

# 1           **Review of Predictive Models for Fusarium Head Blight and** 2                           **Related Mycotoxin Contamination in Wheat**

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11   *Abbreviations:* **CPL**, Critical Period Length; **DON**, Deoxynivalenol; **FHB**, Fusarium Head  
12   Blight; **PI**, Prediction Incidence; **TOX-risk**, risk of toxicity; **ZEA**, Zearalenone.

13  
14   *Keywords:* FHB, mycotoxins, predictive models, wheat.

1 **Abstract**

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

## 1 **1. Mycotoxins and predictive models**

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

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

1 the combined effects of host susceptibility, inoculum strength and meteorological conditions  
2 on disease development (*Xu, 2003*).

3 A model is a simplified representation of a system, which is a limited part of reality and  
4 contains interrelated elements, and attempts to summarise the main processes, to put forward  
5 hypotheses and to verify their coherence and consequences (*Rabbinge and De Wit, 1989; van*  
6 *Maanen and Xu, 2003*). The level of complexity needed for a specific model depends on the  
7 objectives and questions being asked of the model (*Boote et al., 1996*). Static and dynamic  
8 models can be developed, dependent if time is considered in the model. Among dynamic  
9 models; those defined as ‘descriptive’ simply trace the outlines of a system, and only show  
10 the existence of relations between elements, but do not explain these relations. A more  
11 complicated approach is taken when the aim is to describe a more comprehensive system with  
12 its relations therein and ‘explanatory’ models are developed in this case. During World War II  
13 a rational approach was developed in order to study a system in detail: systems analysis.  
14 Systems analysis was developed basically as a tool to consider military options but it was  
15 demonstrated to be useful in different disciplines, where a system is studied by distinguishing  
16 its major components, characterising their changes, and the interconnecting elements  
17 (*Leffelaar, 1993*). The system structure in plant pathology includes pathogen, host,  
18 environment, human actions and their relationships (*De Wit, 1993*). Modelling can be split  
19 into three steps: model development, model analysis and hypothesis testing (*van Maanen and*  
20 *Xu, 2003*). A simple way to represent a complicated system, like a pathosystem, is a relational  
21 diagram as a first step in model development (*Leffelaar, 1993*).

22 Collection of information from different sources (step 1) is the basis of “system analysis” that  
23 starts with drawing a relational diagram translated into quantitative relationships that allow  
24 the quantification of states. Putting together all mathematical functions (step 2), a simulation

1 model able to predict fungal development is finally obtained. Model validation and evaluation  
2 (step 3) is then necessary before building up a final model used on a large scale.

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

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

11

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

13 *Fusarium* head blight, which is caused by several fungal species with *Fusarium* or *Fusarium*-  
14 like anamorphs, is a serious disease of wheat in many parts of the world (Rossi *et al.*, 2003b).  
15 Though FHB can be destructive, its severity varies greatly between years and locations, as  
16 this disease is heavily dependent on favourable epidemiological conditions (Rossi *et al.*,  
17 2004).

18 Infection by *Fusarium* spp. on wheat occurs during the flowering period. In addition to yield  
19 losses, these fungi can also synthesize toxic compounds (mycotoxins) in favourable  
20 environmental conditions, thus representing an important threat for animal and human health.  
21 (Detrixhe *et al.*, 2003). Preventive actions are possible so as control strategies; accurate  
22 predictions of DON in mature grain at wheat heading are needed to make decisions on  
23 whether a control strategy is needed. If weather variables can be quantified into DON-  
24 response relationship, a model could be developed to predict the concentration of DON using

1 both forecasted and actual weather data for specific fields (*Hooker et al., 2002*). On the basis  
2 of the known relationship between fungal biomass and DON, more heavily colonized plant  
3 tissue is likely to have a greater fungal biomass, and consequently, higher DON content than  
4 less colonized tissue. For this reason, visual estimates of disease could also serve as indirect  
5 measures of DON to screen for genotypes with low DON accumulation (*Paul et al., 2005 and*  
6 *references therein*).

7 Attempts to predict head blight have emphasised the importance of both inoculum and the  
8 environment for disease epidemics (*Parry et al., 1995*). In order to predict disease incidence  
9 and to increase the ability of wheat producers to achieve good disease management, several  
10 FHB infection or mycotoxin risk assessment models have been developed (*De Wolf et al.,*  
11 *2003 and 2004; Detrixhe et al., 2003; Madden et al., 2004; Schaafsma et al., 2006*).

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

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

23

## 24 **2.1 Argentina**

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

$$5 \quad \text{PI}\% = 20.37 + 8.63 \cdot \text{NP}_2 - 0.49 \cdot \text{DD}_{926} \quad (1)$$

$$6 \quad \text{PI}\% = 18.34 + 4.12 \cdot \text{NP}_{12} - 0.45 \cdot \text{DD}_{1026} \quad (2)$$

7 where  $\text{NP}_2$  is the number of 2 day periods with precipitation ( $\geq 0.2$  mm) and relative humidity  
 8  $> 81\%$  on the first day and relative humidity  $\geq 78\%$  on the second day;  $\text{NP}_{12}$  is the total number  
 9 of  $\text{NP}_2$  periods plus the total number of days with both precipitation  $\geq 0.2$  mm and average  
 10 relative humidity  $> 83\%$ .  $\text{DD}_{926}$  and  $\text{DD}_{1026}$  represent 926 or 1026 degree days accumulated  
 11 and are calculated as:

$$12 \quad \text{DD}_{926} = \sum[(\text{MaxT}) - 26) + (9 - \text{MinT})] \quad (3)$$

$$13 \quad \text{DD}_{1026} = \sum[(\text{MaxT} - 26) + (10 - \text{MinT})] \quad (4)$$

14 where MaxT is the maximum daily temperature  $> 26^\circ\text{C}$ , MinT is the minimum daily  
 15 temperature  $< 9^\circ\text{C}$  or  $< 10^\circ\text{C}$ , and summation occurs over the days of the critical period length  
 16 (CPL). CPL is the time period beginning 8 days before the heading date and ending when 530  
 17 degree days were accumulated (base temperature:  $0^\circ\text{C}$ ).

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

24

## 1 **2.2 Belgium**

2 In Belgium, in order to assess the risk of head blight infection in winter wheat, an agro-  
 3 meteorological model has been developed on the basis of an interpolation of weather radar  
 4 data (above all rainfall events) to simulate the leaf wetness duration on a grid size of 1 km x 1  
 5 km (*Detrixhe et al., 2003*). Leaf wetness duration has a strong relationship with the  
 6 development and outbreak of plant diseases because many important pathogens require a  
 7 layer of free water to move on the surface of plant organs and start their infective processes  
 8 (Dalla Marta et al., 2005). This model is interesting for two reasons: the first is the  
 9 interpolation of meteorological data on an area of interest and particularly the use of weather  
 10 radar data to spatialise rainfall events in this area. The second is the use of the estimation of  
 11 leaf wetness duration instead of relative humidity, in order to obtain a better characterization  
 12 of risk of *Fusarium* head blight infection in winter wheat. Further calibration/validation tests  
 13 are in progress to optimise the model developed (*Detrixhe et al., 2003*).

14

## 15 **2.3 Canada**

16 In Canada, *Hooker et al. (2002)* developed three equations to predict DON in mature grain at  
 17 wheat heading, based on rainfall and temperature data, and their timing. They measured the  
 18 concentration of DON in 399 farm fields in southern Ontario, Canada, from 1996 to 2000.

19 Equation 5 predicts DON using weather information from 4 to 7 days before heading:

20

$$21 \quad \text{DON} = \exp[-0.30 + 1.84 \text{ RAINA} \\ 22 \quad \quad \quad - 0.43 (\text{RAINA})^2 - 0.56 \text{ TMIN}] - 0.1 \quad (R^2 = 0.55) \quad (5)$$

1 where DON is the concentration of DON ( $\mu\text{g g}^{-1}$ ), RAINA is the number of days of rain  $>5$   
 2  $\text{mm day}^{-1}$  in the period 4 to 7 days before heading, and TMIN is the number of days of  
 3 temperature  $<10^\circ\text{C}$  between 4 and 7 days before heading.

4 Equations 6 and 7 predicted DON using weather information from 7 days before heading to  
 5 10 days after heading:

6 when RAINB  $>0$ , then

$$7 \quad \text{DON} = \exp [- 2.15 + 2.21 \text{RAINA} - 0.61 (\text{RAINA})^2 + 0.85 \text{RAINB} \\ 8 \quad \quad \quad + 0.52 \text{RAINB} - 0.30 \text{TMIN} - 1.10 \text{TMAX}] - 0.1 \quad (R^2= 0.79) \quad (6)$$

9 and when RAINB = 0, then

$$10 \quad \text{DON} = \exp (- 0.84 + 0.78 \text{RAINA} + 0.40 \text{RAINB} \\ 11 \quad \quad \quad - 0.42 \text{TMIN}) - 0.1 \quad (R^2= 0.56) \quad (7)$$

12 where DON = concentration of DON ( $\mu\text{g g}^{-1}$ ), RAINA is the number of days of rain  $>5$  mm  
 13  $\text{day}^{-1}$  in the period 4 to 7 days before heading, RAINB is the number of days of rain  $>3$  mm  
 14  $\text{day}^{-1}$  in the period 3 to 6 days after heading, RAINC is the number of days of rain  $>3$  mm  
 15  $\text{day}^{-1}$  in the period 7 to 10 days after heading, TMIN is the number of days of temperature  
 16  $<10^\circ\text{C}$  between 4 and 7 days before heading, and TMAX is the number of days with  
 17 temperature  $>32^\circ\text{C}$  between 4 and 7 days before heading.

18 DONcast, a robust site specific DON forecaster (*Hooker and Schaafsma, 2003*) was  
 19 commercialised for wheat and has been used commercially for 5 years (*Schaafsma and*  
 20 *Hooker, 2006*). For the first time, in 2004, a web-based interactive model, which allowed  
 21 input of field-specific weather and agronomic variables, was developed for industry. The  
 22 predictions have explained 76% of the variability in DON using a database from 1996 to 2003  
 23 (*Hooker and Schaafsma, 2004*).

24

## 1 **2.4 Italy**

2 In Italy, a predictive model regarding the risk of *Fusarium* head blight and mycotoxin  
 3 contamination (DON and ZEA) in wheat was developed on the basis of meteorological data  
 4 and information about wheat growth stages. *Rossi et al. (2003a; 2003b)* developed a dynamic  
 5 simulation model for the risk of *Fusarium* head blight on wheat based on systems analysis.  
 6 The model calculates a daily infection risk based on sporulation, spore dispersal and infection  
 7 of the host tissue of the four main species causing the disease (*Gibberella zeae*, *Fusarium*  
 8 *culmorum*, *Giberella avenacea*, *Monographella nivalis*).

9 The model was validated over 22 wheat-growing areas of northern Italy in 2002. In each area,  
 10 a risk index (TOX-risk) was calculated daily for *F. graminearum* and *F. culmorum*, and  
 11 accumulated over the growing season until harvest:

$$12 \quad \text{TOX-risk} = \text{SPO} \cdot \text{DIS} \cdot \text{INF} \cdot \text{GS} \cdot \text{INV} \quad (8)$$

13 where SPO is the sporulation rate, DIS is the dispersal rate, INF is the infection rate, GS is the  
 14 host growth stage, and INV is the invasion rate (*Rossi et al., 2003b*). Rates are influenced by  
 15 air temperature, relative humidity, rainfall, sequences of rainy days, wetness duration, and  
 16 free water in the host tissue ( $a_w$ ); fungal species and the host growth stage are also considered.

17 Production of DON and ZEA in the kernels is then calculated by two regression equations,  
 18 elaborated from artificial-inoculation experiments:

$$19 \quad \ln \text{DON} = 3.0894 \cdot \ln (\text{TOX-risk}) - 3.5231 \quad (9)$$

$$20 \quad \ln \text{ZEA} = 0.2113 \cdot \exp (0.054 \cdot \text{TOX-risk}) \quad (10)$$

21 The model produces two indices: one for the risk of FHB on wheat and one of mycotoxin  
 22 content of kernels. Comparison between the actual content of both mycotoxins and the values  
 23 estimated showed good concordance (*Rossi et al., 2003a*).

24

## 1 **2.5 The United States**

2 A series of severe Fusarium head blight epidemics experienced in the United States of  
3 America led to a project to create a forecasting model. Using weather data, crop growth stage  
4 and disease observations from seven states, both spring and winter wheat production areas,  
5 prediction models for FHB of wheat were implemented (*De Wolf et al., 2004; van Maanen  
6 and Xu, 2003*). The final models used hourly temperature, humidity and rainfall to predict the  
7 risk of disease severity greater than 10%. The model deployed in 2004 also contained  
8 variables that allowed users to specify type of wheat (winter vs. spring) and whether winter  
9 wheat was planted into corn residue. Model accuracy was estimated to be near 80% based on  
10 data used to validate the model that was deployed for 23 states in 2004 as part of the National  
11 Fusarium Head Blight Prediction Center ([www.wheatscab.psu.edu](http://www.wheatscab.psu.edu)). Modelling of these field  
12 data showed that environmental conditions prior to flowering were more important than those  
13 during anthesis (*Xu, 2003*). The validation of the model and the development of an updated  
14 version for scab risk prediction are based on additional scab observations, weather data for  
15 different time windows, and the integration of empirical observations of epidemics with  
16 results from field and laboratory studies on scabs. The model was generally accurate in field  
17 testing, but improvements in accuracy are needed (*Madden et al., 2004*).

18

## 19 **3. Limits of predictive models**

20 Mycotoxins can be produced in field as well as during food storage and different  
21 meteorological, environmental and agronomic factors affect their production. For this reason,  
22 it is difficult to predict the occurrence of fungal diseases and toxin contamination in  
23 foodgrains.

1 Crop models have many current and potential uses for answering questions in research, crop  
2 management and policy. The descriptive models are easy to comprehend, often require fewer  
3 inputs, and often are easier to use and apply, but they have to be calibrated to each new site.  
4 On the other hand, the explanatory models are better able to model genotype X environment  
5 interaction, but their complexity makes them more difficult to understand and to use and  
6 apply, and they also require more input information. In many cases the outputs of the  
7 explanatory models may be less stable, particularly if the given information was incorrectly  
8 modelled. Cautions and limitations (table 1) in the model uses are suggested, because  
9 appropriate use for a particular purpose depends on whether the model has been correctly  
10 developed and validated in diverse environments (*Boote et al., 1996*):

- 11 ■ the level of complexity depends on the amount of information (data) and time available  
12 for model building and testing. Most computer models relate only meteorological  
13 variables and do not include field specific effects such as crop rotation, crop variety,  
14 tillage, etc;
- 15 ■ some simple, descriptive models have parameters that are site and year-specific, so that  
16 the model has little predictive ability for other locations;
- 17 ■ field and storage management and human behaviour (habits, customs, etc.) influence the  
18 mycotoxin problem; these factors are normally not included in model development,  
19 because they are difficult to quantify.

20 The application of predictive models, like many weather-driven prediction systems, will  
21 depend on the availability, resolution, and reliability of weather data. As suggested by De  
22 Wolf et al. (2003), a potential limitation of models A (temperature X humidity combination  
23 variable postanthesis) and B (model A X variables summarizing pre-anthesis weather  
24 interaction) was the dependence on weather information during anthesis. While it may be

1 possible to overcome this limitation by using forecasted weather, the uncertainty of predicted  
2 weather variables may reduce model prediction accuracy (*De Wolf et al., 2003*). Further, there  
3 is a tendency to extend the use of models that were developed for bacteria to moulds, but one  
4 important specificity of fungi should be taken in account: spore germination. Free water or  
5 near saturation moisture on the host surface is essential for germination and penetration of the  
6 host for many pathogens. Thus a single parameter indicating water availability is used in  
7 several forecasting systems; but, very few models aimed at assessing the influence of  
8 environmental factors on spore germination (*Dantigny et al., 2005; van Maanen and Xu,*  
9 *2003*).

10 <insert table 1 here>

11

## 12 **4. Conclusions**

13 In order to predict the incidence of diseases and mycotoxin contamination and to increase the  
14 ability of producers to achieve good disease management, several epidemics or mycotoxins  
15 risk assessment models have been set up. The employment of models may be useful for  
16 decision-making purposes: to prevent/reduce yield losses and hazards for human and animal  
17 health based on the correct time for spraying chemicals; predict the final level of  
18 contamination and better organise post-harvest management.

19 Nevertheless, predictive models may present some limits of application and accuracy, and  
20 precise information on the approach to be taken for their development is needed before  
21 correct use can be guaranteed. As stated before, descriptive models are sufficiently reliable in  
22 the geographic area of development or in other very similar places. The amount of  
23 information requested is limited and they can be developed in a reasonably short time.  
24 Explanatory models are based on a considerable amount of information and it takes several

1 years to produce and process the necessary data, both for model development and validation.  
2 Then, they can be run in different areas, and can include different variables, such as  
3 meteorological, phenological and cropping system data and the output is precise and reliable.  
4 The accuracy of this kind of model largely depends on the accuracy of the weather forecast.  
5 In conclusion, modelling is a strategic tool for crop management aimed at preventing  
6 mycotoxin prevention contamination, but a lot of work is necessary to develop explanatory  
7 models with a good predictive capacity. More research is needed, taking into account other  
8 abiotic factors and fungal interactions to improve the microbiological safety and shelf-life of  
9 food products (*Pardo et al., 2006*). According to Paul et al. (2005) differences between  
10 models could be due to factors such as the genotypes planted, the weather conditions, the  
11 pathogen population, crop production, and disease management practices, as well as other  
12 unknown random effects; consideration of moderator variables attempts to explain some  
13 between-study variability (*Paul et al., 2005*). As demonstrated by Baranyi et al. (1996), the  
14 advice of McMeekin on parsimony is vital for predictive models, not only for simplicity but  
15 also to improve the accuracy of predictions (*Baranyi et al., 1996 and reference therein*).

16

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20

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2 **TABLES**

3 **Table 1 - The predictive models**

<b>PREDICTIVE MODELS</b>	<b>Disease/ mycotoxin</b>	<b>Crop</b>	<b>Limits</b>	<b>References</b>	<b>Year</b>
Argentina	FHB	Wheat	Site- and year-specific	Moschini & Fortugno	1996
				Fernandes et al.	2004
Belgium	FHB	Winter wheat	Instrumental (radar) availability	Detrixhe et al.	2003
				Dalla Marta et al.	2005
Canada	DON	Cereal grain	Do not consider: crop rotation, crop variety, tillage, fertilization, etc.	Hooker et al.	2002
				Hooker & Schaafsma	2003 & 2004
				Schaafsma & Hooker	2006
Italy	FHB, DON, ZEA	Wheat	Low accuracy for high TOX-risk	Rossi et al.	2003a & 2003b
The United States	FHB	Spring and winter wheat	Low accuracy	De Wolf et al.	2004
				Van Maanen & Xu	2003
				Xu	2003
				Madden et al.	2004
Italy	F. verticillioides	Maize	Aspect of dynamic cycle of fungi are needed	Rossi et al.	2003a; 2003b & 2006
Europe	P. verrucosum	Cereal grain	Lack of field and storage management effects	Pardo et al.	2006

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