the increasing co-occurrence of multiple mycotoxins in recent years (Vandicke *et al* 2021), driven by the emergence of climatic conditions favouring the growth of different fungal species (Camardo Leggieri *et al* 2019, Perrone *et al* 2020). Finally, for practical implementation, a forecasting approach as presented here should be integrated in a digital platform that combine observational and forecast inputs with intuitive visualization and alerting functions. Such platforms have already demonstrated effectiveness in agricultural contexts (FAO 2020, Dainelli 2022) and are increasingly considered important for climate-resilient agriculture (Hellin and Fisher 2019, Hellin *et al* 2023). Their adoption will depend not only on technical accuracy, but also on user trust, institutional integration, and accessibility (Coventry and Dalgleish 2014, Bruno Soares and Dessai 2016, Palumbo *et al* 2020).

In summary, the findings of this work demonstrate that the AFLA-maize model, when driven by bias-adjusted global meteorological datasets, can deliver spatially and temporally scalable assessments of aflatoxin risk. The hybrid integration of reanalysis and forecasts enables real-time, uncertainty-aware decision support, with potential for global transferability. This provides a foundation for digital early-warning tools to strengthen agricultural resilience against climate-driven food safety risks.

Data availability statement

ERA5-Land reanalysis and ECMWF seasonal forecasts are freely available from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/>). AFLA-maize model is proprietary and cannot be publicly distributed, the model code is available from the authors upon request. All simulation outputs together with the supporting Python scripts for data preprocessing, bias-adjustment and model performance evaluation are publicly available in this repository <https://doi.org/10.5281/zenodo.18247147>.

Supplementary material available at <https://doi.org/10.1088/1748-9326/ae3629/data1>.

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