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A field-specific web tool for the prediction of Fusarium head blight and deoxynivalenol content in Belgium

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ABSTRACT

Fusarium head blight is a worldwide problem in wheat growing areas. In addition to yield loss, *Fusarium* species can also synthesise mycotoxins and thus threaten animal and human health. Models for predicting Fusarium head blight and deoxynivalenol content in wheat provide farmers with a tool for preventing yield loss and mycotoxin contamination. Growers may use the predictions to underpin decision making on cultivation techniques and the application of fungicides. At the end of the growing season, the food and feed industry may use the predictions to make marketing decisions. Furthermore, the predictions are helpful to identify regions with a higher disease pressure and thus improve sampling efficiency. Based on the data of 3100 wheat samples from 18 locations throughout Belgium between 2002 and 2011, various predictive models were evaluated. The most accurate models were implemented in a web tool to provide growers with field-specific predictions of Fusarium head blight incidence and deoxynivalenol content. The predictions are based on the agronomic variables of a specific wheat field and weather data from the nearest weather station. During the growing season several predictions can be asked. The web tool provides a graphical representation of the predicted results together with an advice on management strategies and recommendations for fungicide application.

1. Introduction

1.1. Fusarium head blight

Fusarium head blight (FHB) is a devastating disease of cereals in numerous areas of the world. A total of 17 species of *Fusarium* have been described to be potentially associated with FHB symptoms (Leonard and Bushnell, 2003). The main causal agents of FHB in Europe are *Fusarium graminearum*, *F. culmorum*, *F. avenaceum*, *F. poae* and *Microdochium nivale*. Besides reduced quality and yield loss, most *Fusarium* species of the FHB complex produce a diverse spectrum of mycotoxins that can be hazardous to the health of humans and animals even at low concentrations (Sutton, 1982; Parry et al., 1995; Champeil et al., 2004). The trichothecene deoxynivalenol (DON) is the most prevailing *Fusarium* mycotoxin worldwide. FHB incidence and the presence of mycotoxins vary strongly from one year to another and are influenced by environmental growing conditions, local agronomic systems and the interaction between both factors. No tillage or minimal tillage systems favour FHB infection since *Fusarium* species can survive saprophytically on crop residues of host plants as maize and wheat. Crop residues are considered to be the principal reservoir of *F. graminearum* inoculum. Furthermore, it is known that most *Fusarium* species have a broad spectrum of hosts among gramineous weed species (Fernando et al., 1997; Pereyra et al., 2004; Beyer et al., 2006; Pereyra and Dill-Macky, 2008). In a study conducted by Landschoot et al. (2011), the five predominant *Fusarium* species, *F. avenaceum*, *F. culmorum, F. graminearum, F. poae* and *M. nivale*, were recovered from crop residues and gramineous weed samples.

Around the time of flowering, rainfall and warm weather conditions favour infection of wheat. However, also during the vegetative growth stage weather conditions significantly contribute to FHB incidence (Kriss et al., 2010; Landschoot et al., 2012a). Large efforts are invested throughout the world to determine the main factors responsible for FHB and DON contamination in cereal crops (Doohan et al., 2003; Rossi et al., 2003; Xu, 2003; Ioos et al., 2005; Xu and Berrie, 2005; Klix et al., 2008; Audenaert et al., 2009;

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Isebaert et al., 2009; Kriss et al., 2010; Chandelier et al., 2011; Landschoot et al., 2011; Vogelgsang et al., 2011; Landschoot et al., 2012a) and numerous decision support systems (DSSs) have been developed (Schaafsma et al., 2001; Moschini et al., 2001; Hooker et al., 2002; De Wolf et al., 2003; Klem et al., 2007; Musa et al., 2007; Rossi et al., 2007; Van Der Fels-Klerx et al., 2010; Chandelier et al., 2011).

1.2. Disease forecasting systems

Mathematical modelling of crop diseases is a rapidly expanding discipline within plant pathology (Van Maanen and Xu, 2003), since modelling and predicting crop diseases accurately can help in providing prior knowledge of the time and severity of the outbreak of diseases (Prandini et al., 2009). However, many models remain at the academic level and have not proven useful for disease management (Pavan et al., 2011). The main objective for developing a useful predictive model may be timely accurate predictions, but this must be accomplished using the most simple, easily acquired, and inexpensive data and platforms. If the data required to run the model is too expensive to acquire, or if the model platform is too complicated, it is highly unlikely that the predictive model will be widely deployed or accepted as a predictive tool at the farm level (Schaafsma and Hooker, 2007). Additionally, a predictive model has to be incorporated in a DSS in order to aid growers in an efficient control of plant diseases. DSSs are a class of computer-based information systems including knowledge-based systems that support decision making activities, such as appropriate management strategies and fungicide applications (Singh et al., 2008). DSSs are important in the achievement of a more sustainable agriculture since they can help to reduce the input of fungicides. Some important DSSs in the Benelux are EPIPRE, CerDIS, ProPhy and Plant-Plus (Bouma, 2003). Other DSSs are described in Magarey et al. (2005), Kaundal et al. (2006), Musa et al. (2007), Rossi et al. (2007), Schaafsma and Hooker (2007), Van Der Fels-Klerx et al. (2010), Chandelier et al. (2011) and Pavan et al. (2011).

The main objective of this research was to develop and implement a web-based forecasting system to predict FHB incidence and DON content in winter wheat in Belgium. Although of great interest, the currently available models, of which a review is given in Prandini et al. (2009), cannot directly be transported to a Belgian context. The lack of fit of these predictive models for other countries could probably be explained by regional factors (Chandelier et al., 2011). Although the area of Belgium is small (30,528 km^2), the weather in the coastal region differs from the weather in the east and the more continental Ardennes in the south. Additionally, in contrast to large-scale commercial agriculture in the US, Belgian agriculture is characterised by a complex rotation system of host and non-host crops for *Fusarium* species, which results in a complex *Fusarium* population (Isebaert et al., 2009; Landschoot et al., 2011). Furthermore, the maize and wheat varieties grown vary greatly among countries. Therefore, prediction models must be developed at a regional scale. During this research a DSS for Fusarium head blight, based on an intensive data collection from growing seasons 2001–2002 until 2010–2011 in Belgium, was set up. Before sowing, the tool can be used to calculate the general risk of the FHB incidence of a field based on the previous crop, tillage system and wheat variety. During the growing season the predictions are helpful to underpin fungicide application decisions at the time of flowering. In a short period before harvest the tool is interesting to choose the market destination, which influences the price of the wheat crop. At the end of the growing season, based on the predictions, regions with a higher disease pressure can be identified and thus sampling efficiency and accuracy can be improved.

2. Development of the models

2.1. Description of the dataset

From growing seasons 2001–2002 until 2010–2011, field trials and commercial wheat fields, under natural infection, were monitored at 18 locations throughout Belgium. At each location, at least 10 wheat varieties were grown, ranging from moderately resistant to highly susceptible for FHB, in a randomised complete block design with four replications and an elementary plot surface of 15 m^2. At all locations wheat was produced under standard cropping conditions for Belgium, including a fungicide treatment at growth stage (GS) 59 (Zadoks et al., 1974). The sprayed fungicides, containing a strobilurin and a triazole, were the same at all locations. They were applied at the dosage recommended by the manufacturer. The varieties were sown in common crop rotation systems, which led to different previous crops, comprising host (maize or wheat) as well as non-host crops for *Fusarium* spp. (beans, sugar beets, onions or chicory). Early July at GS 71 or GS 75, all fields were evaluated for the presence of FHB bleaching symptoms. For each variety and replication 100 randomly selected ears were evaluated for the presence of *Fusarium* symptoms using an ordinal scoring system. The infected ear areas were classified into severity classes 1, 2, 3, 4 or 5, meaning approximate infestation of 0%, 1–25%, 26–50%, 51–75% or 76–100%, respectively. The disease index (DI) was then computed as: $\mathrm{DI} = \frac{0n_1+1n_2+2n_3+3n_4+4n_5}{4n} \times 100\%$, with n the number of evaluated ears and n_i the number of ears in class i (Isebaert et al., 2009). At harvest, in August, the DON content of a representative sample of each elementary 15 m^2 plot was measured by an enzyme-linked immunosorbent assay (ELISA), according to Audenaert et al. (2009). The number of ears in each disease class, the DI and DON content together with the agronomic and weather variables were stored in a relational database. The agronomic variables in the database include wheat variety resistance (resistance class 1 till 5), soil type, sowing date, harvest date, soil management techniques, previous crop (host crop or non-host crop for *Fusarium*) and fungicide application. The weather variables include time series of daily weather observations for all years since 2001, including rainfall, air temperature, leaf wetness duration, air pressure, wind speed and relative humidity. Daily weather data were collected by automated weather monitoring equipment of the Soil Service of Belgium within 5 km of the field experiments.

From these daily weather variables, summary statistics, such as monthly averages, minima, maxima, and percentiles (10th, 25th, 50th, 75th, 90th), were computed to extract the most relevant information. In addition, the number of freezing and rainy days per month were calculated. Note that 10th and 90th percentiles of weather variables can be used to estimate the impact of extreme weather conditions (Genton and Furrer, 1998). For infection, shorter time periods could be better. Therefore, the window-pane methodology (Kriss et al., 2010) was employed to determine shorter periods around anthesis, in which weather conditions significantly contribute to the FHB incidence and measured DON content. An in-depth descriptive statistical analysis of this database has been presented in Landschoot et al. (2012a).

2.2. Description of the models

Before modelling a careful variable selection was performed. The selected input variables were agronomic variables (previous crop and wheat variety resistance) and various weather variables related to air temperature, rainfall, relative humidity, air pressure from November till July. The performance of the models was evaluated using cross-year cross-location validation. This cross-year cross-location validation strategy enables to evaluate the predictive