Food and Chemical Toxicology 47 (2009) 927–931

Contents lists available at ScienceDirect

Food and Chemical Toxicology

journal homepage: www.elsevier.com/locate/foodchemtox

Review of predictive models for *Fusarium* head blight and related mycotoxin contamination in wheat

A. Prandini [a,*], S. Sigolo [a], L. Filippi [a], P. Battilani [b], G. Piva [a]

[a] *Institute of Food Science and Nutrition, Catholic University of Piacenza, Agricultural Faculty, Via Emilia Parmense 84, 29100 Piacenza, Italy*
[b] *Institute of Entomology and Plant Pathology, Catholic University of Piacenza, Agricultural Faculty, Via Emilia Parmense 84, 29100 Piacenza, Italy*

ARTICLE INFO

Article history:
Received 27 February 2007
Accepted 19 June 2008

Keywords:
FHB
Mycotoxins
Predictive models
Wheat

ABSTRACT

Mould growth and mycotoxin production are related to plant stress caused by environmental factors such as: extreme weather; insect damage; inadequate storage conditions and incorrect fertilization; these predispose plants to mycotoxin contamination in the field. *Fusarium* species infect wheat during the flowering period. In addition to losses of yield, these fungi can also synthesize toxic components (mycotoxins) in suitable environmental conditions, thus threatening animal and human health. Given the severe consequences and the fact that mycotoxins affect production throughout the world, the ability to predict *Fusarium* head blight (FHB) and deoxynivalenol (DON) and other mycotoxin contamination is important to reduce the year-to-year risk for producers. Owing to these dangerous consequences in Argentina, Belgium, Canada, Italy, the United States and in Europe, computer models, based on weather variables (temperature, rainfall and moisture level), have been developed to predict the occurrence of FHB and DON contamination in wheat.

1. Mycotoxins and predictive models

Mycotoxins are toxic secondary metabolites produced by fungi (commonly called moulds) that colonize crops in field or post-harvest and thus pose a potential threat to human and animal health. Only some moulds produce mycotoxins and they are referred to as toxigenic. The major mycotoxin-producing fungal genera are *Aspergillus*, Fusarium and *Penicillium*. Many species of these fungi produce mycotoxins; moulds can grow and mycotoxins can be produced pre-harvest, during transport, processing or storage (Santin, 2005). The primary classes of mycotoxins are aflatoxins, zearalenones, trichothecenes, fumonisins, ochratoxins and ergot alkaloids. A practical definition of a mycotoxin is a secondary fungal metabolite that causes an undesirable effect when animals or humans are exposed to it. Usually, exposure is through consumption of contaminated food, which causes diseases known as mycotoxicosis. Mycotoxins exhibit a variety of biological effects in animals such as liver and kidney toxicity, effects on the central nervous system, estrogenic effects (Whitlow and Hagler, 2005) and reduction of immunological defences, to name a few. It is important, both for consumers' health and the economic point of view, to prevent mould growth and subsequent mycotoxin production in food products (Pardo et al., 2006).

Mould growth and mycotoxin production are related to: the presence of fungal inoculum on susceptible crops; plant stress caused by extreme weather, faulty water and fertilization balance; insect damage; and inadequate storage conditions. In general, biotic and abiotic stresses (heat, water and insect damage) cause plant stress and predispose plants in the field to mycotoxin contamination (Whitlow and Hagler, 2005), and there is an urgent need to know the level of contamination in real time or in advance. This aspect stimulated efforts to develop models (Dantigny et al., 2005). A disease forecasting system is principally based on the combined effects of host susceptibility, inoculum strength and meteorological conditions on disease development (Xu, 2003).

A model is a simplified representation of a system, which is a limited part of reality and contains interrelated elements, and attempts to summarise the main processes, to put forward hypotheses and to verify their coherence and consequences (Rabbinge and De Wit, 1989; van Maanen and Xu, 2003). The level of complexity needed for a specific model depends on the objectives and questions being asked of the model (Boote et al., 1996). Static and dynamic models can be developed, dependent if time is considered in the model. Among dynamic models; those defined as 'descriptive' simply trace the outlines of a system, and only show the existence of relations between elements, but do not explain these relations. A more complicated approach is taken when the aim is to describe a more comprehensive system with its relations therein

Abbreviations: CPL, critical period length; DON, deoxynivalenol; FHB, *fusarium* head blight; PI, prediction incidence; TOX-risk, risk of toxicity; ZEA, zearalenone.

* Corresponding author. Tel.: +39 523 599263; fax: +39 523 599259.
E-mail address: aldo.prandini@unicatt.it (A. Prandini).

0278-6915/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.fct.2008.06.010

and ‘explanatory’ models are developed in this case. During World War II a rational approach was developed in order to study a system in detail: systems analysis. Systems analysis was developed basically as a tool to consider military options but it was demonstrated to be useful in different disciplines, where a system is studied by distinguishing its major components, characterising their changes, and the interconnecting elements (Leffelaar, 1993). The system structure in plant pathology includes pathogen, host, environment, human actions and their relationships (De Wit, 1993). Modelling can be split into three steps: model development, model analysis and hypothesis testing (van Maanen and Xu, 2003). A simple way to represent a complicated system, like a pathosystem, is a relational diagram as a first step in model development (Leffelaar, 1993).

Collection of information from different sources (step 1) is the basis of “system analysis” that starts with drawing a relational diagram translated into quantitative relationships that allow the quantification of states. Putting together all mathematical functions (step 2), a simulation model able to predict fungal development is finally obtained. Model validation and evaluation (step 3) is then necessary before building up a final model used on a large scale.

Explanatory models are significantly more complicated than descriptive. Due to the consideration of so many elements, as suggested by De Wit, the explanatory models are too complicated to be suitable for prediction in very different conditions.

The goal of this paper is to illustrate models developed for FHB and related mycotoxin contamination in wheat, the most studied disease related to mycotoxins because of the world wide distribution of wheat and *Fusarium*. Almost all models were developed as a descriptive model, and similar approaches have been followed in several countries, while an explanatory model, based on the system analysis, was developed in Italy.

2. *Fusarium* head blight (FHB) in wheat

Fusarium head blight, which is caused by several fungal species with *Fusarium* or *Fusarium*-like anamorphs, is a serious disease of wheat in many parts of the world (Rossi et al., 2003b). Though FHB can be destructive, its severity varies greatly between years and locations, as this disease is heavily dependent on favourable epidemiological conditions (Rossi et al., 2004).

Infection by *Fusarium* spp. on wheat occurs during the flowering period. In addition to yield losses, these fungi can also synthesize toxic compounds (mycotoxins) in favourable environmental conditions, thus representing an important threat for animal and human health. (Detrixhe et al., 2003). Preventive actions are possible so as control strategies; accurate predictions of DON in mature grain at wheat heading are needed to make decisions on whether a control strategy is needed. If weather variables can be quantified into DON-response relationship, a model could be developed to predict the concentration of DON using both forecasted and actual weather data for specific fields (Hooker et al., 2002). On the basis of the known relationship between fungal biomass and DON, more heavily colonized plant tissue is likely to have a greater fungal biomass, and consequently, higher DON content than less colonized tissue. For this reason, visual estimates of disease could also serve as indirect measures of DON to screen for genotypes with low DON accumulation (Paul et al., 2005).

Attempts to predict head blight have emphasised the importance of both inoculum and the environment for disease epidemics (Parry et al., 1995). In order to predict disease incidence and to increase the ability of wheat producers to achieve good disease management, several FHB infection or mycotoxin risk assessment models have been developed (De Wolf et al., 2003, 2004; Detrixhe et al., 2003; Madden et al., 2004; Schaafsma and Hooker, 2006).

Fusarium head blight (FHB) is well-suited for risk assessment modelling because of the severity of epidemics, compounded losses resulting from mycotoxin contamination, and related narrow time periods of pathogen sporulation, inoculum dispersal, and host infection (De Wolf et al., 2003).

Computer models to predict the occurrence of FHB and deoxynivalenol (DON) contamination in wheat at harvest have been based on weather variables (temperature, rainfall and moisture) (Moschini et al., 2001; Hooker et al., 2002; De Wolf et al., 2004; Madden et al., 2004). In general, studies from outside the US in spring and winter wheat regions (Europe, Canada, and Africa) indicated interactions between disease intensity and occurrence of DON comparable with or stronger than that found from US winter wheat areas, and weaker than those found in studies of US spring wheat areas (Paul et al., 2005).

2.1. Argentina

In Argentina, Moschini and Fortugno (1996) developed empirical equations to predict FHB incidence (Predictive Index: PI%) associating mean head blight incidence of many wheat cultivars with temperature and moisture variables. Two of these equations were validated subsequently by Moschini et al. (2001):

$$\mathrm{PI\%} = 20.37 + 8.63 \cdot \mathrm{NP}_2 - 0.49 \cdot \mathrm{DD}_{926} \tag{1}$$

$$\mathrm{PI\%} = 18.34 + 4.12 \cdot \mathrm{NP}_{12} - 0.45 \cdot \mathrm{DD}_{1026} \tag{2}$$

where NP_2 is the number of 2 day periods with precipitation ($\geqslant$0.2 mm) and relative humidity >81% on the first day and relative humidity $\geqslant$78% on the second day; NP_{12} is the total number of NP_2 periods plus the total number of days with both precipitation $\geqslant$0.2 mm and average relative humidity >83%. DD_{926} and DD_{1026} represent 926 or 1026 degree days accumulated and are calculated as:

$$\mathrm{DD}_{926} = \sigma[(\mathrm{MaxT}) - 26) + (9 - \mathrm{MinT})] \tag{3}$$

$$\mathrm{DD}_{1026} = \sigma[(\mathrm{MaxT} - 26) + (10 - \mathrm{MinT})] \tag{4}$$

where MaxT is the maximum daily temperature >26 °C, MinT is the minimum daily temperature <9 °C or <10 °C, and summation occurs over the days of the critical period length (CPL). CPL is the time period beginning 8 days before the heading date and ending when 530 degree days were accumulated (base temperature: 0 °C).

This study showed that meteorological based empirical equations developed for Pergamino can be useful for predicting disease intensity at many northern locations in the Pampas region, making only a few changes in temperature thresholds. Fernandes et al. (2004) used a linked process-based model to assess the risk of FHB at three sites in South America, and stated that the highest risk index of FHB was probably due to the presence of more rainy days during the autumn in a specific climate scenario (Fernandes et al., 2004).

2.2. Belgium

In Belgium, in order to assess the risk of head blight infection in winter wheat, an agro-meteorological model has been developed on the basis of an interpolation of weather radar data (above all rainfall events) to simulate the leaf wetness duration on a grid size of 1 × 1 km (Detrixhe et al., 2003). Leaf wetness duration has a strong relationship with the development and outbreak of plant diseases because many important pathogens require a layer of free water to move on the surface of plant organs and start their infective processes (Dalla Marta et al., 2005). This model is interesting for two reasons: the first is the interpolation of meteorological data on an area of interest and particularly the use of weather radar