Heterogeneity of Fusarium Head Blight of Wheat: Multi-scale Distributions and Temporal Variation in Relation to Environment

Alissa B. Kriss, Laurence V. Madden, and Pierce A. Paul, Department of Plant Pathology, The Ohio State University, Wooster, OH 44691; and Xiangming Xu, East Malling Research, East Malling, Kent, ME19 6BJ, UK

Corresponding author: L. V. Madden. madden.1@osu.edu


Abstract

Fusarium head blight (FHB) is a serious disease of wheat, which is highly variable at several spatial and temporal scales. Different statistical approaches were used to either quantify or partially explain this heterogeneity. First, a generalized linear mixed model was fitted to hierarchical survey data for the incidence of FHB in Ohio. Estimated variance terms indicated large and significant spatial heterogeneity among counties and among fields within counties, with substantially lower variation among sites within fields. Second, window-pane analysis was used to investigate the effects of environment on the inter-annual variation in FHB in four United States (US) states and the spatio-temporal variation across three European countries. Moisture- or wetness-related variables (e.g., average daily relative humidity) were positively associated with FHB intensity for multiple window lengths and starting times, especially for the last 2 months of the growing season. Third, cross-spectral analysis was used to determine whether there was coherency between variation in FHB in Ohio and global climatic patterns. There were significant coherencies at one or more inter-annual time scales (i.e., periods), with peaks in FHB following lows in the climate index (a reflection of a La Niña event) by about 1 year.

Introduction

Fusarium head blight (FHB) of wheat is a disease of foremost importance in many parts of the world, including Europe and the United States of America (US) (28). In the US, the predominant FHB-causing fungal species is Fusarium graminearum (teleomorph: Gibberella zeae), but in Europe and other regions, a complex of Fusarium and Microdochium species is involved. FHB reduces quantity and quality of yield by reducing grain weight and contaminating grain with mycotoxins (especially deoxynivalenol, DON), which are harmful to both humans and livestock (2). The US has set an advisory-level threshold of 2 ppm of DON in harvested grain, and 1 ppm for products processed from wheat intended for human consumption (USDA). However, during major epidemics, such as the pandemic in the Northern Great Plains in 1993, DON levels can exceed 40 ppm (15). Yield can also be negatively impacted; for instance, estimated yield reductions totaled 4.78 million metric tons (15) in the northern plains states in 1993, and an epidemic in Ohio in 1996 resulted in an estimated yield reduction of 40% (13).

The fungus overwinters as a saprophyte on crop residues and in Fusarium-damaged kernels (9) that remain in the field following harvest (24). Under favorable weather conditions, primary inocula (ascospores, macroconidia, hyphal fragments) are produced and transported to wheat spikes (18). Infection mainly occurs at anthesis or shortly thereafter (1), and subsequent colonization of the wheat spike may result in the production of DON. The disease is considered monocyclic, since there is not generally enough time from the beginning of anthesis to harvest for the fungus to complete a secondary cycle.
It has been known for over 80 years that FHB is highly variable in nature, both spatially and temporally (3,24), in terms of disease severity and mycotoxin accumulation. The heterogeneity in FHB intensity occurs at multiple scales. Spatial variability within each year can be at small scales, such as between sites within a field, or at very large scales, such as between fields, between counties, or between states and countries. Similarly, variability can be observed at different temporal scales, such as between assessment times within years (30), between years, or even between decades (15,24). A better understanding of the spatial and temporal variability in FHB intensity can aid in the development of efficient sampling protocols (14) for risk assessment, elucidation of factors that influence epidemics, and development and refinement of forecasting systems. The overall goal was to characterize aspects of the heterogeneity in FHB, either in terms of multi-scale spatial variability or in terms of environmental effects on spatio-temporal variation, in order to ultimately improve disease-forecasting models and develop more science-based sampling protocols. Specific objectives were to: 1) examine the multi-scale spatial variability in disease incidence of FHB in Ohio; 2) relate the temporal and/or spatio-temporal variation in FHB in multiple regions in the US and Europe to weather and climate variation; and 3) relate the temporal variability in FHB epidemics in Ohio to global climate fluctuations as represented by the El Niño-Southern Oscillation (ENSO).

**Spatial Variability in FHB**

A study on the spatial variability of incidence of FHB in Ohio was conducted during the 2002 through 2010 growing seasons. Disease incidence was determined as the proportion of diseased spikes out of about 50 surveyed spikes at each of 10 sampling sites per field, with from 67-159 fields and 12-31 counties per year. Figure 1 shows an example of the variability among sites in one field, among fields in one county, and among several counties in Ohio in 2010. The 10 sites in one field had a range of 21% incidence, the 6 fields in one county had a range of 43% incidence, and the 32 counties surveyed in Ohio had an overall range of 49% incidence.
Fig. 1. Example of variability in Fusarium head blight incidence (A) between 10 sampling sites in one wheat field, (B) between 6 fields in one county, and (C) between 32 counties surveyed in Ohio in 2010.
Spatial variability of incidence was characterized by fitting a generalized linear mixed model (GLMM) to the data. A complementary log-log (CLL) link function was used because it was previously shown (17) that there was a consistent linear relationship between the CLL of incidence and CLL of field severity (known as index by FHB researchers). The model was a generalization of the logistic-normal-binomial discrete distribution proposed by Hughes and Samita (8) for over-dispersed incidence data. Through the fitted model, spatial heterogeneity among sites within fields, fields within counties, and counties within the state was quantified using variance components. Through recent breakthroughs in computer optimization methods for GLMMs involving the Laplace approximation (19), we were able to statistically compare variance components using likelihood-ratio tests and calculate confidence intervals using profile likelihoods. Results are shown for 2009 and 2010 in Table 1. There was highly significant spatial variability of the CLL of incidence among counties and among fields within counties. The magnitude of this variability at the two higher scales was considerably higher than among sites within fields. Even though FHB mean incidence was very different between 2009 and 2010, spatial variability within the hierarchy was similar between the years. Comparable results were found for earlier years (unpublished data). At the county scale, there were clusters of counties with similar levels of incidence; however, the locations of the clusters varied from year to year.

Table 1. Estimated parameters (variances or expected value) and 95% confidence intervals from the generalized linear mixed model fitted to the incidence of Fusarium head blight of wheat in Ohio in 2009 and 2010.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est.</td>
<td>Confidence interval</td>
</tr>
<tr>
<td>Incidence (on CLL scale)</td>
<td>-3.78</td>
<td>(-4.20, -3.35)</td>
</tr>
<tr>
<td>Incidence (on original incidence scale)</td>
<td>2.3%</td>
<td>(1.5%, 3.5%)</td>
</tr>
<tr>
<td>County variance</td>
<td>0.76</td>
<td>(0.37, 1.63)</td>
</tr>
<tr>
<td>Field within county variance</td>
<td>0.42</td>
<td>(0.28, 0.65)</td>
</tr>
<tr>
<td>Site within field and county variance</td>
<td>0.01</td>
<td>(0, 0.05)</td>
</tr>
</tbody>
</table>

Abbreviations: Est., estimate; CLL, complementary log-log, $\text{CLL}(z) = \ln(-\ln(1-z))$.

Using the methodology in Murray (16), the intracluster correlation (ICC) was approximated for incidence based on the variance components; ICC indicates the degree of similarity of the disease status of wheat spikes within sampling sites. ICC was 0.13 for 2010 and 0.03 for 2009; thus, spikes from the same site are just somewhat more likely to share the same disease status relative to spikes from other sites, fields, or counties. Results from the spatial variability study confirmed that FHB is sporadic on a spatial scale, and that regional (county and field) conditions can dominate spatial patterns, a possible consequence of greater variation in regional factors affecting FHB development, including weather conditions, landscape, soil, or cropping patterns. Current research is focusing on expanding the CLL mixed model to evaluate these intra-state factors on disease incidence.

The recent study by Xu et al. (29) demonstrates the heterogeneity of FHB on a larger spatial scale (across four countries in Europe) than utilized in Ohio. Figure 2 shows two examples of the variability found in that investigation. Shown are the average levels of FHB intensity for each field surveyed in Ireland in 2003 and Hungary in 2002, where the percent of spikelets visibly infected ranged from 0.7 to 45.2%. These data were utilized to determine the effects of local environment on disease intensity (see below).
Fig. 2. Example of variability in spikelet incidence (A) between 10 wheat fields surveyed in Ireland in 2003, and (B) between 15 fields surveyed in Hungary in 2002.
**Inter-Annual Variability in FHB**

A study on the inter-annual variability of FHB in relation to environment was conducted for data collected in Ohio, Indiana, Kansas, and North Dakota in the US. Details are given in Kriss et al. (10). Data were either rated on an ordinal scale (Ohio and North Dakota) or consisted of field severity (FHB index) values (Kansas and Indiana), and time periods ranged from 23 to 44 years. Within each state, disease intensity from year-to-year was highly variable (Fig. 3), with low-to-moderate correlation between successive years. For instance, the first-order serial Spearman correlation (and their corresponding standard error) was 0.304 (0.15), 0.319 (0.17), -0.104 (0.20), and 0.314 (0.21) for Ohio, Indiana, Kansas, and North Dakota, respectively. Moreover, there was clear heterogeneity between these four states within the US in terms of temporal variation. There were several years where high FHB intensity in one state did not coincide with high disease levels in other states, and vice versa. Spearman (contemporary) correlations ranged from <0.01 to 0.55 for pairs of states in the same year. We analyzed the data in Figure 3 to determine the extent to which the temporal variation in FHB was related to temporal variation in environment.

**Empirical Relationships Between Local Environment and FHB in the US and Europe**

We utilized window-pane analysis to examine the local environmental effects on FHB. Window-pane analysis (10) is a method of data mining that was used to determine the length (or duration) and starting time of temporal windows where environmental variables (temperature, relative humidity, leaf wetness, etc.) were significantly associated with FHB intensity. A separate analysis was conducted for each US state (10) and for the data pooled from three European countries (12) (the data from Italy was not included because in-field environmental data was not collected).
The concept underlying window-pane analysis is the specification of a time window of defined length, and the construction of summary environmental variables (e.g., means) for the specified window. The fixed time windows for the US states had lengths of 10, 15, 30, 60, 90, 120, 150, 180, 210, 240, and 280 days. The time window (e.g., 30 days) is moved (or slid) along the total time frame of interest (e.g., a year or a growing season), in daily increments, so that environmental data from the entire time frame is ultimately considered in the data analysis. The "beginning" of the time frame in the analysis for the US data was considered the approximate time of wheat maturity (30 June in Ohio; for convenience of expression, given as time "0"), and the windows proceeded backwards over this time frame in daily increments to end at the approximate time of planting (24 September; time "-280").

Summary environmental variables (Table 2) were calculated for each time-window length and starting time. The relationship between each summary environmental variable and disease intensity was quantified with an estimated Spearman rank correlation coefficient (r) (23) for each of the window lengths and starting times. The Spearman correlation coefficient determines the degree to which a monotonic relationship exists between a pair of variables (21); only the order of the variables matters, not the actual values. When one is dealing only with a single test result, a positive correlation is declared if \( P \leq \alpha \), where \( \alpha \) is the prespecified significance level for an individual test and \( P \) is the achieved significance level of the individual test. For window-pane analysis, a large number of correlated test statistics are obtained, which requires adjustments to the simple hypothesis-testing problem in order to avoid excessively large type I error rates and false positive proportions (27). To deal with the multiple-testing problem for a given environmental summary variable, we performed a global test of significance across all window-starting times by using the Simes' method (22) in order to test the null hypothesis that all of the correlations equaled 0 versus the alternative hypothesis that at least one of the correlations did not equal 0. For associations at specific time windows, we compared the individual estimated correlation coefficients with critical values corresponding to individual prespecified significance levels (\( \alpha \) values) of 0.005 (instead of 0.05).

Table 2. Description of a subset of environmental variables, with units in brackets, used in window-pane analysis of Fusarium head blight of wheat in the US and Europe (10,12).

<table>
<thead>
<tr>
<th>Weather variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT</td>
<td>Average mean daily temperature [°C]</td>
</tr>
<tr>
<td>ARH</td>
<td>Average mean daily relative humidity [%]</td>
</tr>
<tr>
<td>MRH</td>
<td>Average maximum daily relative humidity [%]</td>
</tr>
<tr>
<td>NDPD</td>
<td>Average mean negative dew point depression [°C]</td>
</tr>
<tr>
<td>AP</td>
<td>Average mean daily precipitation [mm]</td>
</tr>
<tr>
<td>TP</td>
<td>Total precipitation over window length [mm]</td>
</tr>
<tr>
<td>IP</td>
<td>Number of days with precipitation over window length</td>
</tr>
<tr>
<td>HRH90</td>
<td>Number of hours with relative humidity &gt; 90%</td>
</tr>
<tr>
<td>THRH90</td>
<td>Number of hours with temperature between 15°C and 30°C and relative humidity &gt; 90%</td>
</tr>
<tr>
<td>HRH80</td>
<td>Number of hours with relative humidity &gt; 80%</td>
</tr>
<tr>
<td>THRH80</td>
<td>Number of hours with temperature between 15°C and 30°C and relative humidity &gt; 80%</td>
</tr>
</tbody>
</table>

In the four US states, moisture- or wetness-related variables (e.g., daily average relative humidity [ARH] and total daily precipitation [TP]) were found to be positively correlated with FHB intensity for multiple window lengths and starting times (Table 3) (10); however, the highest correlations were often for
shorter-length windows (especially 15 days). There was no evidence of significant correlations between FHB and temperature-only variables for any time window; however, variables that combined aspects of moisture or wetness with temperature (e.g., duration of temperature between 15 and 30°C and RH ≥ 80% [THR80]) were positively correlated with FHB intensity.

Table 3. Adjusted significance levels based on Simes’ methodX, and maximum Spearman rank correlation coefficient (across all window starting times) between Fusarium head blight of wheat intensity rating and environmental variables for 15 and 60-day window lengths based on data from Ohio, Indiana, Kansas, and North Dakota.

<table>
<thead>
<tr>
<th>VariableY</th>
<th>Ohio 15</th>
<th>Ohio 60</th>
<th>Indiana 15</th>
<th>Indiana 60</th>
<th>Kansas 15</th>
<th>Kansas 60</th>
<th>North Dakota 15</th>
<th>North Dakota 60</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT</td>
<td>0.681</td>
<td>0.456</td>
<td>0.350</td>
<td>0.605</td>
<td>0.997</td>
<td>0.978</td>
<td>0.991</td>
<td>0.966</td>
</tr>
<tr>
<td>ARH</td>
<td>0.006</td>
<td>0.010</td>
<td>0.110</td>
<td>0.016</td>
<td>0.042</td>
<td>0.100</td>
<td>0.079</td>
<td>0.144</td>
</tr>
<tr>
<td>MRH</td>
<td>0.027</td>
<td>0.015</td>
<td>0.109</td>
<td>0.020</td>
<td>0.674</td>
<td>0.650</td>
<td>0.104</td>
<td>0.040</td>
</tr>
<tr>
<td>NDPD</td>
<td>0.011</td>
<td>0.03</td>
<td>0.025</td>
<td>0.004</td>
<td>0.076</td>
<td>0.094</td>
<td>0.086</td>
<td>0.115</td>
</tr>
<tr>
<td>TP</td>
<td>0.037</td>
<td>0.095</td>
<td>0.012</td>
<td>&lt;0.001</td>
<td>0.013</td>
<td>0.041</td>
<td>0.191</td>
<td>0.082</td>
</tr>
<tr>
<td>IP</td>
<td>0.004</td>
<td>&lt;0.001</td>
<td>0.203</td>
<td>0.055</td>
<td>&lt;0.001</td>
<td>0.001</td>
<td>0.323</td>
<td>0.156</td>
</tr>
<tr>
<td>HRH90</td>
<td>0.125</td>
<td>0.089</td>
<td>0.185</td>
<td>0.199</td>
<td>0.098</td>
<td>0.037</td>
<td>0.422</td>
<td>0.125</td>
</tr>
<tr>
<td>THR90</td>
<td>0.135</td>
<td>0.141</td>
<td>0.076</td>
<td>0.184</td>
<td>0.140</td>
<td>0.148</td>
<td>0.202</td>
<td>0.004</td>
</tr>
<tr>
<td>HRH80</td>
<td>&lt;0.001</td>
<td>0.018</td>
<td>0.022</td>
<td>0.018</td>
<td>0.006</td>
<td>0.001</td>
<td>0.036</td>
<td>0.138</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VariableY</th>
<th>Maximum Spearman correlation coefficientz</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT</td>
<td>0.277 0.315 0.454* 0.229 0.312 0.256 0.223 -0.020</td>
</tr>
<tr>
<td>ARH</td>
<td>0.559 0.521 0.489 0.534 0.604 0.489* 0.619* 0.542*</td>
</tr>
<tr>
<td>MRH</td>
<td>0.459 0.462 0.466* 0.531 0.365 0.275 0.608 0.600</td>
</tr>
<tr>
<td>NDPD</td>
<td>0.558 0.471 0.562 0.573 0.573 0.472 0.572* 0.521</td>
</tr>
<tr>
<td>TP</td>
<td>0.522 0.419 0.572 0.681 0.648 0.594 0.522 0.567</td>
</tr>
<tr>
<td>IP</td>
<td>0.573 0.677 0.460 0.489 0.787 0.687 0.569* 0.562*</td>
</tr>
<tr>
<td>HRH90</td>
<td>0.427 0.416 0.468* 0.429* 0.567 0.535 0.558* 0.521</td>
</tr>
<tr>
<td>THR90</td>
<td>0.431 0.399* 0.497 0.426* 0.562 0.490 0.574* 0.703</td>
</tr>
<tr>
<td>HRH80</td>
<td>0.666 0.458 0.567 0.528 0.659 0.723 0.621 0.493</td>
</tr>
<tr>
<td>THR80</td>
<td>0.596 0.606 0.594 0.448 0.718 0.694 0.663 0.704</td>
</tr>
</tbody>
</table>

X Adjustment for multiple correlated test statistics. Single adjusted global P value (Pg) for the collection of time windows, each with different starting and ending dates, of the listed window lengths. Values of Pg less than 0.05 (αg) are considered significant.

Y Variables are defined in Table 2.

Z * Indicates individually significant correlations at P ≤ 0.005. Bold indicates there is at least one cluster of five contiguous correlation coefficients with individual P values of ≤ 0.005.

See Kriss et al. (10) for more details and graphs of individual correlations for different window times and lengths.
Figure 4 shows the association between the yearly FHB ratings in Ohio and ARH for four window lengths from 10 to 60 days. Individual Spearman correlation coefficients are depicted in the form of graphs for each window length. The horizontal axis represents the starting time of each window of a given length (closest to the time of crop maturity) and each vertical bar represents $r$ for the given window. For short window lengths (e.g., 10 to 30 days), ARH was significantly ($P \leq 0.005$) correlated with FHB from late May to mid June (times -10 to -25). This time range included the critical anthesis growth stage (24). There also were significant correlations around late April (-70), early March (-120), and late December (-185). At the 30-day window length (and longer), significant correlations could also be seen for windows around the end of the season (0 to -15). These significant correlations were also found for several other moisture-related environmental variables (Fig. 4). The time period from 0 to -25 days encompasses the approximate time of DON production and fungal colonization of the spike; the period from -25 to -45 the approximate time of infection (anthesis and later); the period from -45 to -120 the approximate time for inoculum production; and the period from -120 to -220 the approximate time of pathogen winter survival (24). Additional graphs and results from other US states are given in Kriss et al. (10).
Fig. 4. Spearman rank correlation coefficients for the association between Fusarium head blight intensity in Ohio wheat and environment. The horizontal axis represents the starting time of the window (closest to the end of the season) of defined length, with day 0 representing 30 June, and day -280 representing 24 September. The labeled time corresponds to the part of the window closest to crop maturity (for instance, with a 30-day window, the labeled time of -40 corresponds to a window from 40 days before crop maturity to 69 days before maturity). Red vertical bars represent correlation coefficients for individual significance at $\alpha = 0.005$.

For each location-year in Europe, the date of anthesis was used as the reference point (day "0") because this date was known for each field. Windows from 5 to 30 days in length, starting around 60 days after anthesis (recorded as positive days), and ending around 25 days prior to anthesis (recorded as negative days) were utilized. Similar environmental variables were determined for each window as used in the US study. In the European study, moisture or wetness variables generally had positive and (globally) significant relationships with FHB intensity, with higher correlations for the shorter window lengths (12). An example is shown in Figure 5. The shorter-length windows of 10 and 15 days showed a cluster of windows with highly significant correlations between FHB and ARH, from about 15 days prior to anthesis (labeled times of -5 to -10) to
about the start of anthesis, and a separate cluster of significant correlations approximately 15 to 25 days after anthesis. Similarly with the results from the US, temperature (without consideration of duration of high moisture) was not correlated with FHB (Fig. 5). Additional graphs and results for the relationships between environment and fungal biomass and mycotoxin concentration in harvested grain can be found in Kriss et al. (12).
Fig. 5. Spearman rank correlation coefficients for the association between incidence of spikelets with symptoms of Fusarium head blight across three European countries (pooled location-years) and environment (see Kriss et al. (12) for details). The horizontal axis represents the “starting” time of the window (closest to the end of the season) of defined length, with day 0 representing anthesis. For example, with a 30-day time window, the labeled time of 20 covers the period from 20 days after anthesis to 9 days before anthesis. Red vertical bars represent correlation coefficients for individual significance at $\alpha = 0.005$.

**Variability of FHB in Ohio in Relation to Global Climate Patterns**

The inter-annual variability of FHB intensity in US states (Fig. 3) may be affected by larger scale climate variability. The climatic patterns, as represented by several different teleconnection indices (25), could be directly affecting local environmental conditions which would, in turn, be affecting FHB. To investigate the effect of climate variability on FHB variability, cross-spectral analysis (26) was utilized. The time-series investigated were the Oceanic Niño Index (ONI), which is a measure of the El Niño-Southern Oscillation (ENSO), the Pacific/North American (PNA) pattern and North Atlantic Oscillation (NAO), which have strong influences in the Northern Hemisphere climate, and FHB intensity in two states. Results from the ONI and Ohio FHB data (1965-2010) are presented here. Additional results are for another US state and the different teleconnections are presented elsewhere (11). The 3-month averaged values of the ONI were obtained from the Climate Prediction Center, part of the National Oceanic and Atmospheric Administration (www.cpc.ncep.noaa.gov/data/indices). Mean climate index values for the boreal winter (December to February) and spring (March to May) were used because winter and spring conditions are important for *F. graminearum* survival and development, thereby affecting disease risk.
We utilized spectral-analytical techniques to relate climate patterns over multiple time (year) scales to FHB because the methodology allows the total variance of a series of observations over time, such as FHB intensity or a climate index, to be partitioned into simpler individual frequency (or period \([1/\text{frequency}]\)) scales, which helps determine which scales contribute most of the variability over time (20,26). The period is the time from peak to peak or valley to valley of each cyclical time series (i.e., one complete cycle). With spectral analysis, each time series in the pair, as well as the joint series, is modeled as the sum of sine and cosine functions (26), where each term in the summation represents a different frequency. From the fitted models, the coherency at each period was estimated for each pair of FHB–climate-index time-series data. The coherency is analogous to a correlation coefficient at each of the frequencies, and large values of coherency indicate a strong relationship at the particular frequency. Interpretation of coherency estimates depends on the univariate spectral density calculated for each time series of the pair being analyzed (26); that is, if one or both univariate spectral densities have a negligible amount of variance at an individual frequency with high coherency, than the coherency at that frequency is not especially important. Coherency was tested for significance by a nonparametric permutation procedure (at \(\alpha = 0.10\)). A phase shift (difference) at each frequency with high coherency was also calculated using the approach in Fuller (7). The phase difference [either \(PS(+)\) or \(PS(-)\)] indicates, in a broad sense, the time (in periods, convertible to years) that the two time series are out of phase. \(PS(+)\) indicates the time from the peak of one series to the peak in the other; \(PS(-)\) indicates the time from the peak of one series to the valley of the other.

Winter and spring ONI were significantly coherent with FHB in Ohio at one or more frequencies (periods) (Fig. 6). The highest coherency was for a period of 5.1 years, although other adjacent periods also had significant results. The coherency graph for winter and spring ONI and FHB are shown in Fig. 6; the corresponding phase difference values for the period with the highest coherency are given in the figures. Based on the \(PS(+)\) values, a peak FHB (high value of FHB) is predicted to occur approximately 3.5 years after a peak in ONI. However, the \(PS(-)\) values indicate that a peak FHB is predicted to occur about 1 year after a valley in ONI (or that a FHB valley is predicted to occur \(\sim 1\) year after a peak in ONI). The smaller of \(PS(+)\) and \(PS(-)\) is the most relevant statistic, because the smaller number shows the estimated time shift for the two series to be aligned (so that either two peaks are at the same time, or a peak of one and a valley of the other series are at the same time). With \(PS(-)\) values of about 1 year, at a dominate period of about 5 years, FHB is near its high point in the series when ONI is at its low point. Low values of ONI signify a La Niña event and high values of ONI signify El Niño events; thus, FHB epidemics in Ohio closely follow La Niña events.
**Discussion and Conclusions**

The sporadic nature of FHB epidemics around the world, with associated high variation in yield and toxin concentrations in harvest grain, make predictions based on environment and other factors very important, yet challenging. The spatial variability study confirmed that FHB is also sporadic on a spatial scale, and that regional (county and field) conditions can dominate spatial distributions, a possible consequence of regional variation in weather conditions. Window-pane analyses confirm findings from others that the intensity of FHB in a region depends, at least in part, on environmental conditions during relatively short, critical time periods for epidemic development (4, 24). Furthermore, the results support the use of real-time disease forecasting systems based on environmental conditions (5) (www.wheatscab.psu.edu) for this sporadic disease. Our findings can also be used as a guide in determining possible modifications or expansions to the current FHB forecasters. The models in the US national forecaster are based on data from a short 7-day window ending at anthesis; thus, use of this system requires an estimate of the time of anthesis (5), a time that is often not exactly known. Our results from the US and European data sets certainly support the importance of times around anthesis for weather effects on FHB. However, based on analyses of US data, environmental summaries from less strictly defined window starting or ending times (relative to a phenological wheat stage) are also significantly related to FHB. Moreover, times closer to harvest also exhibited strong correlations, as did some times much considerably earlier than anthesis (for some variables and/or locations). Thus, there is the possibility to be less stringent in the defined time windows for disease predictions. Although anthesis is approximately the latest time that a fungicide can be applied for effective FHB control, forecasts closer to crop maturity can be of benefit for estimating the magnitude of yield loss or DON contamination before the crop is harvested or sold at grain elevators.

The significant correlations of FHB with environmental factors with fairly long window lengths (30 or more days), especially for US states (10), suggested that larger-scale climate patterns could be associated with the risk of FHB. Previous work in Brazil (6) showed that such climate relations could be seen. Our spectral analysis indicated that there are even larger scale FHB-climate associations. This is similar to findings for wheat rust by Scherm and Yang (20). It is most likely that teleconnection indices, such as the ONI, are affecting local
and shorter-duration environmental conditions, which are then affecting FHB. Therefore, global climatic models have the potential to identify years with high (or low) risk for FHB development well in advance of harvest. However, based on the strength of coherencies and the fact that teleconnection results depend on location and the climate index (11), risk predictions will still need to be customized for the general region and will still likely require use of local weather data during key time periods for sporulation and infection by the pathogen.

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Literature Cited


