Modeling Deoxynivalenol Contamination of Wheat in Northwestern Europe for Climate Change Assessments

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ABSTRACT

Climate change will affect mycotoxin contamination of feed and food. Mathematical models for predicting mycotoxin concentrations in cereal grains are useful for estimating the impact of climate change on these toxins. The objective of the current study was to construct a descriptive model to estimate climate change impacts on deoxynivalenol (DON) contamination of mature wheat grown in northwestern Europe. Observational data from 717 wheat fields in Norway, Sweden, Finland, and The Netherlands were analyzed, including the DON concentrations in mature wheat, agronomical practices, and local weather. Multiple regression analyses were conducted, and the best set of explanatory variables, mainly including weather factors, was selected. The final model included the following variables: flowering date, length of time between flowering and harvest, wheat resistance to Fusarium infection, and several climatic variables related to relative humidity, temperature, and rainfall during critical stages of wheat cultivation. The model accounted for 50% of the variance, which was sufficient to make this model useful for estimating the trends of climate change on DON contamination of wheat in northwestern Europe. Application of the model in possible climate change scenarios is illustrated.

Contamination of cereal grains with deoxynivalenol (DON) is of major concern to grain producers. DON belongs to the group of trichothecenes, a family of structurally related secondary metabolites predominantly formed by Fusarium species in cereal grains. Fusarium graminearum and Fusarium culmorum are the dominant species that produce DON in wheat. They mainly occur in the temperate grain growing regions of America, Asia, and Europe (15). Under favorable environmental conditions related to agronomy and local weather, these Fusarium species may infest the wheat.

DON is chemically very stable; it does not degrade during storage, milling, and subsequent processing of wheat into feed and/or food products (34). Exposure of animals to DON caused a variety of toxic effects (2, 14, 15, 20). Some evidence suggests that DON can cause acute human illness, including vomiting and gastroenteritis. However, long-term effects in humans have not been documented (20, 21, 28).

The European Commission has set maximum limits for the presence of DON in food products to protect human health and guidance limits for the presence of DON in products intended to be fed to animals (3, 4). Recent market studies in several European countries revealed that DON is present in most cereal-based food products but at mostly below the European Commission limits, suggesting the European cereal grain production chain currently is capable of complying with these regulations (21). However, DON contamination in cereal grains is increasing throughout the world, possibly because of expanded use of no-till farming, inappropriate crop rotation, and/or climate change (11, 13, 17). Warm and humid conditions favor Fusarium spp. infection and DON contamination in cereal grains in northwestern Europe. These conditions are expected to occur more frequently with climate change (29); therefore, DON contamination is expected also to increase.

Several recent reviews on the impact of climate change on mycotoxins have pointed to the need for models to quantify the impacts of climate change (17, 18, 31). Preferably, such models should take into account all interactions among climate, plant development, the fungal population, and mycotoxin formation. However, gaps in knowledge make the development of such models difficult. More realistic models should be used to estimate the effects of climate change on mycotoxin contamination. Descriptive models based on weather parameters linked to plant life cycles, as developed by Hooker and coworkers for Canada (8), provide a useful starting point (31). In Europe, such mathematical models for predicting DON concentrations in mature wheat are available for several individual countries, including The Netherlands, the Czech Republic, and Italy.
The Italian model is mechanistic; it represents cause-and-effect relationships between variables and is built from knowledge of the underlying biological processes. Such mechanistic models can potentially be applied outside the country. However, application of the Italian model may be limited because it has been calibrated on only Italian data. The other three models are empirical in nature; they describe relationships among driving factors and response variables and were developed by statistical analyses of data collected in the field. Such statistical models cannot be applied to other geographic areas without new calibrations. So far, a more applicable model for assessment of the impact of climate change has not been developed for Europe.

The objective of the current study was to build a descriptive model to estimate the impacts of climate change on DON contamination of wheat in northwestern Europe.

**MATERIALS AND METHODS**

Field data collected in four northwestern European countries (Norway, Sweden, Finland, and The Netherlands) were used for this study with a two-step approach for model development. The performance of the model for predicting DON concentrations in wheat at harvest in The Netherlands (33) was tested using data from the three other study countries (Norway, Sweden, and Finland), and a new descriptive model for predicting DON concentrations in mature wheat in all four countries (generic DON model) was developed. Both steps used the same data set, which was compiled from national data from each of the four study countries. For demonstration purposes, the developed model was applied to several scenarios related to possible climate change effects in northwestern Europe.

**Variables for model development.** Historical data from wheat fields in each study country were collected. A data recording sheet was designed to enable consistent data collection and storage and included the response variable, i.e., DON concentration in mature wheat, and potential explanatory variables for model development. Each variable was clearly defined based on expert opinions from previous studies on trichothecenes in wheat in the four countries. Potential explanatory variables included agronomical variables and weather variables related to the wheat fields.

Agronomical variables were country of origin (COUN; Norway, Sweden, Finland, or The Netherlands), year (YR; 2000 through 2009), date at mid flowering (Zadoks growth stage 65) or flowering date (FD; ordinal date from 1 January), wheat harvest date (HD; ordinal date from 1 January), cultivar resistance class against Fusarium spp. (RESC; low, medium, or high), and application of late Fusarium fungicides during Zadoks growth stages 61 through 69 (SPRAY; yes or no). When spraying occurred one or more times during Zadoks growth stages 61 through 69, SPRAY was assigned the value “yes”; for earlier spraying or no fungicide use at all, SPRAY was assigned “no.” Spring wheat was designated low RESC, and winter wheat was designated either medium or high RESC, depending on the variety. Although Fusarium species differ among European spring wheat varieties, the Fusarium resistance of these cultivars is lower than that of winter wheat varieties (7).

Weather variables consisted of two different sets of variables, all calculated using hourly data on temperature, relative humidity, and rainfall during critical periods of the wheat cultivation period up to harvest. The first set of variables included the weather variables of the predictive model for DON in wheat in The Netherlands (see Table 1, which is derived from a previous study (33)). This model includes five time periods relative to wheat FD and/or HD, as defined by \( B_i \) (where \( i = 0 \) to 4): 10 days before HD to HD (\( B_0 \), 10 days before HD to HD (\( B_1 \), FD to 10 days after HD (\( B_2 \), FD to 10 days after HD (\( B_3 \), and 10 days before HD to HD (\( B_4 \). For each \( B \) time block, the following five weather variables were calculated: sum of rainfall (\( B_i \) rain in millimeters, where \( i = 0 \) to 4), average temperature (\( B_i \) TEM in degrees Celsius, where \( i = 0 \) to 4), sum of the temperatures (\( B_i \) Tsun in degrees Celsius, where \( i = 0 \) to 4), number of hours that the temperature is 25°C or higher (\( B_i \) Tbk25, where \( i = 0 \) to 4), and number of hours that the relative humidity (RH) is 80% or higher (\( B_i \) RHh80, where \( i = 0 \) to 4). Weather variables of the second set referred to weekly weather in six time periods relative to FD and/or HD, represented by \( W_j \) (where \( j = 0 \) to 5): 1 to 2 weeks before FD (\( W_0 \), 2 to 1 week before FD (\( W_1 \), 1 week before FD to FD (\( W_2 \), FD to 1 week after FD (\( W_3 \), 1 to 2 weeks after FD (\( W_4 \), and 2 weeks after FD to HD (\( W_5 \). For each of these six weekly time periods, the following three weather variables were calculated: number of days that rainfall is 2 mm or higher (\( W_i \) rain in millimeters, where \( j = 0 \) to 5), average temperature (\( W_i \) TEM in degrees Celsius, where \( j = 0 \) to 5), and number of hours that the RH is 80% or higher (\( W_i \) RHh80, where \( j = 0 \) to 5).

**Data collection.** In the beginning of 2010, the data sheet with the variables (in columns) and their definitions was provided to specific research organizations (data owners) in each study country. The data sheet was filled by the data owners by inserting the required information, based on available historical data related to wheat fields up to and including 2009. These national data sets had been collected in the course of previous field studies. Available data referred to 119 fields in Norway for 2004 through 2008, 129 fields in Sweden for 2005 through 2009, 75 fields in Finland for 2000 through 2009, and 511 fields in The Netherlands for 2001 through 2009. In each country, data on agronomical practices were collected by the farmer and included FD, HD, wheat variety, and application of sprayings against Fusarium spp. For each field, the DON concentration (micrograms per kilogram) of the wheat kernels just before and at harvest were available. The limit of quantification (LOQ) differed among countries: 25 \( \mu \)g/kg in Norway, 10 \( \mu \)g/kg in Sweden, 5 \( \mu \)g/kg in Finland, and 5 \( \mu \)g/kg in The Netherlands. Weather data were collected from the meteorological station nearest to the specific wheat field (usually within 20 km) and included observed (or interpolated) hourly temperature, rainfall, and RH.

**Data processing.** Samples of wheat fields that had DON concentrations below the specific LOQ were assigned the LOQ value. For the Dutch data, data on FD and HD were limited; therefore, FD and HD from the specific wheat field were calculated based on the sum of the temperatures (33). For each field, the length between FD and HD (LeFH, in days) was calculated as HD minus FD. When wheat resistance to Fusarium infection was not recorded, RESC levels were assigned based on wheat variety and year.

**Dutch model evaluation.** The records from Norway, Sweden, and Finland were used for fitting the descriptive model for DON concentrations in mature winter wheat in The Netherlands (Table 1) to the conditions of these three countries. The variables of the Dutch model were fitted to these data, and parameter values with standard errors and parameter significance values, were calculated. The variables Region, Spraying, and Resistance level in...
TABLE 1. Summary of the descriptive model for prediction of DON concentrations in mature winter wheat in The Netherlands

<table>
<thead>
<tr>
<th>Model variable</th>
<th>Parameters estimate</th>
<th>SE</th>
<th>Parameter significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-31.39</td>
<td>9.03</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Region North</td>
<td>0.246*</td>
<td>0.194</td>
<td>0.206</td>
</tr>
<tr>
<td>Region West</td>
<td>-0.729*</td>
<td>0.159</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Region South</td>
<td>0.305*</td>
<td>0.260</td>
<td>0.241</td>
</tr>
<tr>
<td>Spraying 1</td>
<td>0.688*</td>
<td>0.165</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Spraying 2</td>
<td>0.842*</td>
<td>0.155</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Flowering date</td>
<td>-0.0647</td>
<td>0.0102</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Resistance level</td>
<td>-0.4281</td>
<td>0.0463</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>LeFH</td>
<td>0.0888</td>
<td>0.0173</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Bo_rain</td>
<td>0.03369</td>
<td>0.00572</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Bo_RHh80</td>
<td>0.00633</td>
<td>0.00252</td>
<td>0.012</td>
</tr>
<tr>
<td>Bo_Tavg</td>
<td>0.1076</td>
<td>0.0477</td>
<td>0.025</td>
</tr>
<tr>
<td>B1_Tavg</td>
<td>-0.0654</td>
<td>0.0402</td>
<td>0.104</td>
</tr>
<tr>
<td>B2_Tavg</td>
<td>2.614</td>
<td>0.965</td>
<td>0.007</td>
</tr>
<tr>
<td>(B3_Tavg)2</td>
<td>-0.0781</td>
<td>0.00271</td>
<td>0.004</td>
</tr>
<tr>
<td>B4_Tavg</td>
<td>2.18</td>
<td>1.02</td>
<td>0.033</td>
</tr>
<tr>
<td>(B4_Tavg)2</td>
<td>-0.0570</td>
<td>0.0277</td>
<td>0.040</td>
</tr>
</tbody>
</table>

a This model was previously published (33). It predicts ln(DON) concentrations in micrograms per kilogram. Nontransformed DON concentrations (in micrograms per kilogram) can be obtained by back transformation using e\(^{(\text{model \ B})}\).

b Regions are North, West, South, and Mid (reference). Spraying indicates the application of fungicides against Fusarium spp. during Zadoks growth stages 61 through 69, with levels of 0 (reference), 1 (spraying once), and 2 (spraying twice). Resistance levels of winter wheat varieties range (in theory) from 1 to 10. LeFH is the length (in days) from flowering date (FD) to harvest date (HD). Time periods B0 through B4 are designated in relation to FD and HD: B0 = -17 days FD to -10 days FD; B1 = -10 days FD to FD; B2 = FD to +10 days FD; B3 = +10 days FD to -10 days HD; B4 = -10 days HD to HD. Bo_rain is the total rainfall in the time period B0. Bo_RHh80 is the total number of hours that the relative humidity is 80% or higher in the B0 period. Bo_Tavg, B1_Tavg, B2_Tavg, and B4_Tavg are average hourly temperatures in the B0, B1, B2, and B4 periods, respectively, with quadratic terms for periods B2 and B4.

c Parameter estimates for the Region and Spraying variables are the differences compared with their reference levels (Mid and 0, respectively).

the Dutch model needed to be redefined. Instead of Region, COUN was included in the model (Norway, Sweden, or Finland); instead of three levels for late Fusarium spraying (0, 1, or 2), two levels of SPRAY were used (no or yes, where 0 = no and 1 or 2 = yes); instead of resistance levels 1 through 10, RESC levels were used, with resistance levels of 7 or higher designated as high RESC and resistance levels of 5 to 7 designated as medium RESC. Spring wheat was designated as low RESC (corresponding to resistance levels <5, which were not included in the Dutch data).

Development of the generic model. The variables COUN, FD, HD, LeFH, SPRAY, RESC, and the two sets of weather variables were used as predictor variables to develop a multiple regression model for DON concentrations in mature wheat in northwestern Europe. DON concentrations were transformed to their natural logarithm, ln(DON), thus representing the response variable (in micrograms per kilogram) to satisfy assumptions of normality. All statistical analyses were performed using GenStat, 11th edition (VSN International, Hemel Hempstead, UK) with a significance level of 0.05.

Univariate regression analyses were performed to estimate the effects of all individual predictors on the DON concentration. Pearson correlation coefficients were calculated for each combination of two weather variables. When the correlation value was outside the interval of −0.5 to 0.5, exclusion of one of the two weather variables was evaluated, also taking into account results of the univariate analyses. Multiple regression analyses then were performed to evaluate all possible subsets (using the “all possible subset selection” procedure of GenStat). Although year-to-year variation in DON concentrations in wheat grown in the four countries was present, YR was excluded as a predictor from the regression models because it was assumed that these yearly differences were due to underlying differences in climate. The number of models will increase exponentially with the number of predictors. Therefore, the procedure was partly done stepwise. First, a model with agronomical variables was selected, then the weather variables were added separately, using the two subsets (B and W) of weather variables. All possible models were evaluated, and the best set of explanatory variables was chosen. Model selection was based on the percentage of variance accounted for (R\(^2\)adj), the number of predictors, and their statistical and biological significance. Because the model was intended to be used for assessment of the impacts of climate change, preference was given to climatic rather than agronomical variables in the model. The final regression model was fitted with the selected variables, and the parameter estimates and their standard errors were calculated. The selected model was then fit to the data, and the predicted DON concentrations were plotted versus the observed DON concentrations. The performance of the model was evaluated by calculating the correlation between predicted and observed DON concentrations. The differences between predicted DON concentrations and observed DON concentrations (residues) also were calculated. The quadratic terms of these residues were calculated with their roots of the mean (RMSEP) (5).

Climate change scenarios. The selected model was used to estimate changes in DON contamination in mature wheat in northwestern Europe under specific climate change scenarios for 2050. The scenarios were chosen based on Intergovernmental Panel on Climate Change (IPCC) estimations regarding climate changes in northwestern Europe (29) and their possible effects on the variables in the selected model.
RESULTS

Available data. The initial data sheet included 834 records, corresponding to the total number of fields in the four countries. Of these, 117 records were deleted because of missing values for one or more of the agronomic or weather variables. Of the remaining 717 records, 96 were from Norway, 45 were from Sweden, 75 were from Finland, and 501 were from The Netherlands. Numbers of records per RESC level were as follows: 105 records (including all 96 Norwegian records) were low RESC, 373 records were medium RESC, and 239 records were high RESC. A summary of the DON concentrations in mature wheat in the four study countries is presented in Table 2 (based on the 717 records). The distribution of the DON concentrations is truncated at the left and skewed to the right. The highest DON concentrations were found in Norway, and the lowest concentrations were found in Finland.

Evaluation of Dutch model. Fitting the model to predict DON concentrations in mature wheat grown in The Netherlands to the data records from the other three northwestern European countries resulted in a model with $R^2_{adj}$ of 59.5% and a rest variance of 1.66. Almost all variables of the Dutch model were not significant, motivating the development of a new generic model for all four study countries.

Generic DON model. Based on the univariate analyses, all individual variables of COUN, FD, HD, LeFH, RESC, and SPRAY were significant. Of these, COUN ($R^2_{adj} = 26.8\%$), LeFH ($R^2_{adj} = 19.8\%$), and FD ($R^2_{adj} = 7.9\%$) were most relevant. Individual effects of RESC ($R^2_{adj} = 3.2\%$) and HD ($R^2_{adj} = 1.0\%$) were lower, and the effect of SPRAY was even smaller. HD was excluded from further analyses because FD, HD, and LeFH are linearly related to each other, and FD and LeFH were more relevant than HD. Selection of agronomical factors thus resulted in a model with five significant predictors: COUN, FD, LeFH, RESC, and SPRAY ($R^2_{adj} = 39.6\%$). Univariate analyses of all B and W weather variables revealed that some of these variables, particularly for periods B$_2$ and W$_4$, were significant ($P < 0.05$) and increased the explained variance of the model. B$_2$ _Tsum was highly correlated with B$_2$ _Th25 for each B period; therefore, B$_2$ _Tsum was excluded from analyses. For each B period, B$_2$ _Th25 was nonzero when B$_2$ _Tavg was 16°C or higher. Therefore, B$_2$ _Th25 was replaced with a new temperature-related variable, B$_2$ _Th16, which was defined as the average temperature when the average was 16°C or higher, i.e., B$_2$ _Tavg$^*$ (B$_2$ _Tavg $\geq$ 16), where $i = 0$ to 4. When the average temperature was below 16, this variable would be zero. This new variable was calculated from the hourly temperature data for all B periods and all W periods (W$_2$ _Th16, where $j = 0$ to 5) and added to further analyses. Adding the two sets of weather variables (separately) to the agronomical model increased the $R^2_{adj}$ to 46.4 to 53.8% for B variables and to 46.6 to 53.7% for W variables. The same procedure without COUN in the model resulted in an agronomical model with FD, LeFH, and RESC ($R^2_{adj} = 34.4\%$) and without an effect of SPRAY ($P > 0.05$). The effects of the other agronomical variables and their signs were comparable to the agronomical model with COUN included. Adding weather variables to this model resulted in an increase of the $R^2_{adj}$ to 40.6 to 47.9% for B variables and to 42.9 to 49.6% for W variables. These results indicate that the best subset models with the W weather variables were consistently better than the models with B variables, both with and without COUN in the model. Inclusion of COUN only slightly increased the percentage of explaining variance in the model. Because the COUN effect was believed to be largely affected by weather, this variable was excluded from further modeling, resulting in a model with FD, LeFH, RESC, and the W weather variables. From the various W weather variables, the variables W$_1$ _Tavg, W$_4$ _Th16, W$_4$ _rain, W$_6$ _RHH80, and either W$_3$ _RHH80 or W$_5$ _RHH80 were consistently present in the subsets of the best models. Because the time blocks W$_2$ and W$_3$ together cover the period from 1 week before FD to 1 week after FD, i.e., the critical infection period for Fusarium spp., it was decided to construct a new variable, which was the average RHH80 in the week around FD (W$_2$ _3–3 _RHH80). The final model thus included FD, LeFH, RESC, W$_1$ _Tavg, W$_2$ _3–3 _RHH80, W$_4$ _Th16, W$_4$ _rain, and W$_5$ _RHH80 ($R^2_{adj} = 47.9\%$, rest variance of 1.8). Two of all possible quadratic effects of individual weather variables, (W$_1$ _Tavg)$^2$ and (W$_4$ _rain)$^2$, were significant and were added to the model. Two of all possible interaction terms between the weather variables, W$_1$ _Tavg $\times$ W$_3$ _RHH80 and W$_2$ _3–3 _RHH80 $\times$ W$_4$ _rain, also were significant. Only the second interaction was added to the model; addition of W$_1$ _Tavg $\times$ W$_5$ _RHH80 could not be justified biologically. An evaluation of all possible single interactions between RESC and the weather variables in the model revealed that none of these interactions were significant ($P > 0.05$). All parameters of the selected model were significant ($R^2 = 50.0\%, R^2_{adj} = 49.3\%$, rest variance of 1.7). Parameter values of the final model with the standard errors and significance levels are presented in Table 3. Predicted and observed DON concentrations are presented in Figure 1. The correlation

<table>
<thead>
<tr>
<th>Country</th>
<th>No. of samples</th>
<th>Minimum</th>
<th>Mean</th>
<th>Median</th>
<th>75th percentile</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Norway</td>
<td>96</td>
<td>25</td>
<td>797</td>
<td>255</td>
<td>700</td>
<td>16,000</td>
</tr>
<tr>
<td>Sweden</td>
<td>45</td>
<td>10.0</td>
<td>223</td>
<td>21.9</td>
<td>63.2</td>
<td>7,206</td>
</tr>
<tr>
<td>Finland</td>
<td>75</td>
<td>5.0</td>
<td>25.7</td>
<td>5.0</td>
<td>5.0</td>
<td>710</td>
</tr>
<tr>
<td>Netherlands</td>
<td>501</td>
<td>5.0</td>
<td>452</td>
<td>160</td>
<td>420</td>
<td>10,400</td>
</tr>
</tbody>
</table>

TABLE 2. DON concentrations in mature wheat cultivated in Norway, Sweden, Finland, and The Netherlands, 2000 through 2009
TABLE 3. Final descriptive model for the prediction of DON concentrations in mature wheat in northwestern Europe

<table>
<thead>
<tr>
<th>Model variable</th>
<th>Parameters estimate</th>
<th>SE</th>
<th>Parameter significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>19.50</td>
<td>2.82</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Flowering date</td>
<td>-0.062</td>
<td>0.006</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Length flowering to harvest</td>
<td>0.048</td>
<td>0.011</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Resistance class, middle</td>
<td>-2.925$^b$</td>
<td>0.212</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Resistance class, high</td>
<td>-3.196$^b$</td>
<td>0.232</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$W_1$Tavg</td>
<td>-0.824</td>
<td>0.280</td>
<td>0.003</td>
</tr>
<tr>
<td>$(W_1$Tavg)$^2$</td>
<td>0.026</td>
<td>0.009</td>
<td>0.014</td>
</tr>
<tr>
<td>$W_{2,3}$RHH80</td>
<td>0.005</td>
<td>0.003</td>
<td>0.092</td>
</tr>
<tr>
<td>$W_4$Th16</td>
<td>0.040</td>
<td>0.006</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$W_4$rain</td>
<td>-0.018</td>
<td>0.027</td>
<td>0.518</td>
</tr>
<tr>
<td>$(W_4$rain)$^2$</td>
<td>-0.0003</td>
<td>0.0001</td>
<td>0.026</td>
</tr>
<tr>
<td>$W_4$rain $\times W_{2,3}$RHH80</td>
<td>0.0007</td>
<td>0.0003</td>
<td>0.010</td>
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<tr>
<td>$W_5$RHH80</td>
<td>0.0025</td>
<td>0.0004</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

$^a$ This model predicts ln(DON) concentrations (micrograms per kilogram). Nontransformed DON concentrations (in micrograms per kilogram) can be obtained by back transformation using $e^{(model)}$.

$^b$ Parameter estimates for the Resistance classes (middle and high) are the differences compared with the reference level (low).

between predicted and observed concentrations was 0.71, and the RMSEP was 1.29.

**Climate change scenarios analyses.** Based on the final model variables, the scenarios chosen to illustrate the use of the model for assessment of the impacts of climate change associated with various scenarios for 2050 included temperature (18) and related FD (12) changes in northwestern Europe. Three scenarios were selected relative to the baseline situation represented by the current data: scenario 1 is a decrease of FD by 15 days (12); scenario 2 is an increase in average weekly (referring to $W_4$) temperature by 2°C (18) and an increase in the number of hours per week (referring to $W_4$) that the temperature is 16°C or higher with 21 h; and scenario 3 is a combination of scenarios 1 and 2. Values of all other model parameters were not changed. The scenarios were chosen arbitrarily for illustration purposes, but scenario 3 is most likely because climate change is expected to result in both increased temperatures and earlier flowering of wheat. Expected effects of climate change on RF and rainfall were not considered in these scenarios because the related model parameter estimates were relatively small. Results of model calculations for these three scenarios revealed that DON contamination changed by a factor of 2.53 (an increase) in scenario 1, a factor 0.54 (a decrease) in scenario 2, and a factor 1.36 (an increase) in scenario 3, all relative to the baseline situation.

**DISCUSSION**

In this study, a descriptive model for prediction of DON contamination of mature wheat in northwestern Europe was developed for use in assessment of the impact of climate change, and an application of the model was illustrated for three possible scenarios of climate change.

Variables in the selected model were comparable to those in published national models, including wheat FD, wheat resistance against Fusarium infection, and various weather variables (6, 8, 10, 33). The results obtained with the model indicated that RH during wheat cultivation, particularly in the period around flowering, increased DON concentrations at wheat harvest. F. graminearum and F. culmorum were the dominant DON-producing Fusarium species in the countries evaluated during the time frame of the current study (30). Humid conditions around flowering time are conducive to infection of wheat by these two Fusarium species (16).

High temperatures from 2 to 1 week before flowering had a decreasing effect on DON concentrations at harvest. The effect of high temperature before flowering is probably due to coinciding effects of dry conditions, which decrease Fusarium spp. infection. High temperatures and low rainfall from 2 weeks after wheat flowering until harvest increased DON concentrations. Such warm and dry conditions after

![FIGURE 1. Predicted (y axis) versus observed (x axis) DON concentrations in mature wheat (micrograms per kilogram on a natural log scale) fitting the selected model (see Table 3) to the data. The solid line represents the 1:1 line.](https://example.com/figure1.png)
flowering create a drought stress for *Fusarium* spp., stimulating their production of DON (9).

Early wheat flowering and a longer period between flowering and harvest (longer growing season) result in higher DON concentrations at harvest, probably because of the longer period in which DON can accumulate in the wheat. The significant but limited effect of the country of origin was apparent when fitting the preliminary full model but was not included in the final model to facilitate future wider applications of the model. A model without a variable for country could be validated in other countries more easily than a model in which such a variable was included. Possible effects of agronomical variables such as previous crops and tillage method on DON contamination also were not considered; agronomical data are difficult to obtain, and future farm management practices are unknown. Available data were too scarce for these variables to be included during model development. In other parts of Europe, growth of maize or wheat as a precrop and use of no or minimal tillage are known risk factors for *Fusarium* spp. infection (11), particularly in combination, but these practices are less common in the countries of the current study. For instance, in The Netherlands, deep tillage is mostly commonly used, and the rotation plan includes noncereals, such as potatoes, onion, and carrots, in addition to wheat.

The performance of the current model, expressed in terms of percentage of explained variance ($R^2$), was somewhat poorer than that of published models for specific European countries (6, 10, 33). These models have been developed for specific regions and conditions, and variation in the data was smaller. Current data was highly variable (Table 2), probably because of different conditions in the four countries. Given the unequal distribution of the data records for the four study countries, the model fit might differ among these countries. However, the current model was considered satisfactory for estimating directions of change in DON contamination due to climate change effects in these northwestern European countries, as determined from the scenario analyses. This model should be particularly useful for industrial and governmental risk managers who must deal with expected climate change impacts on food safety. For making appropriate decisions related to field or farm management such as the application of fungicides, predictions for smaller geographic areas are needed. In such cases, predictive models that better fit the local farm conditions should be used.

Model construction based on data collected in the field is influenced by the level of detail of the data and data aggregation. For instance, in this study wheat resistance levels were coded differently in the four countries, and therefore the data needed to be aggregated into fewer classes. Collection of wheat samples and—too much lesser extent—analysis of DON concentrations are subject to bias (36, 37). In the present study, the LOQ of the DON analysis for the four study countries ranged from 5 µg/kg in The Netherlands and Finland to 25 µg/kg in Norway. The effect of these different LOQs on the final model was investigated by setting all DON concentrations below 25 µg/kg to zero. Results indicated very limited effects on the final model (results not presented).

Several other empirical models that have been used to predict DON contamination in wheat, based on climatic and one or more agronomic variables, have been developed (22, 25). These empirical models have been calibrated with field data from each specific country, i.e., Canada (8, 25) and The Netherlands (6, 33). Some researchers have attempted to fit these models to local conditions in other countries. Tests of the Canadian DONcast model in Uruguay revealed that the model needed some adjustment in parameter estimates (26). However, when the DONcast was implemented under Dutch wheat growing conditions, very poor results were obtained (6). In the present study, attempts to fit the Dutch model for prediction of DON in mature wheat to data from the other three study countries resulted in most of the model variables becoming insignificant. Conditions (particularly those related to climate) under which fungal infection and toxin production become problematic are region specific. Development of predictive models for mycotoxins in cereal grains will require trade-offs between local predictive power and large scale applicability. Consequently, an empirical model calibrated to local conditions cannot be applied to other geographic areas without proper model testing.

Another approach for obtaining generic models with predictive power is to develop a mechanistic model based on system analysis. One such mechanistic model to predict *Fusarium* head blight (FHB) and related DON and zearalenone concentrations in wheat kernels has been developed in Italy (23, 24). Mechanistic models are used to describe the biological process of fungal infection and toxin production based on relevant factors. These models are much more complex than empirical models. Values of the model’s parameters often are unknown, and specific field studies or experiments are needed to obtain estimates of the parameters values (32). Thus, mechanistic models have some empirical influences, as is the case for the Italian model developed by Rossi and coworkers (23). Therefore, such mechanistic models may have restricted geographic applicability because the relevance of known and unknown variables in biological processes may differ between climatic regions. Significant variability has been found in the relationship between FHB symptoms and mycotoxin concentrations (11, 19, 27), and great care should be taken when predicting mycotoxin production based on FHB model outcomes (25). However, some descriptive models for prediction of DON concentrations (6, 33) and the model developed in the present study are not completely empirical because biological processes of *Fusarium* infection and DON production were considered with variable selection.

The model constructed in the present study is the first attempt to develop a descriptive model to predict DON contamination of mature wheat in four European countries. This model was developed for use in climate change impact studies to evaluate the changes in DON contamination in the wider geographic area rather than for quantitative predictions per country or wheat field. The scenario exercise revealed that DON contamination in wheat grown in northwestern Europe is expected to increase with earlier flowering of the wheat and increased temperatures, coinciding with previous theoretical expectations of increasing mycotoxin production with
climate change (17, 18). However, the scenario analyses were meant for illustration only and not for precise estimations. In future research, more realistic estimations could be obtained by using the current model in combination with data on climate change projections based on IPCC scenarios (29) and expected shifts in wheat FDs and HDs based on wheat phenology models. Such an approach was taken by Madgwick et al. (12) to estimate climate change effects on the incidence of FHB in the United Kingdom. However, both this FHB model (12) and the present model were based on the current composition of the Fusarium species complex, and this composition may change with climate change. In the period considered in the present study, F. graminearum was the dominant Fusarium species in The Netherlands. It was found in combination with F. culmorum in the other three more northern European countries. Based on historical trends in The Netherlands (35), F. graminearum may become the dominant species in all four countries as climate change progresses. Because F. culmorum generally produces less DON than does F. graminearum, DON concentrations may consequently increase (1). Wheat resistance to Fusarium spp. was a very relevant variable in the predictive DON model presented here (Table 3). With climate change, farmers could make different future management choices, such as changing wheat varieties, crops, and/or the application of fungicides to mitigate the impacts of climate change on mycotoxin contamination. When modeling the impacts of climate change on mycotoxin production, various farming strategies could be considered.

Prediction of future mycotoxin contamination under different scenarios in a relatively large part of Europe requires a model that performs well over a wide range of geographic areas and conditions. The model should have minimal input and should not need local and temporal adaptation or calibration. The model developed in this study meets these requirements; it is relatively simple and has a minimum of predictor variables, the values of which could easily be obtained.

In conclusion, this model was developed to predict DON concentrations in mature wheat in northwestern Europe and can be used when making assessments of the impacts of climate change on agriculture. Application of this model under three scenarios indicated that climate change could result in increased DON contamination by 2050. The model could be used by governmental agencies and risk managers to assess the impact of climate change on food safety.

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