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Improving fungal disease forecasts in winter wheat: A critical role of intra-day variations of meteorological conditions in the development of Septoria leaf blotch

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ABSTRACT

Meteorological conditions are important factors in the development of fungal diseases in winter wheat and are the main inputs of the decision support systems used to forecast disease and thus determine timing for efficacious fungicide application. This study uses the Fourier transform method (FTM) to characterize temporal patterns of meteorological conditions between two neighbouring experimental sites used in a regional fungal disease monitoring and forecasting experiment in Luxembourg. Three meteorological variables (air temperature, relative humidity, and precipitation) were included, all conducive to infection of wheat by *Zymoseptoria tritici* cause of Septoria leaf blotch (STB) in winter wheat, from 2006 to 2009. The intraday, diurnal, dekadal and intra-seasonal variations of the meteorological variables were assessed using FTM, and the impact of existing contrasts between sites on the development of STB was analyzed. Although STB severities varied between sites and years ($P \leq 0.0003$), the results indicated that the two sites presented the same patterns of meteorological conditions when compared at larger temporal scales (diurnal to intra-seasonal scales, with time periods > 11 h). However, the intraday variations of all the variables were well discriminated between the sites and were highly correlated to STB severities. Our findings highlight and confirm the importance of intraday meteorological variation in the development of STB in winter wheat fields. Furthermore, the FTM approach has potential for identifying microclimatic conditions prevailing at given sites and could help in improving the prediction of disease forecast models used in regional warning systems.

1. Introduction

Integrated disease management based on decision support systems and disease forecasting models has become important more recently due to the increased need for sustainable practices in agriculture (Moreau and Maraite, 2000; Verreet et al., 2000; Audsley et al., 2005; Langvad and Noe, 2006). Reliable and timely information on plant fungal diseases epidemics are crucial for optimizing the use of fungicides while ensuring economic benefits (Fones and Gurr, 2015).

Plant disease epidemics of fungal origin result from the interaction between the pathogens, presence of susceptible hosts, and favourable meteorological conditions. Meteorological variables are most often the data used as inputs of disease forecasting models for fungal diseases of winter wheat (*Triticum aestivum* L.). Among the meteorological conditions, air temperature (T), relative humidity (RH), and precipitation (namely rainfall, R), are by far the most important. Numerous studies (e.g., Shaw and Royle, 1993; Eyal, 1999; Gladders et al., 2001; Lovell et al., 2004) have highlighted the effects of T, RH, and R on infection and progress of Septoria leaf blotch (STB, caused by *Zymoseptoria tritici* (Desm.) Quaedvlieg & Crous) in winter wheat. For the development of STB, T determines the rate at which fungal development and spore dispersal processes occur (Eyal, 1999; Gladders et al., 2001). A prolonged period of T below −2 °C has adverse effects on the fungus resulting in low survival and thus reduces inoculum to infect the wheat crop (Shaw and Royle, 1993). This, in turn, leads to a late or very slow development of the epidemic in the following spring even if weather

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conditions are favourable (Lovell et al., 2004; El Jarroudi et al., 2009; Beyer et al., 2012). RH can affect the rate of plant disease epidemic development because micro-organisms generally grow (spore germination and infection) only when there is sufficient moisture (RH ≥ 60%) (Moreau and Maraite, 1999; El Jarroudi et al., 2009; Suffert et al., 2011). Rainfall is a key requirement for the development of STB as it allows for the swelling of pycnidia and aids the dispersal of spores in splash to the upper leaves of wheat plant (Shaw and Royle, 1993; Lovell et al., 1997; Gladders et al., 2001).

For disease risk assessments at the regional scale, the meteorological data used as main inputs for forecasting models originate from meteorological networks with automatic weather stations (AWS) (Gladders et al., 2001; Magarey et al., 2001; El Jarroudi et al., 2009; Te Beest et al., 2009; Beyer et al., 2012; Junk et al., 2016). Most often, these forecast models are based solely on the meteorological data from the nearest AWS or interpolated from a set of neighbouring sites. Interpolation procedures such as the nearest neighbour method, kriging, co-kriging, or inverse weighted-distance method are typically performed (Lam, 1983; Hartkamp et al., 1999; DeGaetano and Belcher, 2007). Although these schemes are used widely, they do suffer from some potential sources of error, e.g. difficulty in capturing small scale variation, failure to account for topographical features, etc. Furthermore, the choice of location for an AWS within a field or the distance between AWS locations are both factors that hamper accurate forecasting of fungal diseases at regional scales (Jones et al., 2012). Thus, to develop reliable disease forecasting models that can be applied efficiently in operational disease monitoring (i.e. embedded in a decision support system and applied at sub-regional and regional scales), a detailed analysis of weather data, both spatially and temporally, is of great importance (Henshall et al., 2016; Donatelli et al., 2017). Indeed, the difference in weather conditions between neighbouring wheat fields (5–15 km, straight line) is often not perceptible, yet crucial in disease forecast models.

Fourier transform methods (FTMs) constitute one of the most widely used operations to obtain a spectral representation of a time series of discrete data samples (Chatfield, 1996; Blommfield, 2000; Brillinger, 2002; Craigmile and Guttorp, 2011; Mikosch and Zhao, 2014). Although they have been used for several and various purposes (e.g. Estrada-Pena et al., 2014; Mikosch and Zhao, 2014), their application for weather data analysis and plant disease development has yet to be fully investigated. In this study we investigate the causes of difference in STB expression across neighbouring locations based on the analysis of weather patterns at various temporal scales. First, a comprehensive theoretical framework of linear spectral analyses based on FTM, along with a conceptual framework, was devised. Then the approach was applied to a case study of two neighbouring sites included in a regional fungal disease monitoring and forecasting experiment.

2. Materials and methods

2.1. Theoretical framework of the Fourier transform method

FTM principles have been discussed extensively (e.g., Jones, 1964; Bergland, 1969; Chatfield, 1996; Blommfield, 2000). Only some general principles were summarized in the following paragraphs.

A filtered series Y_t is a weighted sum of the time series (the discrete data samples) X_t defined as,

$$Y_t = \sum_{k=-\infty}^{+\infty} a_k X_{t-k},$$

where the basis numbers a_k verify $\sum_{k=-\infty}^{+\infty} a_k = 1$. The sequence $a = (a_k)_{k \in Z}$ is called a linear filter. The Fourier transform of the filtered series, $F_Y(\lambda)$, is the product of the Fourier transform of the filter a and the Fourier transform of the original time series X_t, that is (Chatfield, 1996; Blommfield, 2000),

$$F_Y(\lambda) = F_a(\lambda)\cdot F_X(\lambda).$$

where λ is the frequency, and $F_a(\lambda)$ is the Fourier transform of the filter a given as,

$$F_a(\lambda) = \sum_{k=-\infty}^{+\infty} a_k e^{-i\lambda k}$$

and $F_X(\lambda)$ is the Fourier transform (or discrete-time Fourier transform) of the time series X_t given for a finite duration sequence of length n by

$$F_X(\lambda) = \sum_{t=0}^{n-1} X_t e^{-i\lambda t} ,$$

where $i = \sqrt{-1}$. For $\lambda = \frac{2\pi k}{n}$, k = 0, 1,…, n − 1, we obtain the discrete Fourier transform applied to the discrete-time series X_t through

$$\hat{X}(k) = F_X\left(\frac{2\pi k}{n}\right) = \sum_{t=0}^{n-1} X_t e^{-i\frac{2\pi kt}{n}},$$

with the corresponding inverse discrete Fourier transform

$$X_t = \frac{1}{n}\sum_{k=0}^{n-1} \hat{X}(k) e^{i\frac{2\pi kt}{n}},$$

where $\hat{X}(k)$ represents the frequency domain function and X_t the time domain function. Using this pair of formulae, we can move back and forth between a time representation of data $(X_t)_{t=0,\dots,n-1}$ and its frequency domain representation $(\hat{X})_{t=0,\dots,n-1}$ that is, the discrete Fourier transform is invertible. Also, it is possible to modify the frequency spectrum in order to change the time representation, i.e. to allow the filtering.

The Fourier transform of the linear filter a (denoted B) is called the transfer function of the linear filter. The transfer function B describes how the amplitude (corresponding to the standard deviation) is transferred from X to Y, and the quantity $|B|^2$ describes how the energy (variance) is transferred from the original series X to the filtered series Y. For a simple moving average filter q defined through $a = (a_k)_{k \in Z}$, with

$$a_k = \begin{cases} \frac{1}{2q+1} & \text{if } k \in \{-q, \dots, +q\}, \\ 0 & \text{otherwise}, \end{cases}$$

we have $B = \frac{1}{2q+1}\sum_{k=0}^{2q} e^{-ik\lambda} = \frac{1}{2q+1}\frac{1-e^{-i\lambda(2q+1)}}{1-e^{-i\lambda}}$ and $|B|^2 = \left(\frac{1}{2q+1}\right)^2 \frac{\sin^2\left(\frac{\lambda(2q+1)}{2}\right)}{\sin^2\left(\frac{\lambda}{2}\right)}$.

2.2. Conceptual approach of the FTM

The conceptual approach uses a mathematical function called *KZ* transformation (Zurbenko, 1986; Hogrefe et al., 2000) which is based on a linear filter q. This linear filter is a simple moving average iterated k times. The function *KZ* is identified as a function of the variables *X, q, k*, where X is a given meteorological variable, q is the linear filter associated to the moving average, and k refers to the iterations (in our study k varies between 1 and 3). *KZ* can be expressed in terms of the Fourier transform involving a series of equations with a sampling interval (or time frequency) 1/2 Δt (indeed the time scale is a minimum of 2 h, thus 1/2 Δt = 1 h). To find the power transfer function for the *KZ(q, k)*-function, the rule of sequential filtering is applied, that is,

$$|B|^2 = \left\{\left(\frac{1}{2q+1}\right)^2 \frac{\sin^2\left(\frac{\lambda(2q+1)}{2}\right)}{\sin^2\left(\frac{\lambda}{2}\right)}\right\}^k$$

Based on the *KZ*-function and the filter q, a given meteorological variable is decomposed in a series of filtered data. For each