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Development and evaluation of a forecasting system for fungal disease in turfgrass

Richard Palmieri[1], Lane Tredway[2], Dev Niyogi[3] &Gary M. Lackmann[1]
[1]*Department of Marine, Earth, and Atmospheric Sciences, North Carolina State University, Campus Box 8208, Raleigh, NC 27695-8208, USA*
[2]*Department of Plant Pathology, North Carolina State University, Campus Box 3415, Raleigh, NC 27695-3415, USA*
[3]*Purdue University, Department of Agronomy and Department of Earth and Atmospheric Sciences, West Lafayette, IN 47907, USA*
Email: dniyogi@purdue.edu

*A forecasting system for fungal infection of turfgrass using weather-based empirical indices (the 'Fidanza' and 'Schumann' models) was developed and evaluated for its ability to predict the occurrence of brown patch (*Rhizoctonia *blight) infection episodes at an experimental site in southeastern USA. Disease observations took place at the Turfgrass Field Laboratory in Raleigh, North Carolina between 8 June and 17 August 2003. Three meteorological data sources were used to generate disease risk indices using the empirical models: an on-site observing station, an observing station at a nearby airport, and the US National Weather Service's operational Eta weather forecast model. Visual observations of brown patch activity were conducted in the field and used to evaluate the accuracy of the disease prediction models. Results indicate that the Fidanza and Schumann models correctly predicted brown patch activity on 48% and 30% of the days on which disease occurred, respectively. A diagnosis of the model performance of these disease indices was undertaken. Results are dependent on occurrence of high temperatures and rainfall and independent of the source of the meteorological information (on-site, airport and the Eta model); therefore, regional meteorological information can be effectively applied to develop turfgrass disease forecasting systems. Ongoing efforts are directed towards developing new disease indices and modifying existing indices before an operational disease forecasting system can be implemented.*

Keywords: turf disease forecast system, plant pathology, agriculture meteorology, plant disease, Eta model

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1. Introduction

Turfgrass is a perennial agricultural product, and is often grown on the same land for many years. This practice favours the long-term build-up of turfgrass pests, including many fungi that cause disease. Currently, most turfgrass managers use a calendar-based pesticide application schedule, which is based principally on the manufacturer's recommendations for the duration of the pesticide's effectiveness (typically one to two weeks).

The turfgrass industry in the United States is one of the largest agricultural industries in the country. In North Carolina alone, turf is grown on over 2 million acres, with annual maintenance costs of approximately US$2 billion (Neas & Smith 2000). A large portion of the expenditure for turfgrass maintenance is for the application of pesticides. In 1993, nearly half of all US golf course pesticide budgets were spent on fungicides, totalling approximately US$85 million, and these costs continue to rise (Jackson 1994).

In addition to the financial costs of application, certain fungicides may be harmful to humans and the environment. Such concerns have motivated the creation of a new generation of 'reduced risk' fungicides that are safer to humans and the environment. However, these are more expensive per application and have a narrower control spectrum, requiring application of several products to control all of the diseases that may develop at a given time. Furthermore, reduced risk fungicides are generally more prone to the development of fungicide resistance, which may reduce the effectiveness of the fungicide over time. These changes in the turfgrass industry have sparked interest in methods to reduce the number of fungicide applications required to maintain quality turfgrass. Weather-based decision aids for the timing of pesticide applications represent one such method of disease control (Tredway et al. 2004).

Nutter et al. (1983) showed that fungal pathogens of turfgrasses are omnipresent but that the pathogens require favourable weather conditions to become active. By identifying the weather factors that trigger disease development, it is possible to develop indices for prediction of turfgrass disease development. Schumann et al. (1994) developed one such weather-based disease prediction system and demonstrated that up to 50% of fungicide applications could be avoided while still providing adequate protection against disease. With fungicide applications ranging in price from several hundred to several thousand dollars per acre, the elimination of even one application per season would make a significant cost saving for turf managers.

Dickinson (1930) published one of the first studies relating turf disease with environmental conditions. Dickinson observed that the symptoms of brown patch (a disease caused by *Rhizoctonia solani*) were often present on days following afternoon irrigation when the daytime maximum air temperature was between 26 °C and 35 °C, and the overnight minimum air temperature was between 15 °C and 21 °C. Similarly, Dahl (1933) observed that brown patch occurred on 82% of days when the minimum air temperature was ≥ 21 °C. These studies were met with scepticism and generated very little interest in the use of disease prediction systems, probably on account of the uncertainty in the disease prediction indices and the accuracy of weather forecasts. As a result, studies of the environmental dependence of turfgrass diseases were largely abandoned for over half a century. However, with improvements in weather forecasting, interest in developing weather-based disease forecasting systems re-emerged in the 1980s and 1990s (e.g. Nutter et al. 1983; Hall 1984; Schumann et al. 1994; Fidanza et al. 1996; Gross et al. 1998).

Brown patch has been recognised as a turf disease since 1919, and most turfgrasses cultivated in the United States are susceptible to it (Smiley et al. 1992). In 1993, nearly 30% of all fungicide expenditures in the turfgrass industry were for control of brown patch (Jackson 1994). In the mid-1990s two disease forecasting systems for brown patch development were developed: one by Schumann et al. (1994) and the other by Fidanza et al. (1996). Schumann and colleagues (hereafter S94) developed a system based on observations of brown patch development on creeping bentgrass in Massachusetts, USA (which they tested in Massachusetts, New Jersey, and Georgia), while Fidanza and colleagues (hereafter F96) developed a system based on brown patch observations in perennial ryegrass in Maryland, USA. While both systems proved to be accurate in the regions in which they were developed, an evaluation of their accuracy over other regions needs to be made. For example, S94 showed that when the system used meteorological data from Massachusetts for regions in Georgia, false alarms occurred. Similarly, Gross et al. (1998) showed that the F96 system frequently overpredicted brown patch incidence when tested in Indiana.

In North Carolina, a project is under way to develop a weather-based turf disease prediction system. Participants in this collaborative project include turfgrass managers as well as the county extension and research community, and is aimed at making predictions of turfgrass disease vulnerability available on the internet. Turfgrass managers and citizens would ultimately use such a system to decide the best time to apply fungicide applications in order to minimise disease occurrence and the associated costs of integrated pest management.

This article discusses the field experiments conducted to test the brown patch forecasting indices developed by S94 and F96 in terms of their ability to predict brown patch development in North Carolina. In addition, the effect of different meteorological data sources (i.e. on-site versus local/regional observing stations and/or operational weather forecasting models) on the performance of the disease indices was evaluated.

Section 2 outlines the design of the turf disease forecasting system and reviews the S94 and F96 brown patch forecasting systems. Section 3 presents the experimental design for evaluating the turf disease forecasting system, and the results are presented in Section 4. Section 5 contains a discussion of the results, some conclusions and suggestions for future research.

2. Turfgrass disease indices and system design

F96 uses two separate environmental favourability indices – one using a criterion-based method of assigning risk, the other a multiple-regression technique to develop an equation for disease risk. S94 is a condition-based model that requires that a set of meteorological parameters is met or exceeded for disease to occur.

2.1. System design

A flow chart depicting the turfgrass disease forecasting system employed in this study is shown in Figure 1. For the current study, the disease indices developed by F96 and S94 were used and separate disease indices were applied using meteorological data from on-site observations, airport/regional observations, and the Eta weather forecasting model. At the time of this study, the US National Centers for Environmental Prediction (NCEP) ran the North American Mesoscale (NAM-Eta) model four times per day. The NAM-Eta was a primary source of forecast information for the US operational forecasting community, but was replaced by a different dynamical core, the NAM-NMM, in June 2006. When observed meteorological conditions are used as inputs into the system, the system is being

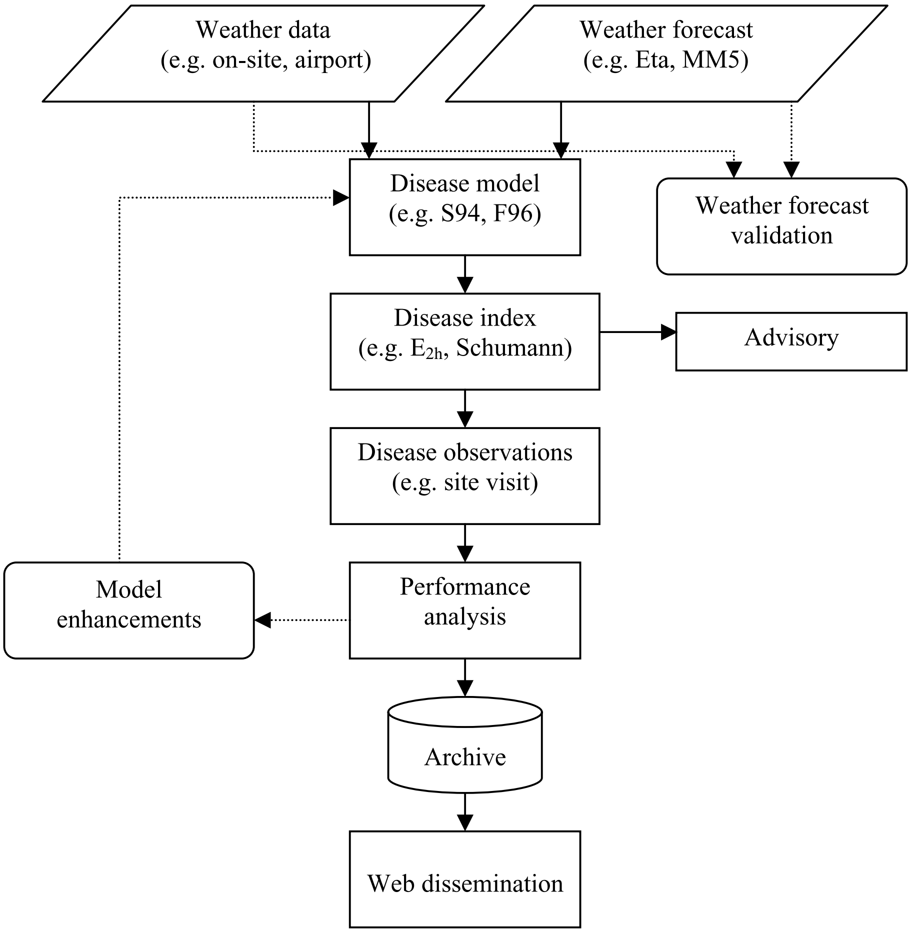

Figure 1. *Flow chart illustrating the turf disease forecasting system used in the current study.*

implemented in a warning mode, with turfgrass managers having only hours after the issue of a disease warning to apply fungicides to prevent possible turf damage. When forecasted meteorological data are used as inputs into the system, the system is being used in a forecast mode, and the increased lead-time allows turfgrass managers to prepare fungicide applications for delivery.

The resulting disease indices were compared with daily observations of brown patch activity in the field. The meteorological data and forecasts, as well as disease indices, are archived and made available for analysis (to facilitate future index improvement) and for dissemination to the public.

2.2. Fidanza model

F96 monitored environmental conditions and brown patch activity on perennial ryegrass at the University of Maryland Turfgrass Research Facility in Silver Spring, Maryland, from June 1991 through August 1993. A weather-observing station was set up at the research facility and was equipped with instruments to measure air temperature and relative humidity (RH) (at 300 mm above canopy surface), leaf wetness duration, soil temperature and moisture (at a depth of 25 mm), precipitation, and incoming solar radiation. Using 1991 and 1992 data, F96 developed an environmental favourability index (E). Their study indicated six variables that could be related to brown patch occurrence: the number of hours of RH $\geq$ 95%, mean RH, leaf wetness duration and precipitation during the 48 hours prior to sunrise (0600 LT, or 1000 UTC), minimum air temperature, and minimum soil temperature. These six variables were combined to create a condition-based index, called E_6, where integer point values are assigned to each of the six variables based on how favourable the variable is for disease development (e.g. minimum air temperature of $\geq 16\,^{\circ}$C is allocated one point, while minimum air temperature of $< 16\,^{\circ}$C is allocated minus two points). A value of $E_6 \geq 6$ is indicative of a high-risk for brown patch development. Because some of the input required for the E_6 index is not readily available to turfgrass managers (e.g. hours of leaf wetness duration, soil temperature), F96 showed that just two of the above variables – mean RH and minimum air temperature – provided sufficient information to create forecasts similar to those produced by the E_6 index. Thus, the following index (E_2) was developed through stepwise multiple regression:

$$E_2 = -21.5 + 0.15RH + 1.4T - 0.033T^2 \qquad (1)$$

where RH is mean 24-h RH, and T is minimum air temperature. As with E_6, the output of E_2 was interpreted in such a way that a value ≥ 6 indicated a high risk for brown patch development.

2.3. Schumann model

Greenhouse studies conducted by Rowley (1991) demonstrated that *R. solani* was capable of infecting turfgrass at 12 °C when the foliage remained wet for 8–12 consecutive hours. In an effort to expand on those studies, S94 conducted a four-year field study to analyse the link between brown patch activity in creeping bentgrass and local environmental conditions. To establish the initial environmental thresholds to be used as a positive disease forecast, S94 erected a meteorological observation station on their test site in Massachusetts which measured air temperature and relative humidity (at a height of 25 mm above the turfgrass canopy), precipitation, and soil temperature. Meteorological data and field observations of brown patch activity were subjected to statistical analysis to determine the parameters that were indicative of disease risk. S94 found that RH $\geq$ 95% for at least 10 consecutive hours consistently preceded brown patch occurrence. When the above RH criterion was met, any one of the following sets of conditions was found to be conducive to brown patch development:

(i) minimum and 24-h mean air temperatures of 15 °C and 20 °C, and minimum and 24-h mean soil temperatures of 18 and 21 °C, for the 24-hour period ending on the 10th consecutive hour when RH $\geq$ 95%, and rainfall of $\geq$ 2.54 mm over the 36-hour period ending on the 10th consecutive hour when RH $\geq$ 95%;

(ii) rainfall of $\geq$ 15 mm for a period of 48 hours after commencement of the rainfall episode, in addition to the air and soil temperature thresholds in (i); and,

(iii) prolonged (> 36 hours) high humidity ($\geq$ 95%) and rainfall (> 15 mm) in combination with the soil temperature requirements listed in (i), even when the air temperature thresholds in (i) were not met.

These criteria were then used to develop an environmental condition-based warning system for brown patch.

3. Experimental design

The following experiments were designed to determine whether previously developed brown patch prediction indices are suitable for use in North Carolina (NC), and if weather observations collected from a remote site, or forecasted weather conditions obtained from an operational weather model (or both), can serve as an adequate proxy for on-site weather observations.

Daily observations of brown patch activity were conducted at the Faculty Club Turfgrass Field Laboratory (TFL) in Raleigh, North Carolina from 8 June to 16 August 2003. This covers the period during which the threat of brown patch infection is typically highest in the piedmont region of North Carolina. Brown patch observations were conducted on creeping bentgrass (*Agrostis palustris* Huds.) maintained under golf course putting green conditions. The experimental area was established with 116.13 m^2 blocks of the cultivars 'SR1119', 'G-6'', 'G-2', 'Crenshaw', 'L-93', 'Penncross', 'A-4' and 'A-1'. Mowing was performed three times per week with a cutting height of 4 mm and the clippings were collected. The site was irrigated to prevent drought stress. Fertilizer was applied as 24-5-11 (i.e. 24% Nitrogen, 5% Phosphorous, 11% Potassium, 60% carrier) on 9 April (2.44 kg N 1000 m^{-2}), as 18-3-18 on 5 May (2.44 kg 1000 m^{-2}), and as 18-4-0 on 15 May (2.44 kg 1000 m^{-2}). Since brown patch activity typically occurs during the night when humidity is high and dew is present on the turfgrass foliage, disease observations were made around 0800 LT (1200 UTC) daily. In this analysis, a 'day' is the period from 1200 UTC to 1200 UTC the next day (e.g. 6 May refers to 6 May 1200 UTC through to 7 May 1200 UTC). When brown patch is actively developing, a dark outer ring (a 'smoke ring') surrounds the affected turf. Although the symptoms of brown patch may remain evident for several days following an outbreak, the smoke ring is present only when the disease is actively developing. Brown patch activity was assessed visually based on the presence or absence of a smoke ring. Disease observations were then compared with the output from the brown patch forecasting systems for the day that ended at the same time the disease observations were taken (i.e. disease observations taken at 7 May 1200 UTC were compared with weather conditions from 6 May). This comparison was used to evaluate the performance of the disease indices.

An on-site weather observing station was established to record hourly precipitation, air temperature, relative humidity, soil temperature (at 0.1 m), soil moisture, incoming solar radiation, and wind direction and speed (at approximately 0.30 m). These data were used as inputs for the disease indices (F96 and S94) to assess disease risk.

During the experiment, weather observations made at the Automated Surface Observing Station (ASOS) at the Raleigh-Durham International Airport (RDU), approximately 17.7 kilometres from TFL, were also compiled. Unlike the observation station located at the TFL, the RDU ASOS site is operated and maintained by the US National Weather Service, and all measurements are made at standard levels using standard citing guidelines. These data were used as inputs into the F96 and S94 brown patch indices (see Figure 1). The disease indices derived from the brown patch forecasting system were generated using inputs from both on-site and airport data. The indices were then compared to determine whether off-site, regional data might be used as a proxy for on-site data in determining disease risk. This was of interest in determining whether existing meteorological networks may be used to provide a regional scale analysis of disease risk rather than a site-specific analysis.

In addition to the on-site and airport weather observations, operational Eta model output was processed and used as an input for the disease indices. The Eta model was chosen because of its widespread use as a forecasting model in the United States at the time the study was conducted (this operational forecast model has since been replaced at NCEP by a version of the Weather Research and Forecasting (WRF) model known as the Non-hydrostatic Mesoscale Model, dubbed the WRF-NMM or NAM-NMM). Additional experimentation using various configurations of the WRF model for these applications is currently under way. Eta model output was averaged for all grid points within 35 km of the Turf Field Lab on the Eta 215 grid (20 km grid spacing; 10 total grid points averaged). The resulting averages were used as an input to the brown patch forecasting system to produce disease risk indices using F96 and S94. In this mode, the turf disease system was being applied in a 'forecast mode', i.e. forecasted meteorological conditions were used with the disease indices as opposed to using observed conditions in 'warning mode'. The Eta-based disease indices were also compared with disease observations at TFL. It was anticipated that if the ability to forecast disease risk can be demonstrated by the Eta model, turfgrass managers would have sufficient warning to make preventative fungicide applications before a disease outbreak occurred.

The meteorological data collected from TFL and RDU, along with the Eta model output, were input to a spreadsheet application for analysis. Eta model output was used to develop Fidanza model (F96) indices alone. Four separate F96 indices were produced for each data source – two E_2 indices and two E_6 indices, one with an index using a (max + min)/2 average for mean relative humidity (E_{2m} and E_{6m}), and one using a time average derived from all hourly observations for the day (E_{2h} and E_{6h}). A Schumann model (S94) index was also generated. Although the Schumann model (S94) uses a moving 36-hour window in order to produce brown patch warnings, for verification purposes a 12 UTC to 12 UTC day will be considered, allowing comparison with output from the Fidanza model (F96). Therefore, if all the criteria for a disease warning are met during any single hour of a day, a disease risk warning for that day is issued.

4. Results

In this section, the accuracy of the brown patch prediction indices is discussed, with the results being grouped by the source of the weather data. A review of the disease observations made on-site is presented first, followed by discussion of disease indices generated from meteorological data collected at TFL. The indices produced from meteorological data at RDU are then compared with the indices produced at TFL, and finally, these data are compared with indices produced from Eta model forecasts. The results are presented first for the E_6 indices, then for the E_2 indices, and finally for the Schumann model (S94) indices.

4.1. Disease observations

Brown patch activity was observed on 23 of the 70 days during the experimental period: five days in June, 13 days in July, and five days in August. These 23 days can be grouped into seven episodes. An 'episode' is defined as a period beginning on a day disease activity is observed and continuing as long as there is no more than one consecutive day during which disease activity is not observed, with no minimum or maximum limit to the number of days in an episode (e.g. the first episode of this season consisted of only one day, while the fourth lasted for eight days). When two consecutive days pass with no observed disease activity, the episode is defined to have ended on the last day disease activity was observed. Table 1 shows a summary of the disease episodes observed during the experimental period.

4.2. Disease indices from on-site weather observations

In this subsection, the brown patch indices generated by the Fidanza (F96) and Schumann (S94) models using on-site weather observations as the inputs are discussed. The E_6 indices (E_{6h} and E_{6m}) generated at TFL were generally similar, differing on only nine days during the experimental period. E_{6h} and E_{6m} differed in their prediction of brown patch development on 30 June, when E_{6h} produced a disease index of 6 whereas E_{6m} produced a disease index of 5. As shown in Figure 2, the E_{6h} index matched observed conditions on 39 of the 70 days (56%) in the forecast period, while E_{6m} did so on 40 days (57%).

Table 2 is a 2×2 contingency table summarising the performance of the brown patch forecasting system using the E_6 indices. Dates listed in the upper-right quadrant are those when the index issued a false alarm, while those in the lower-left quadrant are when the index missed a disease event. Of the 23 days when brown patch activity was observed, both E_{6h} and E_{6m} correctly produced brown patch warnings on seven days, but missed 16 days. The E_{6h} index produced 15 false alarms, while the E_{6m} index produced 14 (the E_{6h} index produced an additional false alarm on 30 June). Both indices produced an accurate disease warning for the onset of episode 2 (15–19 June; Table 1).

More variability was evident between E_{2h} and E_{2m} than was evident between the two E_6 indices (Figure 3). The E_{2h} index produced a total of 27 disease warnings, only 11 of which agreed with field observations (the other 16

Table 1. *Brown patch disease events grouped by disease episode, with forecasting system indices from TFL, RDU and the Eta model, and actual disease observations.*

	Date	Turf				RDU			Eta		Disease
		E_{6m}	E_{6h}	E_{2m}	E_{2h}	E_6	E_{2m}	E_{2h}	24-h E_{2h}	48-h E_{2h}	obs
Episode 1	12-Jun	3	3	5.3	6.2	3	5.5	5.9	5.4	5.1	yes
Episode 2	**15-Jun**	**6**	**6**	**5.8**	**6.9**	**5**	**5.8**	**6.7**	**5.9**	**6.3**	**yes**
	16-Jun	6	6	6.3	6.8	5	6.6	6.9	6.7	5.7	no
	17-Jun	**5**	**5**	**7.0**	**7.4**	**5**	**7.2**	**7.3**	**7.2**	**6.1**	**yes**
	18-Jun	5	5	5.9	6.6	5	6.0	6.7	6.2	6.1	no
	19-Jun	**5**	**5**	**6.0**	**7.1**	**6**	**6.1**	**7.5**	**5.0**	**7.1**	**yes**
Episode 3	23-Jun	2	2	2.6	1.9	0	2.1	2.3	1.5	1.3	yes
	24-Jun	**2**	**2**	**2.8**	**2.6**	**2**	**3.1**	**3.0**	**2.6**	**2.5**	**no**
	25-Jun	2	2	3.1	2.7	2	3.4	3.4	3.2	2.6	yes
Episode 4	**11-Jul**	**4**	**5**	**4.4**	**5.5**	**5**	**4.6**	**5.7**	**5.9**	**5.0**	**yes**
	12-Jul	4	4	3.9	4.4	5	4.3	4.6	0	3.8	yes
	13-Jul	**6**	**6**	**5.8**	**6.8**	**6**	**5.7**	**6.4**	**6.4**	**0**	**no**
	14-Jul	6	6	5.7	6.6	6	5.9	6.5	5.9	6.4	yes
	15-Jul	**3**	**3**	**4.8**	**5.2**	**3**	**5.2**	**5.4**	**5.6**	**4.9**	**yes**
	16-Jul	3	3	4.6	5.5	4	5.0	5.2	0	4.7	yes
	17-Jul	**3**	**3**	**4.7**	**5.0**	**3**	**5.4**	**5.4**	**4.9**	**0**	**yes**
	18-Jul	6	6	5.1	6.1	5	5.1	5.7	5.4	4.4	yes
Episode 5	**23-Jul**	**3**	**3**	**6.0**	**6.7**	**5**	**6.8**	**7.2**	**0**	**5.9**	**yes**
	24-Jul	4	5	4.3	5.3	5	4.2	5.1	3.8	3.5	yes
Episode 6	**27-Jul**	**2**	**3**	**4.4**	**5.2**	**3**	**5.0**	**5.1**	**5.3**	**5.2**	**yes**
	28-Jul	2	2	4.1	4.2	3	4.4	4.5	4.4	4.5	yes
	29-Jul	**7**	**7**	**5.4**	**6.6**	**6**	**5.7**	**6.9**	**6.3**	**6.0**	**yes**
	30-Jul	7	7	6.5	6.9	6	7.0	7.5	7.4	6.8	no
	31-Jul	**3**	**3**	**5.6**	**6.4**	**5**	**6.1**	**6.9**	**7.2**	**6.4**	**yes**
	1-Aug	6	6	5.1	6.8	6	5.7	6.8	7.6	7.4	no
	2-Aug	**6**	**6**	**6.4**	7.0	**4**	**6.8**	**7.3**	**6.9**	**6.5**	**yes**
Episode 7	13-Aug	3	3	4.7	5.3	5	5.4	6.2	7.4	5.9	yes
	14-Aug	**5**	**5**	**5.8**	**6.3**	**6**	**5.3**	**6.4**	**6.8**	**4.2**	**no**
	15-Aug	6	6	4.5	4.5	7	5.0	6.1	0	5.6	yes
	16-Aug	**6**	**6**	**5.8**	**6.7**	**7**	**6.2**	**6.8**	**7.0**	**0**	**yes**

Table 2. *Contingency table illustrating the performance of the brown patch forecasting system used in this study, using Turf Field Lab (TFL) derived (a) E_{6h} and (b) E_{6m} indices. The upper-left and lower-right quadrants are the number of days that the brown patch forecasting system's output matched observed conditions, while the upper-right quadrant represents false alarms, and the lower-left quadrant represents missed events.*

(a)	Observations		
Index = E_{6h}	Yes	No	
Yes	7	15	22
No	16	32	48
	23	47	70

(b)	Observations		
Index = E_{6m}	Yes	No	
Yes	7	14	21
No	16	33	49
	23	47	70

resulted in false alarms; Table 3a). The E_{2h} index also missed 12 disease days but proved more proficient than the E_6 indices at predicting the onset of disease episodes. It produced disease warnings for the onset of episodes 1, 2 and 5, while producing indices in the 5s for episodes 4, 6 and 7 (Table 1). E_{2m}, on the other hand, indicated that a high risk of brown patch occurrence existed on only eight days during the observation period, with disease being observed on only half of those days, indicating that the index missed 19 events and produced four false alarms (Table 3b). The E_{2m} index was able to predict the onset of one disease episode, producing a warning at the onset of episode 5.

The S94 model produced 16 brown patch warnings during the experimental period, of which six were consistent with field observations and 10 were false alarms (Table 3c). Additionally, the index missed 17 disease events. The S94 model was able to produce a warning for the onset of only one of the seven disease episodes observed during the test period (episode 2; Table 1).

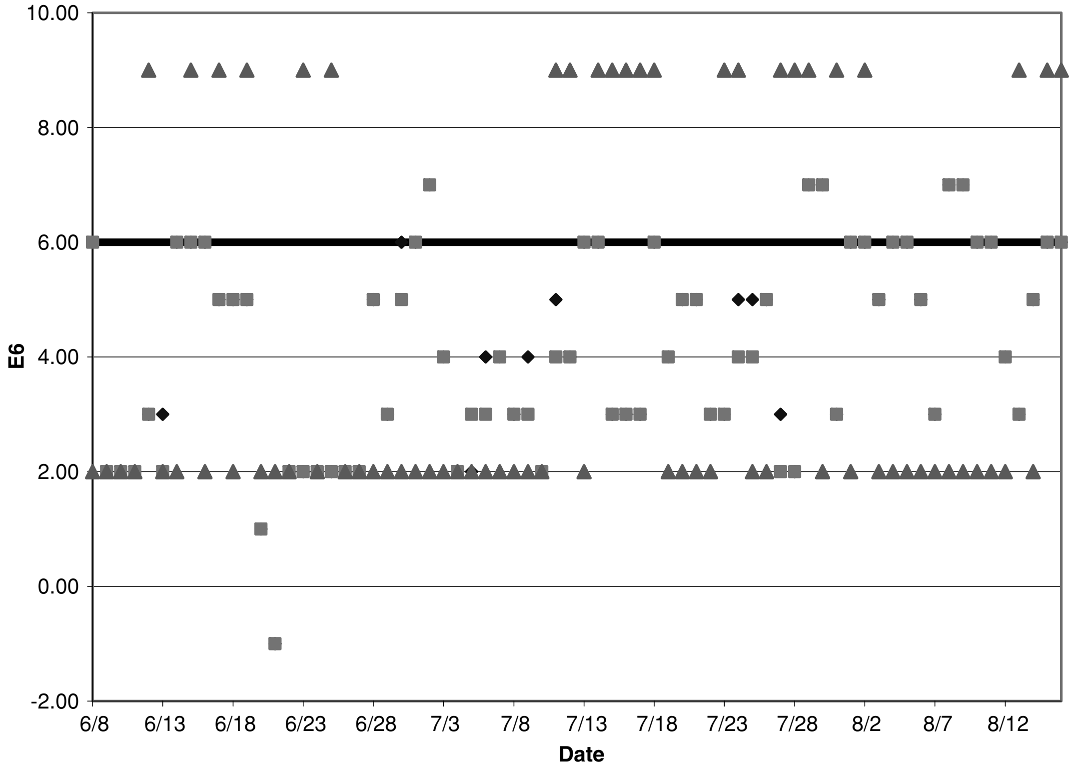

Figure 2. *TFL-derived E_{6m} and E_{6h} indices over the entire experimental period, with observations of disease activity overlaid. The series of squares is E_{6m}, and the series of diamonds is E_{6h}. The series of triangles represents disease observations, where they lie below the solid line at $E_6 = 6$ when disease was not observed, and above the line when disease was observed.*

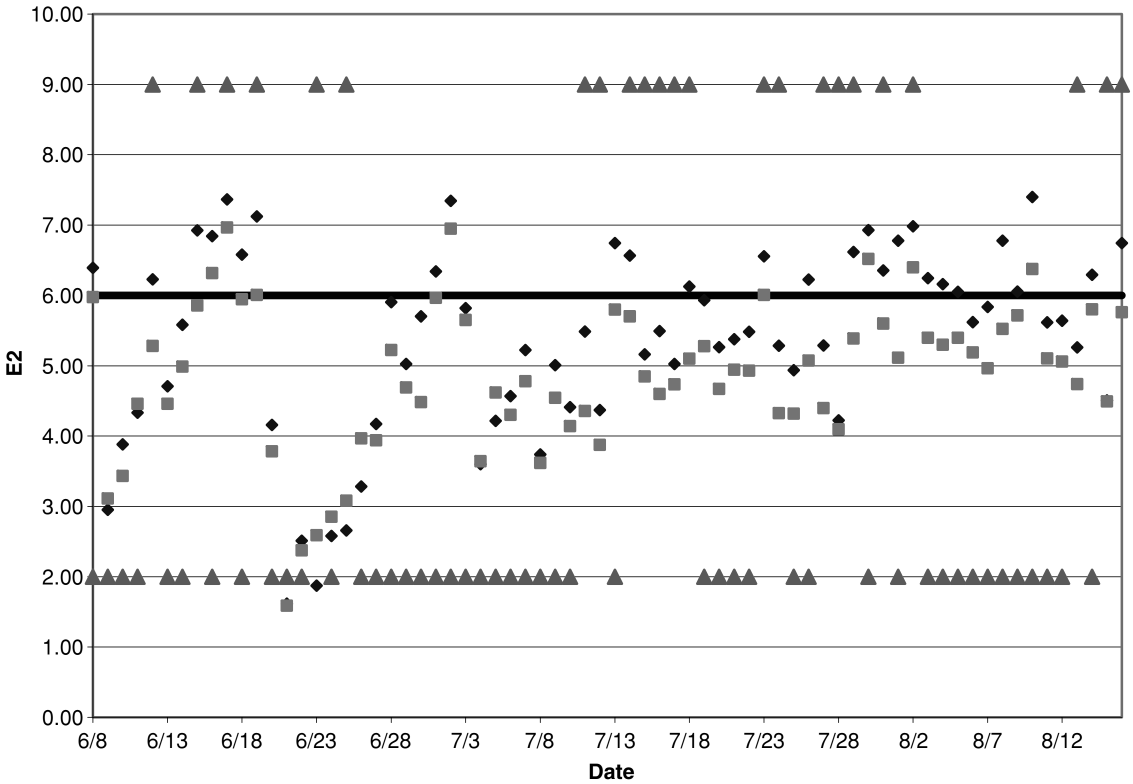

Figure 3. *As in Figure 2, except the series of squares represents TFL-derived E_{2m}, and the series of diamonds represents E_{2h}.*

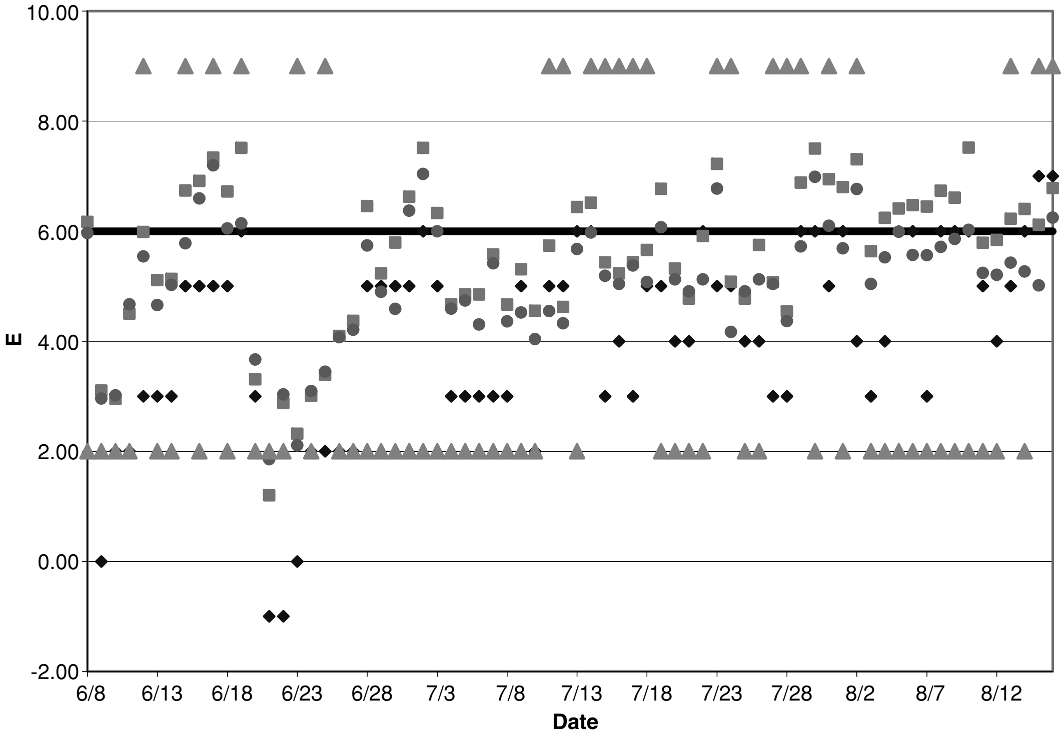

Figure 4. *As in Figure 2, except the series of diamonds represents RDU-derived E_6, the series of circles represents E_{2m}, and the series of squares represents E_{2h}.*

Table 3. *As in Table 2, except using TFL derived (a) E_{2h}, (b) E_{2m}, and (c) Schumann indices.*

(a)	Observations		
Index = E_{2h}	Yes	No	
Yes	11	16	27
No	12	31	43
	23	47	70

(b)	Observations		
Index = E_{2m}	Yes	No	
Yes	4	4	8
No	19	43	62
	23	47	70

(c)	Observations		
Index = Schumann	Yes	No	
Yes	6	10	16
No	17	37	54
	23	47	70

Table 4. *As in Table 2, except using Raleigh-Durham International Airport (RDU) derived (a) E_6, (b) E_{2h}, (c) E_{2m}, and (d) Schumann indices.*

(a)	Observations		
Index = E_6	Yes	No	
Yes	5	12	17
No	18	35	53
	23	47	70

(b)	Observations		
Index = E_{2h}	Yes	No	
Yes	11	19	30
No	12	28	40
	23	47	70

(c)	Observations		
Index = E_{2m}	Yes	No	
Yes	6	7	13
No	17	40	57
	23	47	70

(d)	Observations		
Index = Schumann	Yes	No	
Yes	7	12	19
No	16	35	51
	23	47	70

4.3. Disease indices from airport weather observations

Using weather observations from RDU, the E_6 indices (E_{6m} and E_{6h}) were identical throughout the experimental period; reference will therefore be made only to E_6 in general. The E_6 index was able to match disease observations on 40 of the 70 days (57%) in the forecast period (Figure 4; Table 4a). E_6 produced 17 disease warnings, but brown patch activity only occurred on five of those days, i.e. there were 12 false alarms and 18 missed

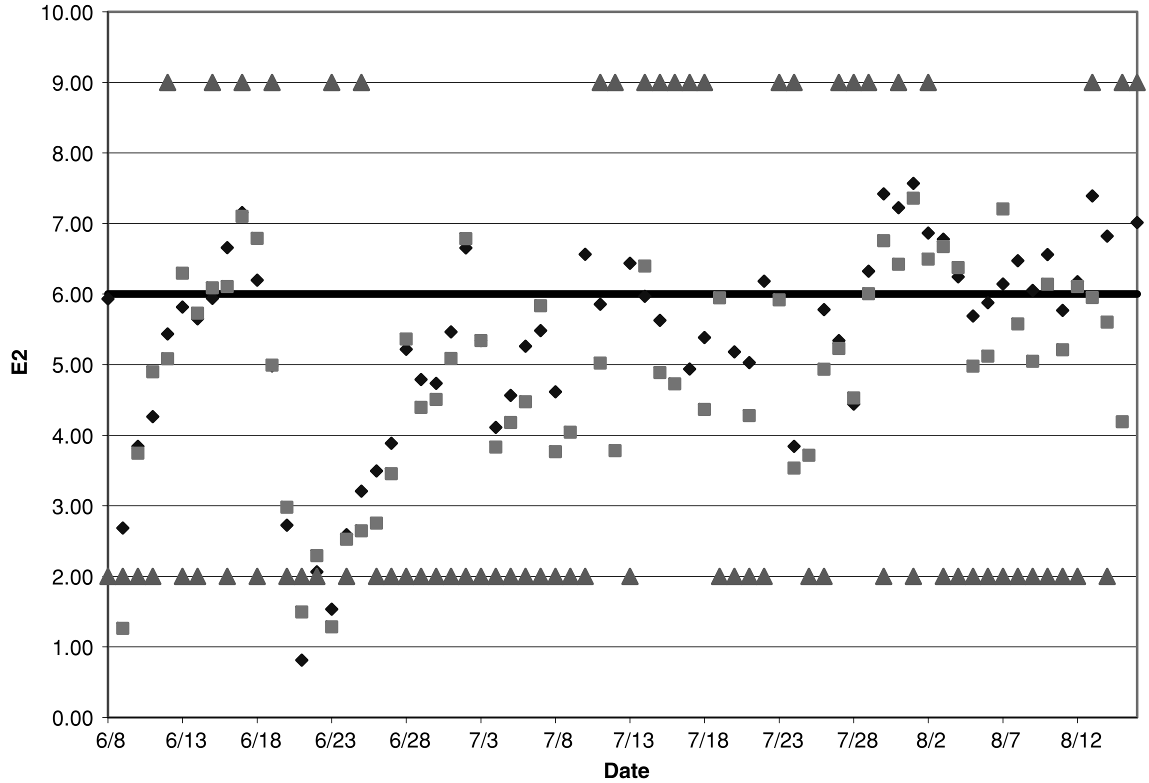

Figure 5. *Same as Figure 2, except the series of diamonds represents Eta-derived 24-h forecasts of E_{2h}, and the series of squares represents 48-h forecasts of E_{2h}.*

events. When analysed on an episode-by-episode basis (Table 1), E_6 was unable to identify the onset of any of the seven disease episodes using RDU data.

As with the TFL data, large variability existed between the two E_2 indices based on RDU meteorological data. The E_{2h} index produced 30 brown patch warnings, of which 11 were verified, and 19 were false alarms (Figure 4). The E_{2m} index produced 14 brown patch warnings, of which seven were verified and seven were false alarms. The E_{2h} index agreed with field observations of brown patch development on 39 of 70 days (56%), while the E_{2m} index did so on 46 of 70 days (66%) (Tables 4b, 4c). E_{2h} correctly predicted the onset of three of the seven brown patch episodes (episodes 2, 5 and 7), while E_{2m} correctly predicted only one (episode 5; Table 1).

The S94 model output matched observed disease conditions on 42 days of the 70-day experimental period (60%; Table 4d), with brown patch observed on seve of these days, leaving 12 brown patch infection events unforecasted. In total, S94 produced 19 disease warnings, of which 12 were false alarms. This index was able to indicate correctly the onset of disease episode 2 (Table 1).

4.4. Disease indices from operational Eta forecasts

Given the above results, E_{2h} appears to be most accurate for predicting brown patch development on creeping

Table 5. *As in Table 2, except using Eta model derived (a) 24 h- and (b) 48-h E_{2h} forecasted indices.*

(a)	Observations		
Index = 24 h-E_{2h}	Yes	No	
Yes	6	16	22
No	13	28	41
	19	41	63

(b)	Observations		
Index = 48 h-E_{2h}	Yes	No	
Yes	6	11	17
No	14	30	44
	20	41	61

bentgrass in North Carolina. Therefore, Eta forecasts were used to generate only the E_{2h} indices based on one-day (F24) and two-day (F48) forecasts (Figure 5). Eta model one-day forecasts were available for 63 days during the experiment (9, 12, 16, 19, 23 and 25 July, and 15 August were not available). A summary of the performance of the one-day Eta model forecasts of E_{2h} is provided in Table 5a. The one-day forecasts of E_{2h} produced 22 brown patch warnings. On days when the Eta model one-day forecast produced a warning, disease was observed six times, leaving 13 events unpredicted (four on days when indices were unavailable), with 16 false alarms. When evaluated for its ability to predict

Table 6. *Skill scores (FAR, POD, and CSI) for all generated disease indices.*

	FAR	POD	CSI
TFL E_{6m}	0.67	0.30	0.19
TFL E_{6h}	**0.68**	**0.30**	**0.18**
TFL E_{2m}	0.50	0.17	0.15
TFL E_{2h}	**0.59**	**0.48**	**0.28**
TFL Schumann	0.62	0.26	0.18
RDU E_6	**0.71**	**0.22**	**0.14**
RDU E_{2m}	0.54	0.26	0.20
RDU E_{2h}	**0.63**	**0.48**	**0.26**
RDU Schumann	0.63	0.30	0.20
Eta 24-h E_{2h}	**0.73**	**0.26**	**0.15**
Eta 48-h E_{2h}	0.65	0.26	0.18

the onset of a disease episode (Table 1), the Eta model one-day forecasts predicted only the onset of episode 7, though a warning was very nearly issued for the onset of episode 2 ($E_{2h} = 5.94$; no forecast was available for 23 July, the onset of episode 5).

Eta model two-day forecasts were unavailable for 8 June, 10, 13, 17, 20 and 22 July, and 16 August. A summary of the generated indices is provided in Table 5b. This E_{2h} index produced 17 disease warnings, of which six were verified against observations. Seventeen brown patch infection events were missed by this index (though three of these infection events fell on days when an index was unavailable), and 11 false alarms were issued. The one- and two-day E_{2h} forecasts nearly predicted the same two disease episodes (Table 1), with the two-day forecast producing a warning for episode 7, while very nearly issuing one for episode 2 ($E_{2h} = 5.95$).

5. Discussion and conclusions

5.1. Skill of the system

The primary objective of this study was to develop and evaluate a forecasting system for fungal infection of turfgrass (specifically brown patch) for use in North Carolina, USA using presently available brown patch forecasting indices (F96 and S94). A secondary objective was to determine whether off-site, regional weather observations or weather model forecast output might serve as a suitable proxy for on-site observations for use in brown patch forecasting systems. To summarise the performance of all the brown patch forecasting indices tested with the brown patch forecasting system, several skill scores have been calculated (Table 6). The false alarm ratio (FAR) is the ratio of warnings without events to total warnings, the probability of detection (POD) is the ratio of warned events to total events, and the critical success index (CSI) is:

$$\mathrm{CSI} = \frac{1}{(1 - \mathrm{FAR})^{-1} + \mathrm{POD}^{-1} - 1} \qquad (2)$$

As shown in Table 6, high FARs and low PODs and CSIs were obtained for the study period. This is not desired in an operational system. An attempt was therefore made to use a lower threshold for E_2 and E_6 indices to increase the POD, but this caused the already high FARs to increase even more, lowering the utility of the indices (not shown).

While it is apparent that the brown patch forecasting indices used within the system will need some modification, it appears likely from the results of this study that using both off-site, local weather observations and forecasted weather conditions with brown patch forecasting systems can serve as an adequate proxy for on-site weather observations. Calculation of correlation coefficients between the TFL-E_{2h} index and the RDU-E_{2h} index, Eta 24-h-E_{2h} index, and Eta 48-h-E_{2h} index provides values of 0.944, 0.872, and 0.873, respectively. The indices correlate well with one another, implying that observations of relative humidity and minimum temperature are also well correlated. More specifically, the correlation coefficient for hourly temperature readings between TFL and RDU is about 0.906, with a mean absolute difference between hourly temperature readings of less than 1.3 °C. This degree of correlation indicates that, in this case, spatial variability in the disease indices is of secondary importance, and the primary concern is the actual formulation of the model.

5.2. Utility of the system

To assess the utility of the forecasting system, a fungicide application schedule was developed based on disease warnings produced by each index for two different protection intervals: seven days and 14 days. Additionally, fungicide application schedules were developed for a calendar-based, continuous protection schedule, and for a 'perfect' forecast system (one developed in hindsight based on actual disease observations). The hypothetical application schedules are summarised in Table 7. Calendar-based schedules using the two protection periods required five fungicide applications using a 14-day schedule and 10 applications using a seven-day schedule.

Using TFL-derived E_6 indices to create fungicide application schedules, a 14-day fungicide would have resulted in the same number of applications used in the calendar-based system, while leaving the turf unprotected on four (E_{6h}) or five (E_{6m}) days, respectively, when brown patch was observed. Using the RDU-derived E_6 index would have resulted in 14- and seven-day fungicide application schedules that both would have left the turf unprotected on five days when disease was observed, while saving one and two fungicide applications over the 14- and seven-day calendar-based schedules, respectively.

Application of a fungicide with a 14-day protection interval based on the TFL-E_{2h} index would have saved

Table 7. *Hypothetical fungicide application schedules using a calendar-based system, a 'perfect' system (one created in hindsight based on actual disease observations), and systems based on all of the disease indices, using two different minimum spray intervals (a) 14 days, and (b) 7 days). X indicates that an application was not necessary.*

(a)	14-day minimum spray interval										
Application	Turf				RDU			Eta			
	E_{6m}	E_{6h}	E_{2m}	E_{2h}	E_6	E_{2m}	E_{2h}	24-h E_{2h}	48-h E_{2h}	calendar	'perfect'
1	6/8	6/8	6/16	6/8	6/8	6/16	6/8	6/16	6/13	6/8	6/12
2	**7/1**	**6/30**	**7/2**	**7/1**	**7/2**	**7/1**	**6/28**	**7/2**	**7/2**	**6/22**	**7/11**
3	7/18	7/14	7/23	7/18	7/22	7/19	7/13	7/22	7/29	7/6	7/27
4	**8/1**	**7/29**	**8/10**	**8/1**	**8/5**	**8/2**	**7/29**	**8/7**	**8/12**	**7/20**	**8/13**
5	8/15	8/15	X	8/16	X	8/16	8/13	X	X	8/3	X

(b)	7-day minimum spray interval										
Application	Turf				RDU			Eta			
	E_{6m}	E_{6h}	E_{2m}	E_{2h}	E_6	E_{2m}	E_{2h}	24-h E_{2h}	48-h E_{2h}	calendar	'perfect'
1	6/8	6/8	6/16	6/8	6/8	6/16	6/8	6/16	6/13	6/8	6/12
2	**6/15**	**6/15**	**7/2**	**6/15**	**6/19**	**7/1**	**6/15**	**7/2**	**7/2**	**6/15**	**6/19**
3	7/1	6/30	7/23	7/1	7/2	7/19	6/28	7/10	7/14	6/22	7/11
4	**7/13**	**7/13**	**7/30**	**7/13**	**7/13**	**7/30**	**7/13**	**7/22**	**7/29**	**6/29**	**7/18**
5	7/29	7/29	8/10	7/23	7/22	8/10	7/23	7/29	8/7	7/6	7/27
6	**8/5**	**8/5**	**X**	**7/30**	**7/29**	**X**	**7/30**	**8/7**	**X**	**7/13**	**8/2**
7	8/15	8/15	X	8/8	8/5	X	8/6	8/14	X	7/20	8/13
8	**X**	**X**	**X**	**8/16**	**8/14**	**X**	**8/13**	**X**	**X**	**7/27**	**X**
9	X	X	X	X	X	X	X	X	X	8/3	X
10	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**8/10**	**X**

no fungicide applications and would have left the turf susceptible on six of the 23 days when brown patch was observed. A seven-day protection interval would have resulted in eight fungicide applications, saving two over the calendar-based schedule, but leaving the turf unprotected on five days during which brown patch actually developed. Had a 14-day application schedule been based on the RDU-E_{2h} index, the turf would have been left vulnerable on five days when disease was observed, while an E_{2m}-based schedule would have left the turf vulnerable on six days when disease was observed. Seven-day application schedules based on RDU-E_{2h} and RDU-E_{2m} would have resulted in unprotected turf on four and 12 days, respectively, when brown patch occurred.

Basing fungicide application schedules on the RDU-derived Schumann model would have called for five applications for a 14-day application interval and six applications for a seven-day application interval. Using these schedules would have resulted in unprotected turf on three and 10 days, respectively, when disease was observed. While the 14-day Schumann model based schedule did not reduce applications over the 14-day calendar-based schedule, the seven-day index-based schedule saves four applications, but allows for an unacceptable level of disease incidence.

One way to assess all of the above fungicide application schedules is to compare them to a hypothetical 'perfect' schedule, or one created in hindsight based on actual disease occurrence. A schedule based on a fungicide effectiveness of 14 days would require four applications, while one based on a seven-day efficacy would require seven applications. Given these results, it is apparent that there is room for improvement over the current indices, and that the creation of an appropriate index would result in fewer applications than a calendar-based system (four and seven applications versus five and 10 applications).

5.3. Future work

Ongoing research is being directed at developing a new, region-specific disease index, similar to the multiple-regression technique used in the development of F96. The experiment described above will be repeated using only on-site weather observations to best determine the meteorological conditions most favourable for the formation and spread of brown patch in central North Carolina. Once the current system has been enhanced, the next step will be to determine if, using an accurate epidemiological model, off-site or model-predicted meteorological information can be used as a suitable proxy for on-site weather observations.

When the system begins to provide suitably accurate predictions, output will be made available in graphical form on the North Carolina State Center for Turfgrass Environmental Research and Education website (http://

www.turffiles.ncsu.edu/) to help turfgrass managers determine whether or not to apply fungicides for brown patch.

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