Variability in Fusarium Head Blight Epidemics in Relation to Global Climate Fluctuations as Represented by the El Niño-Southern Oscillation and Other Atmospheric Patterns

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ABSTRACT

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Cross-spectral analysis was used to characterize the relationship between climate variability, represented by atmospheric patterns, and annual fluctuations of Fusarium head blight (FHB) disease intensity in wheat. 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 the North Atlantic Oscillation (NAO), which are known to have strong influences on the Northern Hemisphere climate, and FHB disease intensity observations in Ohio from 1965 to 2010 and in Indiana from 1973 to 2008. For each climate variable, mean climate index values for the boreal winter (December to February) and spring (March to May) were utilized. The spectral density of each time series and the (squared) coherency of each pair of FHB-climate-index series were estimated. Significance for coherency was determined by a nonparametric permutation procedure. Results showed that winter and spring ONI were significantly coherent with FHB in Ohio, with a period of about 5.1 years (as well as for some adjacent periods). The estimated phase-shift distribution

indicated that there was a generally negative relation between the two series, with high values of FHB (an indication of a major epidemic) estimated to occur about 1 year following low values of ONI (indication of a La Niña); equivalently, low values of FHB were estimated to occur about 1 year after high values of ONI (El Niño). There was also limited evidence that winter ONI had significant coherency with FHB in Indiana. At periods between 2 and 7 years, the PNA and NAO indices were coherent with FHB in both Ohio and Indiana, although results for phase shift and period depended on the specific location, climate index, and time span used in calculating the climate index. Differences in results for Ohio and Indiana were expected because the FHB disease series for the two states were not similar. Results suggest that global climate indices and models could be used to identify potential years with high (or low) risk for FHB development, although the most accurate risk predictions will need to be customized for a region and will also require use of local weather data during key time periods for sporulation and infection by the fungal pathogen.

Additional keywords: disease forecasting, *Fusarium graminearum*, *Gibberella zeae*, wheat scab.

The intensity of Fusarium head blight (FHB) of wheat (*Triticum aestivum* L.), a disease caused predominantly by the *Fusarium graminearum* species complex (35), is greatly influenced by meteorological factors (9,39), giving rise to high variability in disease from year-to-year and from location-to-location (29). Recently, Kriss et al. (29) showed that annual variability in FHB over decades in four states in the United States was related to environmental conditions at both shorter and longer time scales. In particular, they found that FHB intensity ratings were significantly correlated with summary environmental variables, especially those based on atmospheric moisture and precipitation, for shorter (<30 day) and longer (>30 day) length time windows. The time windows giving rise to the highest correlations were typically during the last 2 months of the growing season, but earlier time windows (during the winter and early spring months) also gave rise to high correlations in some cases.

Kriss et al. (29) hypothesized that the relationship between FHB and the environment for the longer time scales (i.e., time windows of 30 days or longer) could be studied using climatic

patterns. Climatic conditions can be serving a dual role in this context, both directly affecting components of the FHB disease cycle, or by influencing (short-term) weather conditions (e.g., atmospheric moisture over a few days at critical times during the year) which can, in turn, be affecting components of the FHB disease cycle.

Variation in the climate of a geographical region can be the result of several different environmental phenomena, including teleconnections (51). Teleconnections refer to simultaneous variations in climate patterns in different regions of the globe (i.e., one region may be cooler and drier than average, while another is warmer and wetter). The El Niño-Southern Oscillation (ENSO) is one such teleconnection, and is one of the most important factors driving interannual global climate variability (42). The ENSO refers to the variation in sea-surface temperatures (SST) across the Pacific Ocean. On average, there is an ENSO warm event (El Niño) about every 4 years. However, this is highly variable, as sometimes there are only 2 years between events and sometimes there are several years (51). One of the principal measures used to monitor the ENSO is the Oceanic Niño Index (ONI) (28). The ONI is the 3-month mean SST anomaly for the El Niño 3.4 region (i.e., 5°N–5°S, 120°–170°W) (50). There are two phases of the ONI, a positive phase and a negative phase. Large positive values (>0.5) of the ONI coincide with El Niño episodes, while large negative values (<–0.5) coincide with La Niña episodes. El Niño events are known to be associated with increased precipitation in

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* The e-Xtra logo stands for “electronic extra” and indicates that the online version contains one supplemental file on spectral analysis.

the central (5) and southeastern United States and in the southern Rocky Mountain region (42), and La Niña events have been found to be associated with warmer and drier conditions in the U.S. Corn Belt than neutral years (40). Although the ENSO is centered in the equatorial Pacific Ocean, there is an “atmospheric bridge” that spans from the equatorial Pacific to the other oceans by way of alterations of the atmospheric teleconnections in regions remote from the ENSO. Therefore, ENSO-related SST anomalies in remote locations tend to peak after a peak in the ENSO, which can ultimately affect the air temperature, humidity, and wind around the world (1).

Whereas the ENSO affects climate variability—and ultimately weather—worldwide (42), other teleconnection anomalies such as the North Atlantic Oscillation (NAO) and the Pacific-North American (PNA) pattern have strong influences in the Northern Hemisphere, especially in the winter months (24,52). The NAO has its greatest influence on North America during the cold-season months (November–April) when the atmosphere is most dynamically active. There are also two phases of the NAO and PNA, a positive phase and a negative phase. Positive values of the NAO during winter relate to higher air pressure in eastern North America, which can lead to fewer cold-air outbreaks and decreased storminess. Negative values tend to result in lower air pressure, which can produce more storms and strong cold-air outbreaks (34). The PNA describes the atmospheric circulation patterns over the Pacific Ocean and North America (30). During a positive PNA pattern, above average temperature and below average precipitation tend to be observed throughout the Ohio Valley and the Northeast United States. The negative phase of the PNA is nearly the reverse pattern of the positive phase, with cooler temperatures and above average precipitation (34). The PNA has significant variability even in the absence of the ENSO, but it has been shown to be generally associated with the ENSO

(30). The positive phase of the PNA tends to be associated with El Niño conditions, and the negative phase tends to be associated with La Niña conditions.

The teleconnection series have well-defined, naturally occurring, oscillations (cycles) as represented by the positive and negative phases. To specifically account for this cyclical structure in the investigated time series, a spectral analysis technique was utilized. Quantification of the relationship between climate variability, as determined from large-scale climate indices, and plant diseases has been attempted in the past. For instance, Scherm and Yang (45,46) used cross-spectral analysis to investigate the relationship between the ENSO and other teleconnection patterns and wheat rust in China and the United States. Del Ponte et al. (12) showed the ENSO may be used to determine the predicted risk of soybean rust epidemics in Brazil.

The objective of this study was to determine the relationship between the ONI, NAO, and PNA, and the annual variation of FHB intensity in two U.S. states. We utilized spectral-analytical techniques (3,18) to relate climate patterns over multiple time (year) scales to FHB because the methodology provides for a temporal decomposition of one or a pair of (possibly correlated) time series of observations into multiple frequencies (or periods). Results for different frequencies can be related to different scales of temporal associations. Analysis was based on yearly observations of FHB intensity from Ohio (46 years) and Indiana (36 years). Other data sets originally analyzed by Kriss et al. (29) in a recent window-pane analysis could not be used here because of insufficient number of years for the spectral analysis.

MATERIALS AND METHODS

Disease data. In Ohio, FHB intensity in the state (broadly defined to include estimated yield impact) was rated from 0 to 9 at the end of each wheat season for 46 years (1965 to 2010) (Fig. 1). Details are given in Kriss et al. (29). The total time span in Ohio includes data from 2009 and 2010, which were not available when the Kriss et al. (29) study was conducted. In Indiana, disease was assessed for 36 years (1973 to 2008) in variety nurseries by Purdue University researchers (Fig. 1). Observations used here were obtained from the susceptible “check” cultivars. For all years, FHB disease index (field severity) was estimated as the mean percentage of spike area with symptoms (including the spikes with no symptoms). The square root of the disease intensity observations were calculated to obtain a more symmetrical distribution of values and more linear relation with environmental variables (*unpublished*). More details on disease assessment are given in Kriss et al. (29).

Climate indices. Monthly values of the NAO and PNA and 3-month averaged values of the ONI were obtained from the Climate Prediction Center, part of the National Oceanic and Atmospheric Administration (<http://www.cpc.ncep.noaa.gov/data/indices>). Two additional teleconnection indices, the Southern Oscillation Index (SOI; a measure of the ENSO) and Arctic Oscillation (AO), were also used in the analyses, but these indices are closely linked to the ONI and NAO, respectively (32,50), and the spectral-analytical results were very similar to that found for the ONI and NAO (*unpublished*). Two sets of 3-month averages of the indices were evaluated in the analysis (Fig. 2). Boreal winter (December to February) and boreal spring (March to May) index values were used because winter conditions are important for *F. graminearum* survival and spring conditions are important for disease development (sporulation, dispersal, infection, and colonization) (9,14,21,38,39). Moreover, winter or spring teleconnections could affect shorter-term concurrent weather, or later climate or weather conditions (1,36).

Spectral analysis. Spectral and cross-spectral analyses were used to characterize the disease and climate time series. Spectral analysis utilizes the Fourier transform to approximate a function

Fig. 1. A, Scaled (transformed) Fusarium head blight (FHB) intensity for Ohio (1965 to 2010) and Indiana (1973 to 2008). B, Spectral density of yearly values of FHB intensity in Ohio and Indiana. The square root of disease intensity was used for all analyses. Interior tick lines on the lower Period axis are the Fourier frequencies (converted to periods) for Ohio and on the upper Period axis are the Fourier frequencies (converted to periods) for Indiana. The scaled disease data points overlap completely in 1986 and only one point can be seen.

(i.e., a Fourier series) by a sum of sine and cosine waves of different amplitudes and frequencies. The temporal-domain series (i.e., the time-series of observations) is effectively then transformed into a frequency-domain signal. This allows the total variance of a series of observations over time, such as FHB intensity or climate teleconnection index, to be partitioned into simpler individual frequency (or period [=1/frequency]) scales, which helps determine which scales contribute most of the variability over time. The SPECTRA procedure in SAS (SAS Institute, Inc., Cary, NC), which utilizes the fast Fourier transform developed by Cooley and Tukey (7), was used to conduct the spectral analysis. Based on the length (N) of the disease time series (46 years in Ohio, 36 in Indiana), periods >23 years and >18 years, respectively, were not considered in the modeling because there would only be one complete cycle per series (and thus insufficient data for model fitting).

The Fourier transform decomposition of a series X_t is given by

$$X_t = \sum_{k=1}^M [a_k \cos(w_k t) + b_k \sin(w_k t)]$$

where t is the observation number or time in this case (1, 2, ..., N); X_t is the response variable at time t , M is the number of Fourier frequencies in the decomposition and is the smallest integer greater than or equal to $(N - 1)/2$ ($M = 23$ for Ohio and $M = 18$ for Indiana), a_k and b_k are coefficients of the cosine and sine functions, respectively; and $w_k = 2\pi k/N$ is the Fourier frequency (in radians) for $k = 1, 2, \dots, M$ (18,27). For ease of the reading, frequencies were converted to periods using the inverse function (i.e., period = N/k) (27).

The estimates for a_k and b_k form the basis of the spectral density at each period $[S(w_k)]$. The spectral density is a stan-

dardized and smoothed version of the partial sum of squares resulting from the estimates of the two coefficients. Peaks (periods with high amplitude values) in the spectral density designate which periods are associated with a high amount of variance of the time series.

Cross-spectral analysis. For each pair of disease-climate time series (denoted X_t and Y_t), a cross-spectral analysis was conducted as described by Brocklebank (3), also using the SPECTRA procedure in SAS. In cross-spectral analysis, the cross-spectral density is found, which is analogous to a cross-covariance function of two temporal series, showing how two (possibly) correlated series co-vary over time. Similarly to the univariate spectral density, the amplitude of the cross-spectral density at each period $[A_{XY}(w_k)]$ is a measure of the variance accounted for between the two time series. Peaks in the amplitude spectrum (a plot of the amplitude, $A_{XY}(w_k)$, at each period) indicate periods where there are possible strong associations between the two series.

The squared coherency spectrum provides estimates of the proportion of the variance in one series that is predictable from the other series for each period, and is analogous to a coefficient of determination in regression analysis. We call the squared coherency simply “coherency” for ease of presentation. Large values of coherency indicate a strong relationship at the particular period. The coherency at period k is given by

$$C_{XY}^2(w_k) = \frac{[A_{XY}(w_k)]^2}{[S_X(w_k)][S_Y(w_k)]}$$

where $[A_{XY}(w_k)]^2$ is the squared amplitude of the cross-spectral density, and $S_X(w_k)$ and $S_Y(w_k)$ are the univariate spectral density estimates at each period. The coherency spectrum was determined for each pair of FHB and climate-teleconnection-index time-

Fig. 2. Time-series and corresponding spectral densities of winter (December to February) and spring (March to May) Oceanic Niño Index (ONI), North Atlantic Oscillation (NAO), and Pacific/North American pattern (PNA). On the spectral density plots, interior vertical lines on the Period axis are the Fourier frequencies (converted to periods) for Ohio.

series data. Interpretation of coherency estimates depend on the univariate spectral density of each time series; that is, if one or both univariate spectral densities have a negligible amount of variance [i.e. a small amplitude in $S_X(w_k)$ or $S_Y(w_k)$] at a period of interest, then the coherency at that period is not especially important (47,53).

Because the cross-spectral density is generally a complex-valued function (27), a temporal difference (lead or lag) between each pair of time-series, the so-called phase shift, may result. The phase shift can only be reliably estimated for periods with a high coherency because sampling errors of the shifts are large at low coherency values (47,53).

All phase differences displayed in the SPECTRA procedure output have been scaled from $-\pi$ to $+\pi$ radians. A phase difference of 0 means that the two series (predicted from the spectral model fitted to the data) are in perfect phase at a particular period (peaks or valleys of the cyclical series occur at the same times for the two series). Phase differences of exactly π and $-\pi$ radians are indistinguishable from each other, and indicate the two (predicted) series have a negative relationship at that period; that is, a peak in one series occurs at the same time as a valley (low) in the other series. Either series can be considered to lead or lag the other series (53) for other phase differences (e.g., series X_t leading Y_t by less than π radians is the same as Y_t leading X_t by more than π radians). For ease of presentation, all phase shifts are calculated in terms of the climate index leading the FHB series and are given as positive numbers.

The phase shift (at a given period) for the lead of the climate series (from peak to peak or valley to valley) is given by $PS(+)$. One can also determine (at a given period) the phase shift from a peak of the climate series to the next valley of the FHB series, or from a valley of the climate series to the next peak in the FHB series, this is given as $PS(-)$. The smaller of $PS(+)$ and $PS(-)$ for a given period indicates the most apparent relation between the two series (positive or negative). The phase can be rewritten in terms of years for ease of understanding [phase in years = (phase in radians) $\cdot$ period/(2π)]. Full details on this analysis are given in the Supplemental file.

Nonparametric significance testing of coherency. The coherency at each period was identified and tested for significance by a permutation procedure (37). Although there are test statistics based on distributional assumptions for normally distributed series that had been smoothed with a uniform filter, they may be biased for nonnormally distributed data (27,47). Because of the nonnormal data used in this study, a permutation-based approach is preferred. The procedure involved creating 1,000 randomly permuted versions of the FHB data sets (for Ohio and Indiana, separately). Coherency estimates with the teleconnection time series were obtained from each permuted data set by the SPECTRA procedure in SAS and used to create a sampling distribution of coherency values under the null hypothesis of no coherency. That is, at each period, 1,000 values of the coherency were determined and used to find the 90th percentile, which corresponds to the critical value for hypothesis test at significance level (α) of 0.10. That is, if the estimated coherency value for the observed time series was greater than the 90th percentile for the randomly permuted series, then the observed coherency was declared significantly greater than 0 ($\alpha = 0.10$).

RESULTS

Univariate statistics. As described previously in Kriss et al. (29), there was wide inter-annual variation in FHB intensity in Ohio and Indiana (Fig. 1A), and the covariation in the two disease series was not great over time (highs and lows in intensity did not necessarily occur in the same years). Univariate spectral densities for disease time series at both locations (Ohio FHB and Indiana FHB) and the three climate indices (ONI, NAO, and PNA) during

winter and spring were analyzed first to find periods (or frequencies) that were associated with a larger proportion of the variation of each individual series. This was to help ensure that results from the cross-spectral analysis and the coherency analysis (see below) were meaningful biologically or physically, and not artifacts. In other words, both individual series in the pair being analyzed must show a reasonable proportion of explained variation (peaks in the spectral density) at one or more periods in order to use the coherency estimates (47,53). The univariate spectral density for Ohio FHB (Fig. 1B) showed a high proportion of the variance explained (peak) at periods between 4.6 and 7.7 years and had a small peak around a period of 3 years. A period of 5, for example, indicates that when there is a high amount of disease in a given year, then approximately 5 years later, there will be another high disease year. The univariate spectral density for Indiana FHB showed high peaks around periods of 3, 6, and 9+ years (Fig. 1B). The relatively flat spectrum at 9+ years indicates these periods account for equal amounts of variance.

The winter ONI had larger amplitudes overall than the spring ONI. However, for both winter and spring ONI, positive values (those related to the El Niño) in general were of stronger amplitude than negative values (those related to the La Niña). The ENSO is known to have a cycle of 2 to 7 years (33). In this analysis of 3-month ONI index values for the ENSO, the winter and spring spectra had peaks around similar periods (e.g., 3.5 to 5.8 years) (Fig. 2).

Long-term variations were apparent in the historical record of the NAO. For about 20 years prior to 1965 (data not shown) the NAO was in a decreasing trend. However, since that time, it has been in an upward trend, which resulted in the NAO index being mostly positive since the early 1980s (49), although there is considerable inter-annual variation. One main exception is the 2009/10 winter where the NAO had a strong negative index. These patterns are most pronounced in the Winter NAO index (Fig. 2). However, the spring NAO index is similar in that it tended to be mostly negative until the early 1980s and then in a positive trend until the early 1990s, but it appears to be fairly neutral since then. For the spectral density of the winter NAO teleconnection index, there was a slight maximum peak in amplitude around periods of 2 to 3 years. Then, beginning at periods of about 4 years, the spectral density of the winter NAO index also generally increased as the period increased (32), with the largest peaks around periods of 7 to 8 years (Fig. 2). The amplitude peaks at the longer periods in the spectral density reflects the long-term trends (49) in the index (Fig. 2), with extended years below or above 0 (on average); in contrast, the peaks at short periods reflect the smaller variations in the index over short time spans. Similar trends in the winter NAO spectrum and detailed discussion can be found in Marshall et al. (32), although our results are based on data through 2010, whereas their analysis was based on the index values up to 1998. The spring NAO spectrum had one peak in amplitude around periods of 2 to 3 years, and no evidence of strong peaks at the longer time scales (Fig. 2).

The PNA is similar to the NAO in that both patterns have been in a general upward trend over the time of our study and their largest amplitudes occur during the winter months. The winter PNA has also been mostly positive since the early 1980s. The winter PNA spectrum had a large peak in amplitude around periods of 2.5 to 4 years, with a smaller peak around periods of 3.5 to 5.8 years. The spring PNA spectrum had a peak around 2.2 to 2.6 years, with a smaller peak around periods of 3.5 to 5.8 years and declining amplitude after these periods. Therefore, the PNA had mostly dominant temporal patterns over shorter periods.

ONI and FHB. Coherency values and the amplitude of the cross-spectral densities varied greatly with period for FHB in the two states and the different teleconnection indices. The largest significant coherency values for each pair of time series (FHB and

teleconnection index) are shown in Table 1. For instance, 71% of the variation in Ohio FHB could be explained by variation in the winter ONI at a period of about 5.1 years [i.e., $C_{XY}(w_9) = 0.71$] (Fig. 3, Table 1). For the spring ONI, similar results were found, with the largest coherency peak at a period of 5.1 years, but with an even higher percentage of explained variation [$C_{XY}(w_9) = 0.91$; Table 1]; the coherency values were also significant for nearby peaks at periods of 4.6 and 5.8 years (Fig. 3). The large significant coherency values for the relationship between Ohio FHB and the ONI were at or around the periods that showed a high percentage of the variance explained in each univariate time series (Figs. 1 and 2).

Because the phase shift for periods with the highest coherency was not 0, π or $-\pi$, different shifts were calculated from the output of the SPECTRA procedure. These are demonstrated in Figure 4, which correspond to the predicted FHB and winter ONI temporal patterns for a period of 5.1 years (Table 1) over an arbitrary 10-year time span. FHB led the winter ONI series (from peak to peak or valley to valley) by an estimated 0.65π radians (equal to 1.66 years). This is equivalent to the winter ONI leading the FHB series by $PS(+) = 2\pi - 0.65\pi = 1.35\pi$ radians (3.45 years) (Fig. 4). Thus, for the dominant period of 5.1 years, when the winter ONI is high/low, FHB intensity in Ohio is high/low approximately 3.5 years later. Moreover, the estimated negative relation between the series is $PS(-) = 0.35\pi$ radians (0.9 years) (Fig. 4). That is, when winter ONI is at a peak, FHB is in a valley ≈ 1 year later. Similar results were found for spring ONI and FHB (Table 1).

As with the results from Ohio, the amplitude of the cross-spectral density and coherency graphs for the Indiana FHB data and winter ONI showed clear peaks for selected periods of 4 years or less, as well as for 12 years (Fig. 5). The coherency,

however, was significant only at a period around 2.8 years (Table 1), which is shorter than the periods identified for Ohio. However, the univariate spectral densities at this period were fairly low compared to the other periods (i.e., they were not at peaks); therefore, the coherency found may be an artifact.

NAO index and FHB. There were several peaks in the coherency graph and cross-spectral density for FHB intensity in Ohio and the winter NAO teleconnection index (Fig. 3). Coherency values were significant at periods of 4.2 to 5.1 years (Fig. 3), and about 75% of the variation in FHB was explained by variation in winter NAO [$C_{XY}(w_{10}) = 0.75$; Table 1]. The amplitude spectra and univariate spectral densities for FHB and winter NAO also had peaks with fairly large amplitudes at similar periods (Figs. 1 and 2), but there were even larger peaks in the univariate spectral density at periods of 6 or more years for winter NAO (Fig. 2). The positive phase difference, $PS(+)$, indicates, for periods around 4.2 to 5.1 years, that there was a peak in the FHB series about 1.1 to 1.7 years after a peak in winter NAO (or a valley in FHB 1.1 to 1.7 years after a valley for winter NAO) (Table 1).

The spring NAO and Ohio FHB had significant coherencies at shorter periods (2.2 years) than found for the winter NAO. Because the Ohio FHB univariate series only had a small peak around these periods, the coherencies found may be artifacts.

Results for the relationship between FHB in Indiana and winter NAO were similar to those found in Ohio, except that the highest coherencies were for longer periods of 6 and 7.2 years (Fig. 5, Table 1). Univariate spectral densities were high for these periods. For the periods of 6 and 7.2 years, the small $PS(-)$ values of 0.4 and 0.2 years, respectively, indicated there was a negative relationship between winter NAO and FHB intensity in Indiana in the same year; that is, a peak in winter NAO was

TABLE 1. Coherency with associated period and phase difference for climate variables and Fusarium head blight intensity (FHB) in Ohio or Indiana for the three largest coherency values if they were determined to be significant by the permutation procedure ($\alpha = 0.10$)

		Ohio				Indiana				
		Phase ^b				Phase				
				<i>PS</i> (+)	<i>PS</i> (−)			<i>PS</i> (+)	<i>PS</i> (−)	
		Peak coherency	Period (1/frequency)	Radians (years ^c)	Radians (years)	Peak coherency	Period (1/frequency)	Radians (years)	Radians (years)	
Climate variable (index) ^a										
Winter	ONI	0.706	5.111 ^{†d}	1.35π (3.451)	0.35π (0.900)	0.539	2.769	0.18π (0.252)	1.18π (1.637)	
		0.556	5.75 [†]	1.41π (4.060)	0.41π (1.185)					
	NAO	0.753	4.6 [†]	0.59π (1.347)	1.59π (3.647)	0.701	6 [†]	1.14π (3.405)	0.14π (0.405)	
		0.665	5.111 [†]	0.68π (1.745)	1.68π (4.300)					
		0.523	4.182 [†]	0.54π (1.138)	1.54π (3.229)					
	PNA	0.930	2.191	0.39π (0.429)	1.39π (1.524)	0.541	2.571 [†]	0.14π (0.185)	1.14π (1.471)	
		0.870	2.3	0.41π (0.471)	1.41π (1.621)					
		0.779	5.111 [†]	1.54π (3.937)	0.54π (1.382)					
	Spring	ONI	0.914	5.111 [†]	1.44π (3.687)	0.44π (1.131)	NS ^e			
			0.813	4.6 [†]	1.47π (3.372)	0.47π (1.072)				
			0.715	5.75 [†]	1.46π (4.194)	0.46π (1.319)				
NAO		0.754	2.191	1.24π (1.355)	0.24π (0.259)	NS ^e				
		0.546	2.3	1.24π (1.427)	0.24π (0.277)					
PNA		0.658	2.875	1.68π (2.409)	0.68π (0.972)	0.734	3 [†]	1.55π (2.325)	0.55π (0.825)	
		0.649	3.067	1.53π (2.348)	0.53π (0.814)					
										0.695
					0.678	6 [†]	1.40π (4.212)	0.40π (1.212)		

^a Climate variables are the Oceanic Niño Index (ONI), North Atlantic Oscillation (NAO), and Pacific-North American pattern (PNA). Winter climate index values represent the mean of December, January, and February values. Spring climate index values represent the mean of March, April, and May values.

^b Phase shifts were always put in terms of positive numbers with the climate series leading the FHB series. $PS(+)$ is used to quantify the positive phase shift between the series, and $PS(-)$ is used to quantify the negative phase shift between the series.

^c Phase in years = (phase in radians) $\cdot$ period/(2 π).

^d The symbol [†] is used to indicate that there was a noticeable peak (although there could be larger peaks elsewhere) in the univariate spectral density at the identified period.

^e NS indicates not significant.

followed about an estimated 5 and 2.5 months later with a predicted valley in FHB. Phase shifts less than 6 months indicate that the peaks in NAO are estimated to occur in the same year as the valleys in FHB.

PNA pattern and FHB. Winter PNA was related to FHB intensity in Ohio at periods of 2.1 to 2.9 years and 5.1 to 5.8 years, with the highest coherencies at the shorter periods (Fig. 3; Table 1). However, the coherencies at the shorter periods should be examined with caution, as the Ohio FHB univariate spectral density series had only a small peak around a period of 3 years (Fig. 1). With $PS(-) = 1.4$ years at the 5.1-year period, a low in the FHB series was estimated to follow a high in the PNA series by about 1.5 years, showing the general negative relation between the series. The spring PNA time series was significantly coherent with FHB in Ohio at periods around 3 years (Table 1). However, the univariate spectral density for the spring PNA did not have peaks at these periods, so these may be artifacts.

Peaks in coherency were found for disease intensity in Indiana and winter PNA at short periods around 2.6 years (Fig. 5; Table 1). The univariate spectral densities also had peaks in amplitude at these periods (Figs. 1 and 2), although there were larger peaks at other periods. For these short periods, a peak in winter PNA was followed by a peak in FHB in an estimated 2 months ($PS(+) = 0.16$ to 0.19 years); that is, the phase shifts showed a positive relation, because the peaks (or valleys) occurred in the same years.

There were several peaks in the coherency graph for the Indiana FHB and spring PNA series for periods between 3 and 6 years (Fig. 5). However, the coherencies for the middle of this range (periods between 4 and 5 years) likely are artifacts because of the low amplitude of the univariate spectral density for the FHB series at these periods (Fig. 1). The largest coherency between Indiana FHB and spring PNA was at a period of 3 years

(Table 1). The phase shift at this period ($PS(-) = 0.8$ years) indicates there was a negative relationship between the spring PNA and FHB intensity because peaks in one series were estimated to occur near the same years as valleys in the other series. The other significant coherencies all also indicated negative relationships (i.e., $PS(-) < PS(+)$).

Fig. 4. Example phase relationship between the predicted winter Oceanic Niño Index (ONI) (solid line) and (scaled) predicted Fusarium head blight (FHB) intensity rating in Ohio (dashed line) for a period of 5.1 years. Predictions are given for an arbitrary 10-year time span. Three relevant estimated phase shifts are demonstrated. $PS(+) = 3.451$ years, $PS(-) = 0.900$ years.

Fig. 3. Coherency relationships among time series of annual Fusarium head blight intensity values in Ohio and the Oceanic Niño Index (ONI), North American Oscillation (NAO), and Pacific/North American Pattern (PNA) from 1965 to 2010. Insert graphs are the amplitude of the cross-spectral density for each pair of time series. Interior vertical lines on the Period axis are the Fourier frequencies (converted to periods). Asterisks denote periods where the coherency is significant as determined by the permutation procedure ($\alpha = 0.10$).

DISCUSSION

Several authors have shown significant relationships between generally short-term environmental conditions near flowering or during the later part of the growing season and FHB intensity (8,39). Forecasting models have been developed that use local weather conditions around these times to predict the risk of disease or high toxin contamination (9,10,23,44). Recently, Kriss et al. (29) found that FHB was significantly associated with longer-term environmental variables (30 days or longer) and with environmental variables for different times during the growing season. These results suggested that large-scale climatic patterns may provide information for determining the risk of FHB on a regional scale, and possibly lead to earlier predictions of high (or low) risk years, than the current forecasters. However, whether large-scale climate variables can be incorporated into forecasters for this disease in the United States to enhance their skill has been unknown, given the importance of environmental conditions near anthesis for spore production and infection. With the long-term goal of discovering (small- and large-scale) environmental effects on FHB and the possibility of ultimately improving disease forecasting, we attempted here to determine if the ENSO and various climatic teleconnections around North America were associated with FHB in two U.S. states, Ohio and Indiana.

We followed the work of Scherm and Yang (45,46) and Workneh and Rush (54) and utilized cross-spectral analysis to characterize the relationship between teleconnection indices and inter-annual variation in FHB. We further extended the approach by using a nonparametric method for testing of coherency of the series. Clear amplitude peaks were found in univariate spectral densities for FHB and the teleconnection indices, which justifies the characterization of relationships using cross-spectral densities and coherencies (2,27,53). We primarily discuss coherency and

phase-shift results for situations with peaks in the univariate spectra. Indices for the ENSO (such as the ONI) are probably the most commonly considered when relating biological variables to climate patterns (17,22,26,48), possibly because of the well-known strong effect of the ENSO on temperature (43) and precipitation (42) patterns. Results for the cross-spectral analysis in our study showed that winter and spring ONI were significantly coherent with FHB intensity in Ohio, with a period of about 5.1 years. Coherency can be interpreted as the estimated proportion of variance that is shared between the two time series within that period. Therefore, FHB intensity in Ohio and the ONI share a significant proportion of variance when they are both modeled by cycles that repeat about every 5.1 years. Moreover, for spring ONI, periods neighboring 5.1 years were also significantly coherent. In general, the phase differences at the significant coherencies indicate that the ONI series and FHB series were negatively related because the estimated negative phase shift ($PS(-)$) was smaller than the estimated positive phase shift ($PS(+)$) (Table 1), with phase shifts of 0.47π to 0.35π radians. This indicates that the peak in FHB disease intensity is estimated to occur about a year after a low in the winter ONI series, and with a dominant period of ≈ 5 years for the series, FHB is close to its peak when ONI is at its low. Thus, for a La Niña year, when ONI is at a low, there tends to be more disease in Ohio. This can be seen also with the observed series: 2 years with the highest amounts of FHB (1986 and 1996) both followed persistent La Niña episodes. The La Niña winter has been associated with an increase in heavy rainfall frequency south of the Great Lakes (Ohio-Mississippi River valley) compared with the El Niño (20) winter, with the heaviest precipitation west of the Appalachian mountains (15). The spectral analytical results are also consistent with the well-known result that the ENSO has a cycle of 2 to 7 years (33).

Fig. 5. Coherency relationships among time series of annual *Fusarium* head blight intensity values in Indiana and the Oceanic Niño Index (ONI), North American Oscillation (NAO), and Pacific/North American pattern (PNA) from 1973 to 2008. Insert graphs are the amplitude of the cross-spectral density for each pair of time series. Interior vertical lines on the Period axis are the Fourier frequencies (converted to periods). Asterisks denote periods where the coherency is significant as determined by the permutation procedure ($\alpha = 0.10$).

In addition to the winter and spring ONI coherency for Ohio, there were significant coherencies between FHB intensity and one or more of the other evaluated teleconnection indices for Ohio or Indiana. Although there was a significant coherency for winter ONI in Indiana, this could be an artifact (46,52). In Ohio, the highest coherencies for NAO and PNA were for similar periods as found for ONI (from about 2 to 5.8 years; Table 1), but in Indiana, the highest coherencies for NAO and PNA could be for periods as high as 7.2 years. For Indiana, the winter NAO had, in general, a negative relationship with the FHB series based on the estimated $PS(-)$ values being less than 6 months (and because $PS(-)$ was much lower than $PS(+)$). Positive values of the NAO during the winter are correlated with fewer cold-air outbreaks and decreased storminess and negative values tend to produce more storms and stronger cold-air outbreaks (34). The NAO is the dominant pattern of winter climate variability over the North Atlantic, but it only explained a fraction of the total variance of the FHB series in Indiana (25). Interestingly, there was also a positive relation between winter NAO and FHB in Ohio, but with peak values of FHB occurring an estimated 1.1 to 1.8 years after peaks in NAO. This indicates FHB in Ohio and Indiana does not respond similarly to variation in the NAO.

The winter and spring PNA index had significant coherencies with FHB in the two states. A negative relationship was found between the winter PNA index and FHB intensity in Ohio at a period of 5.1 years, and between the spring PNA index and FHB intensity in Indiana for several periods. That is, a peak in the PNA series was followed, in an estimated 10 to 16 months, by a valley in the FHB series. Coleman and Rogers (6) showed that the PNA index was inversely related to winter precipitation in the Ohio River Valley region, with the strongest relationship found in southern Indiana. Notaro et al. (34) reached the same conclusions for Ohio as Coleman and Rogers did for Indiana, and they showed that there was a negative relationship between maximum temperature and the PNA. Ge et al. (19) showed that the PNA is associated with snow pack in several parts of the United States, and recent work (13,41) has begun to investigate the effect of winter/spring snow mass anomalies on the spring/summer season. One would expect increased precipitation (low PNA value) to lead to an increase in disease, and the winter and spring PNA and FHB should have a negative relationship. However, a negative relation was not found at the shorter significant periods for winter PNA and FHB in Indiana.

Even though there was a clear coherency of the teleconnection indices and FHB in two different states, the temporal pattern to the coherency was different in terms of the periods with the largest coherencies and the direction of the phase shifts. This was expected because the inter-annual variation in FHB was clearly different for Ohio and Indiana (Fig. 1), where the highest disease intensities occurred in different years for the two locations. Interestingly, our previous work (29) showed that the correlations of FHB with local weather variables for a range of time windows during the season were quite similar for the two locations, demonstrating a generally consistent biological response to local environment. The results in our current study suggest that the weather in Indiana and Ohio respond differently to changes in the teleconnection patterns. Although this has not been investigated specifically, it is consistent with other results showing differences among regions for a given change in a teleconnection index (43). All three climate patterns investigated had some significant relationships with FHB intensity in Indiana or Ohio. The ONI appeared to have a significant relationship with FHB in Ohio, but not on disease intensity in Indiana. The NAO had significant coherencies at more periods with the Ohio series than the Indiana series, but the univariate spectral densities were not at their largest amplitudes at these periods. The winter or spring PNA was significantly coherent with the FHB intensity series in both Ohio and Indiana at several periods, but the smallest estimated phase

shift could be positive or negative. All of the climate patterns should be investigated further and possibly combined in a future multivariate analysis to identify how they jointly affect FHB.

The tendency that more of the evaluated climate patterns for the boreal winter had significant relationships with FHB than did the spring patterns was expected. It is well researched in the climatology literature that the amplitude (in absolute value) of the climate patterns are strongest during the winter season (32), which corresponds to most of the variability in the climate pattern occurring during this part of the year. Interestingly, even though there were fewer significant coherencies found for the relationship between FHB and spring climate indices than winter climate indices, the coherency values with spring indices in some cases were of stronger magnitude than their winter counterparts.

The possible link between global climate patterns and FHB has been investigated in other countries. Zhao and Yao (55) studied relationships between Pacific sea-surface temperatures and FHB outbreaks in eastern China, and Del Ponte et al. (11) found that the frequency of the predicted risk of FHB in southern Brazil was higher during El Niño and “neutral” years than during La Niña years. In this region of the Western Hemisphere, rainfall in the spring months is usually higher during El Niño years. In an expansion of past work with this wheat disease, we were able to show long-term periodic trends in the FHB–climate relationships through the spectral analyses. Del Ponte et al. (11) also suggested that there is a possible decadal variability of FHB seasonal risk in their data from southern Brazil. With this methodology, we could not only determine if yearly changes in the climate correlate with yearly changes in FHB, but also if changes in the climate lead to changes in FHB at some later point in time. We found that often there was not necessarily a concurrent (one-to-one, same year) correspondence between a particular climate index and disease. Instead, the phase differences showed the time series investigated had lead-lag relationships. This is usually due to the understanding that a certain state of the climate pattern can persist for several consecutive years (4). This is also consistent with the results from Scherm and Yang (45,46) as they found coherent relationships at periods of greater than 1 year with various phase differences.

Epidemics of FHB depend, in part, on local environmental variables because the local conditions affect survival, sporulation, dispersal, infection, and spike colonization in a given area (14,16, 21,38). The teleconnection patterns can be linked to FHB intensity because the climate patterns can influence the local environment where epidemics occur. However, certain parts of the disease cycle, primarily infection, take place over a narrow time window, with increased atmospheric moisture around anthesis leading to increased risk of epidemics (9,39). In other words, the environmental conditions around anthesis can have a disproportionately large influence on epidemics. In addition, wheat across a state tends to reach the critical anthesis stage over a few weeks. Thus, the large-scale climate patterns discussed here can only account for a portion of the inter-annual variability in disease in a state or region that is attributable to environment. Even with a very high coherency between teleconnection indices and local weather, monthly or 3-month averaged climate indices (as used here) are not capable of capturing this short-term variability in weather. For instance, a very short-term dry spell at the “right” time in an otherwise wet spring could negate the overall impact of the wet climate (in contrast to weather) on the epidemic (31). This means that there is an upper limit to the predictive ability of any teleconnection index, or any local measure of overall climate (“wet spring”, “dry June”, etc.), for risk of FHB. In addition, the observed dynamics of the FHB series in Ohio and Indiana are not strictly dependent on climate and weather in the region. Over such a large number of years, changes in cultivars grown, cultural practices used, and population dynamics of the pathogens have implications to the disease series that are not specifically ac-

counted for. Despite these qualifications, cross-spectral analysis was useful for showing significant coherencies between FHB and climate patterns, and as found by Scherm and Yang (45,46) for other pathosystems, this type of analysis helped to discern some of the complex relationships between large-scale climate patterns and disease. Although the coherencies clearly suggest that teleconnection indices can be used to improve disease forecasters, direct utilization of the indices in real-time predictive models will be challenging. This is because the form of the climate-disease relationship depended on location, the effects of climate indices were “spread out” over years, and because of the phase shifts that vary with index. For the latter situation, results showed that the coupling may involve changes in disease that are shifted by years from the changes in the teleconnection index. Nevertheless, we suggest that further studies of climate variability on FHB are important as they will continue to increase our understanding of these climate–disease relationships and the best statistical methods for finding them.

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