The impact of fungicide treatment and Integrated Pest Management on barley yields: analysis of a long term field trials database

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Abstract

This paper assesses potential for Integrated Pest Management (IPM) techniques to reduce the need for fungicide use without negatively impacting yields. The impacts of three disease management practices of relevance to broad acre crops –disease resistance, forecasting disease pressure, and fungicide use – were analysed to determine impact on yield using a long-term field trials database of Scottish spring barley, with information from experiments across the country regarding yield, disease levels, and fungicide treatment. Due to changes in data collection practices, data from 1996 – 2010 were only available at trial level, while data from 2011 – 2014 were available at plot level. For this reason, data from 1996 – 2014 were analysed using regression models, while a subset of farmer relevant varieties was taken from the 2011- 2014 data, and analysed using ANOVA, to provide additional information of particular relevance to current farm practice. While fungicide use reduced disease severity in 51.4%of a farmer-relevant subset of trials run 2011 – 2014, and yields were decreased by 0.62t/ha on average, this was not statistically significant in 65% of trials. Fungicide use had only a minor impact on profit in these trials, with an average increase of 4.4% for malting and 4.7% for feed varieties, based on fungicide cost and yield difference; potential savings such as reduced machinery costs were not considered, as these may vary widely. Likewise, the1996 – 2014 database showed an average yield increase of 0.74t/ha due to fungicide use, across a wide range of years, sites, varieties, and climatic conditions. A regression model was developed to assess key IPM and site factors which influenced the difference between treated and untreated yields across this 18-year period. Disease resistance, season rainfall, and combined disease severity of the three fungal diseases were found to be significant factors in the model. Sowing only highly resistant varieties and, as technology improves, forecasting disease pressure based on anticipated weather would help to reduce and optimise fungicide use.

I. Introduction

Fungicides are widely used in arable agriculture to reduce disease burden and its impact on yields and quality, yet the effect of fungicides on yield is far from clear. While some field studies show overall increases in yield (Kelley 2001working on winter wheat; Paul et al. 2011, maize; Willyerd et al. 2015, winter wheat), others find no increase (Poysal, Brammallz, and Pitblados 1993, tomato; Swoboda and Pedersen 2008, soybean), and many present highly mixed results (Cook et al. 2002, wheat; Cook and King 1984, barley and wheat; Gaspar et al. 2014, soybean; Mycroft 1983, barley and wheat; Priestley and Bayles 1982, barley and wheat; Wiik 2009, winter wheat). Given that intensive fungicide use also has a variety of concurrent detrimental effects, such as negative impacts on soil health and soil ecosystems (Chen et al., 2001; Walia et al., 2014), and non-target toxicity linked to biodiversity loss in agricultural areas (McLaughlin & Mineau, 1995; Robinson & Sutherland, 2002; Geiger et al., 2010), alternative approaches to managing pests and diseases are increasingly sought after. One such alternative is Integrated Pest Management (IPM), an ecosystem based approach, first proposed by Stern et al. (1959), which combines diverse management practices in order to minimize the use of pesticides while protecting crops from pests and pathogens. IPM is an ecosystem approach which combines diverse management practices in order to minimize the use of pesticides while protecting crops from pests and pathogens (FAO 2017), and has been found to improve the overall environmental sustainability of farms, as compared to conventional pesticide use situations (Lefebvre, Langrell, and Gomez-y-Paloma 2014). IPM can encompass a number of techniques to reduce pathogen population levels or impact on crops, including spraying pesticide where appropriate, crop rotation, varietal disease resistance, forecasting disease pressure, adjusting product dose and timing, sowing early/late in the season, and monitoring disease in field so that inputs can be adjusted accordingly.

In order to target and reduce fungicide inputs, while maintaining high yields, it is necessary to understand under what conditions (i.e. weather, varietal resistance level, previous crop, etc.) fungicide application impacts yields. Applications can then be tailored to situations where a yield increase is likely to occur, and eschewed when yield is unlikely to be impacted. An understanding of the situations in which various IPM strategies impact yields is also necessary, in order for uptake of these techniques to be optimised.

Proving direct links between fungicide use, yields, management strategies, and disease is difficult. For example, several experiments on wheat have linked fungicide use to yield increases. Work on fungicide control of powdery mildew (caused by *Blumeria graminis* f. sp. *tritici*) and septoria (caused by *Zymoseptoria tritici*) diseases found wheat yield increases of up to 2.7 t/ha (Jørgensen et al., 2000). Cook and King (1984) conducted field surveys of winter wheat, and found yield responses to fungicide use of up to 89%, with the most damaging leaf disease being mildew. However, many experiments have reported inconsistent results – in wet conditions, for example, fungicide use increased yields in winter wheat grown in the US, while in dry years this was not seen (Wegulo et al., 2012). In a long-term field experiment on wheat in Sweden, only 52% of the years between 1983 and 2007 showed significant increases in yield from fungicide use (Wiik & Rosenqvist, 2010). Priestley and Bayles (1982), working on spring barley in England found that yield impact from fungicide use varied between years from a 2.4% increase in yield to 13.8%. The relationship between fungicide use, reduced disease, and increased yields therefore remains unclear, complicating management decisions. A number of factors likely contribute to this variation, including disease development, changes in yield potential, disease tolerance in the crop (Bingham et al. 2009), and the physiological effects of fungicide on barley, which may be beneficial even in the absence of disease (Bingham et al. 2012).

Analysing data collected across a range of sites, in different fields, with different weather conditions, and different management practices, can offer useful insight into which factors are most influential in determining the impact of treatment on yield. Much of the literature on the use of key IPM techniques is based on experiments running for less than five years (e.g. Makowski et al. 2005 working on sclerotinia in French oilseed rape; (Loyce et al. 2008) working on diseases of French winter wheat; (Mazzilli et al. 2016) working on wheat in Uruguay). The work by Twengström et al. (1998) and Yuen et al. (1996) on sclerotinia stem rot of oilseed rape is an example of an attempt to link yield and disease, providing both a forecast of the likely disease severity and a risk algorithm, and considering a range of factors, including crop rotation, rainfall, and previous disease incidence. Here, each factor was assessed first in an individual regression, then a full model was compiled, including all terms, and a given factor removed to determine whether or not its inclusion improved the model’s ability to predict epidemics (Twenström et al. 1998). While this work provided a useful tool for farmer decision making, one issue which was specifically raised by Twengström was the lack of data going back further than six years – longer term experimental work was suggested as a way of improving predictive power. While few studies on long-term data have thus far been conducted which explicitly test the impact of fungicide use on yield and disease levels, Wiik and Ewaldz's (2009) work on winter wheat in Sweden using data from 1983 – 2005, followed by further analysis done by Wiik (2010) of the data for 1977 – 2005 are notable exceptions, and both suggest that yield increases from fungicide treatments are highly variable. Maximum yield increase from a single fungicide treatment in 1983 – 2007 was found to be 1.9 t/ha and minimum yield increase was under 0.3 t/ha (Wiik & Ewaldz, 2009). Similarly, Cook and Thomas (1990), working on winter wheat in the UK, saw large fluctuations in yield response to fungicide across years, with one fungicide application per season leading to average yield increases of 0.77 t/ha in 1985, but as little as 0.38 t/ha in 1984. Due to this variability, calls have been made for further analysis of long-term field trials which compare yield, disease, and treatment, to allow optimisation of fungicide use (Wiik, 2009).

Long-term databases can potentially provide useful information regarding IPM efficacy, as data can be collected in a number of weather and agronomic situations, within the same region. However, assessing long-term data can be problematic, as data collection and storage methods are likely to have changed over time, especially where the data has been initially collected for purposes other than long-term analysis. In addition, the institutional funding and dedication required to produce long-term datasets is often lacking, due to other institutional pressures. Long-term datasets therefore often provide information with varying levels of quality and consistency (Clutton-Brock and Sheldon 2010). Despite these drawbacks, the use of long-term data continues to be considered a useful way of teasing apart complex relationships and causality in ecological studies (Clutton-Brock and Sheldon 2010; Lindenmayer et al. 2012), and, along with information regarding between-year weather variation, can therefore provide a useful starting point for considering disease prevention.

The present study makes use of a long-term field trials database collected regarding spring barley in Scotland to assess the impact of spraying fungicide and implementing IPM on crop yields. Barley is one of the most widely grown crops in the world, with an average of 53,572,792 hectares harvested each year, globally (FAOSTAT, 2013), and is of particular importance in Scotland, where spring barley is the main cereal crop, accounting for approximately 50% of arable land (excluding permanent grassland) in 2016 (Scottish Government, 2016b). The key pests of barley are fungal pathogens, which have been estimated to cause a total yield loss of 15% worldwide (Oerke and Dehne 2004) and 14% in the USA (James, Teng, and Nutter 1991). To combat these diseases, a total of 187,173 kg of fungicide was applied to Scottish spring barley in 2014 representing 42% of the total amount of pesticide applied to the crop (Scottish Government 2014). Fungicide use in Scottish spring barley therefore provides a useful case study opportunity to assess the potential for reducing pesticide use, in a system which is of both local and global importance.

Three fungal diseases of particular importance to spring barley production were assessed as part of this work: mildew (caused by *Blumeria graminis* formae specialis *hordei*), Rhynchosporium (caused by *Rhynchosporium commune*) and Ramularia (caused by *Ramularia collo-cygni*). Humidity has been proposed as a key risk factor for all three diseases (mildew: Channon, 1981; Rhynchosporium: Ryan & Clare, 1975, Salamati & Magnus, 1997 ; Ramularia: Havis et al, 2012). Similarly, temperatures between 15 and 21°C have been identified as a risk factor (mildew: Polley and King, 1973; Rhynchosporium: Salamati & Magnus 1997, Ryan & Clare, 1975, Xue & Hall, 1992; Ramularia: Havis et al., 2015).

Reducing fungicide use – if this can be achieved without impacting yields – could offer an opportunity to reduce the negative environmental and health impacts associated with crop production. This study aims to identify key management and environmental factors which drive yield difference between sprayed and unsprayed spring barley. A basic economic analysis is also presented to assess the potential impact on farmer's profits, had they opted not to use fungicides in 2011 – 2014, providing insight into what is likely to be a key driver of farmer behaviour.

II. Materials and methods

a) Field Trials data as a platform for analysis

Data has been collected from field trials at a range of locations across Scotland since 1983 regarding yield, disease levels and fungicide treatment, along with a range of other management factors. As the trials included widely used cultivars across this period, the Field Trials database can provide a particularly farmer-relevant set of analyses. After an extensive review of the Field Trials database, information from 1996 (the year in which reports began to be stored electronically) onwards was retrieved for analysis; due to quality issues in the older data, this paper analyses solely the information from 1996 - 2014 (see Table 1 for a summary of the geographical spread of this database).

Trials used a randomised block design with three or four replicates per trial and plots ranging in size from 20 to 40m^2. For each block within the trial, data for one untreated plot was recorded in the database, alongside one fungicide treated: the 'best practice' treatment for that year as determined by expert opinion (obtained from the lead plant pathologist at

Scotland's Rural College [SRUC], based on the results from the larger trials programme from which this data set is extracted), allowing direct comparison of within-block differences between treated and untreated plots. The 'best practice' treatment varied in chemistry, timing, and number of applications between years and locations across the database. For each trial in the Field Trials database, information is recorded about key farm management features (e.g. varietal selection, preceding crop, sowing date, etc.), fungicide use information (type, dose, and timing of application), disease information (percentage disease severity for a number of key diseases at several growth stages during the crop growing season), and yield. The number of disease assessments and the growth stages at which these were measured during the growing season varied between trials, and by year and location. Trials were assessed for disease at each application timing and usually 2-3 weekly thereafter until the crop was senesced (less than 50% green leaf area on last remaining leaf). Though data regarding the quality of the barley yield was collected for some trials, this was not consistently recorded throughout the database, and so is not considered in these analyses.

Table 1: Summary of the geographical spread across Scottish Government sub-regions in the 1996 – 2014 database

	Clyde Valley	Dumfries & Galloway	Fife	Lothian	North East	Scottish Borders	Tayside	Total trials in this year
1996				4		3		7
1997						1		1
1998				7				7
1999		1		2		2		5
2000				3		1	1	5
2001						1	1	2
2002				1			1	2
2003		2		1		1	1	5
2004		3	2	4			2	11
2005			1		1		1	3
2006						3	1	4
2007				2		3	1	6
2008						1		1

	Clyde Valley	Dumfries & Galloway	Fife	Lothian	North East	Scottish Borders	Tayside	Total trials in this year
2009							3	3
2010				2			1	3
2011	1		1	4			3	9
2012	2		1	6			1	10
2013	4			9			1	14
2014	5			7	1		1	14

b) **Data collection and preparation**

Additional data regarding weather, varietal disease resistance, and area under the disease progress curve were added to the Field Trials database for analysis as described below. Monthly regional weather data for each year were downloaded from the Met Office for the two regions relevant to the trials database; Eastern and Western Scotland (Met Office, 2016). A list of the trial locations in each region is presented in Table 2. As anomaly weather data, showing variation from the mean, were not directly available from the Met office for the growing seasons (March – August, inclusive, based on average growing season within the Field Trials database), mean temperature and rainfall were calculated using Met Office weather data for each region from 1981 – 2010, the most recent baseline available from the Met Office, for the full growing season. Anomaly values were then calculated in accordance with the levels used in the Met Office (2016b) 1981 – 2010 anomaly maps (for more details on the methods used to produce these maps, see Met Office 2016b). A growing season was therefore classed as 'wet' if the percent of average rainfall in that period was 110% or more, and 'dry' if under 90% of the average; it was classed as 'hot' if more than 0.5°C higher than average, and 'cold' if more than 0.5°C colder than average, as per the Met Office anomaly map classes (see Table 3). Additional classifications of 'very hot' and 'very dry', etc. were trialled in initial stages of exploratory data analysis, but due to a lack of variability in the weather, these were not used in the final version of the database.

Table 2: Regions corresponding to trial locations in the 2011 – 2014 database

Region	Trial location	Latitude	Longitude	Average yield (t/ha)	Average sow date
East of Scotland	Burnside BDE	56° 28′ 56.40″ N	003° 27′ 28.99″ W	5.8	75
	Balruddery BRY	56° 28′ 55.77″ N	003° 07′ 48.16″ W	7.1	82
	Balgonie BIE	56° 11′ 02.65″ N	003° 06′ 24.36″ W	6.5	83
	Boghall BLL	55° 52′ 16.78″ N	003° 12′ 29.25″ W	6.6	87
	Cauldshiel CEL	55° 53′ 35.87″ N	002° 50′ 04.68″ W	5.6	76
West of Scotland	Drumalbin DIN	55° 37′ 26.80″ N	003° 44′ 25.73″ W	6.9	93

Table 3: Rainfall and temperature anomalies for each region in the 2011 – 2014 database

Region	Growing season rainfall anomaly value				Growing season temperature anomaly value			
	2011	2012	2013	2014	2011	2012	2013	2014
East of Scotland	Wet	Wet	Dry	Wet	Average	Cold	Average	Hot
West of Scotland	Wet	Wet	Dry	Average	Average	Average	Average	Hot

Varietal disease resistance information was added to the database using the SRUC/Scottish Agricultural College & Home Grown Cereals Authoritycereal recommended lists for Scotland (1996 – 2014). Where a variety was not included in the recommended lists, and therefore could not be compared with other trials, it was removed from the database.

In order to provide a quantitative measure of disease intensity which could be used to assess impact of fungicide use on disease, AUDPC was calculated using the standard trapezoidal method, after Madden et al. (2007), such that:

$$\mathrm{AUDPC} = \sum_{j=1}^{n_j-1} \left(\frac{y_j + y_{j+1}}{2}\right)\left(t_{j+1} - t_j\right)$$

Where *tj* is the sample at a given time point *j*, *yj* is the disease level at the time point *j*, and *nj* is the number of time points. Growing season AUDPC was calculated for each of the three diseases (Rhynchosporium, Ramularia, and mildew) for each trial, as was Total AUDPC (the sum of AUDPC for the three diseases).

In a number of cases for trials prior to 2011, yield and disease severity measurements were recorded only as means for a given treatment, rather than at plot level. Where possible, plot level data was retrieved from old trial reports, but in a majority of cases plot level data was unavailable. A means database was therefore created, running from 1996 - 2014, by taking means of plot level data, where available, in order to render the database internally consistent.

Prior to analysis of the full dataset, a subset of the data chosen for its direct relevance to current commercial farmers was first analysed. This subset comprised the last four years of information available (2011 – 2014), for the varieties which were in use by farmers during this period (as determined by a farmer survey, reported in Stetkiewicz et al. (2018)) to provide information which is relevant to current farmer decision making. Data in this subset was available at individual plot level, which also allows for statistical analysis within trials, something which is not possible for the full dataset, due to the lack of plot level data.

c) **Analysis of the 2011 – 2014 plot level subset**

First, overall mean and median difference in yields between treated and untreated plots in the Field Trials database were calculated using the within-trial block data, which was summarised for the variety. As an assessment of the impact of treatment on trial yields and disease severity, ANOVA was conducted on each individual trial and variety combination, using Genstat 16 (VSN International, 2013), and using within-trial block as the blocking structure. The impact of treatment was tested for yield, mildew AUDPC, Ramularia AUDPC, Rhynchosporium AUDPC, and Total AUDPC. Significance was set at $p<0.05$.

A simple economic analysis was then conducted, using fungicide application cost data (not including labour and machinery costs) from the SAC Farm Management Handbook calculations, which was available for spring barley in 2013 and 2014 (SAC Consulting, 2014; SAC Consulting, 2013). For 2011 and 2012, fungicide cost data was not recorded separately from total treatment costs, which included herbicides, insecticides, growth regulators and trace elements (SAC Consulting, 2011; SAC Consulting, 2012). Fungicide applications represented, on average, 69.2% of the total application costs for the years 2013 – 2016 (SAC Consulting, 2015; SAC Consulting, 2016; SAC Consulting, 2013; SAC Consulting, 2014). The cost of fungicide applications in 2011 and 2012 was therefore assumed to be 69.2% of the total reported treatment costs. Spring barley price information was taken from the AHDB's market data centre, where two-monthly average prices for spring barley were available separately for both feed and malting varieties (AHDB, 2016c). Feed varieties were not included in the Field Trials database for 2013 and 2014, meaning profit margin calculations were not possible for this period. Average Scottish prices for each market type were calculated by year for use in the analysis. This allowed a simple estimate of the difference in profit per hectare between treated and untreated systems to be calculated. The impact of fungicide treatment on difference in profit was assessed across the four years for each variety use type using two-way ANOVA.

d) Absolute yield difference regressions

Models

Stepwise regressions using GLM (generalised linear model) in Minitab 16 (2010) were elaborated for two databases: the full means Field Trials database (1996 – 2014), and the plot level Field Trials database (2011 – 2014). One of the objectives of this work was to compare which variables were included in the final stepwise regression for each of these datasets.

The 2011 – 2014 plot level data gave a high level of detail over a short period of time; this shortened period thus provided less factor variability to test, as there were necessarily a relatively small number of varieties, preceding crops, and weather conditions. Using the full dataset for 1996 – 2014 provided the opportunity to compare a larger number of factor levels, though with means rather than plot level data, and thus is useful for assessing a wider range of potential management situations.

The regression model results presented in this paper are based on the yield difference between treated and untreated plots/trials. For the 2011 – 2014 plot level data, this yield difference was calculated in order to compare within-block treated and untreated yields; for the 1996 – 2014 means database, data were not available for within-block comparisons, and so yield differences are analysed at trial level (each trial was comprised of one variety of spring barley). For a summary of the data types and analysis, see Table 4.

The variables included in the stepwise regressions were: sowing date; preceding crop – barley or non-barley; any resistance – disease resistance rating of seven or more to at least one of the three diseases; AUDPC; and season rainfall and temperature anomaly levels of wet/dry/average and hot/cold/average, respectively. A normal error distribution and identity link function were used, as residuals were distributed relatively normally, as determined by a review of standardized residual histograms and half-normal plots. Errors likely to arise due to aliasing were identified, and these interactions were excluded from the analysis. Random effects were unable to be fitted in the model.

While models were developed to consider the three individual diseases, in a majority of instances, a lack of data for mildew AUDPC through incomplete field recording meant trials without this information were removed from the analysis, rendering the results from these regressions misleading. As such, the results presented in this paper represent only those models which assessed Total AUDPC, rather than individual disease AUDPC.

Table 4: Summary of data types and analysis for each dataset

	1996 - 2014 dataset	2011 - 2014 dataset
Data available at	trial level	plot level
Data for	all varieties trialled in this period	only farmer-relevant varieties
Analysis	stepwise regression	stepwise regression
		within-trial ANOVA

III. Results

a. 2011 – 2014 plot level initial analysis

Fungicide treatment does not significantly impact yield in the majority of trials

Though treated plots had, on average, higher yields than untreated by 0.62 t/ha (see Table 5), the majority of trials (65%) did not show a statistically significant impact of fungicide treatment on yields. In cases where disease was present, disease severity, particularly Total AUDPC, was more likely than yield to be reduced by the fungicide treatment (see Table 6, below). The significance of treatment impact on yield varied across years and locations, with 2013 (the only one of the four years with a growing season classed as 'dry' in both East and West Scotland) having no trials showing a significant impact. Not all diseases were present in every trial; the majority of instances where disease was not recorded occurred in trials where treatment did not significantly impact yields.

Table 5: Mean and median of the treated and untreated yields and the difference between treated and untreated yields of spring barley

	Mean yield (t/ha)	Standard error of mean (t/ha)	Median yield (t/ha)
Untreated	6.23	0.11	6.38
Treated	6.84	0.12	6.82
Difference	0.62		0.44

Table 6: Significance of impact of fungicide treatment on yield and disease severity*

	Number of trials significantly different	**Number of trials not significantly different**	**Percent of trials significantly different****	**Number of trials with no disease pressure**
Yield	14	26	35.0	
Total AUDPC (all diseases)	19	18	51.4	3
Rhynchosporium AUDPC	17	19	47.2	4
Ramularia AUDPC	13	13	50.0	14
Mildew AUDPC	6	11	35.3	23

*Significance at $p<0.05$

**Trials with no disease pressure (a value of zero) are not included in percentage significantly different, nor in the number of trials (not) significantly different

Fungicide use increases profit only marginally

The simple economic analysis conducted compares the mean reduction in yields from a lack of use of fungicide to the cost saved by not purchasing fungicides, and assumes barley quality for treated and untreated is the same. The resulting difference in profit between treated and untreated fields is small, averaging 4.4% (£50.30/ha) for malting varieties and 4.7% (£56.80/ha) for feed varieties (see Table 7). Fungicide cost margins do vary by year, with malting varieties having, for example, net losses in 2013, compared with the +7.5% difference in profit in 2012. This difference in margin was significant at $p \leq 0.05$ for distilling varieties, but was not significant for feed varieties (see Table 7). This analysis disregards other possible savings from lack of treatment (e.g. lower labour costs).

Table 7: Cost benefit analysis for malting and feed barley from 2011 – 2014 in Scotland, based on Field Trial database yields

	Mean Malting Barley Price (£/t)	Mean Feed Barley Price (£/t)	Difference in fungicide cost margin for malting varieties		Difference in fungicide cost margin for feed varieties	
			£/ha	%*	£/ha	%*
2011	193.1	152.1	83.7	6.1	102.4	8.1
2012	200.1	169.4	79.8	7.6	11.1	1.2
2013	145.4	140.2	−24.4	−2.8	-	-
2014	119.3	115.1	62.0	6.9	-	-
Overall	164.5	144.2	50.3[a]	4.4	56.8	4.7

*Percent difference is based on the treated profits[a] Indicates the relevant difference in cost margin is significant at $p \leq 0.05$

b. Modelling the full 1996 – 2014 dataset

Yield Difference

The mean yield difference between treated and untreated across all trials in the 1996 – 2014 dataset was 0.74 t/ha (standard error: 0.06).

Factors retained in the model for the full 1996 – 2014 dataset

Stepwise regressions developed for the 1996 – 2014 data identified Any Resistance, season rainfall, and disease severity as significant factors (see Table 8). Season rainfall had the highest R^2 when tested individually (12.5%) and when removed from the model (5.7%). Any Resistance had the second highest impact on R^2 (9.5% and 5.5%, respectively), and Total AUDPC, the only other factor included in the model, had the third largest impact (5.2% and 4.3%, respectively).

Table 8: Comparison of R^2 impact of significant factors in the 1996 – 2014 stepwise regressions and individual factor analyses

	Change in R^2 when removed from the stepwise model (%)	R^2 when tested individually (%)
Any Resistance	5.5	9.5
Season rainfall	5.7	12.5
Total AUDPC	4.3	5.2

Regression models - comparisons

The final stepwise models for both the 1996 – 2014 means dataset and 2011 – 2014 plot level dataset included Total AUDPC, though other factors varied between the models (see Table 9). Only the 1996 – 2014 dataset included Any Resistance, for example, while growing season temperature was significant in only the 2011 – 2014 plot level data. For the 1996 – 2014 means dataset there was complete agreement between the stepwise models and the individual factor regressions. The 2011 – 2014 plot level dataset had only one factor which was significant when tested individually, but which did not remain in the stepwise model: growing season rainfall.

Table 9: Final stepwise regressions for each dataset, including Total AUDPC*

	Model 1 – stepwise regression (1996 – 2014) including Total AUDPC			Model 2 – stepwise regression (2011 – 2014 plot level data) including Total AUDPC		
	Significance	**Coefficient**	**Difference to R^2 when removed from model (%)**	**Significance**	**Coefficient**	**Difference to R^2 when removed from model (%)**
Season rainfall	Wet: 0.017 Dry: 0.110	0.2187 −0.186	−5.7			
Season temperature				Hot: 0.009 Cold: N/A	0.291	−3.8
Any Resistance	<0.001	−0.2817	−5.5			
Total AUDPC	<0.001	0.000489	−4.3	<0.001	0.000574	−13.4
Model R^2	21.2%			22.3%		

*Factors highlighted in solid grey were significant in both the stepwise regression model and the individual regressions. Those with grey dots as highlights were significant only individually. Significance was tested at p<0.05.

IV. Discussion

a) Fungicide treatment impact on yield is variable

The mean impact of fungicide treatment on yields from 2011 -2014 was 0.62 t/ha, however, the difference in yield between treated and untreated was statistically significant only 35% of the time. From 1996 – 2014, mean yield difference was 0.74 t/ha. Farmer survey work indicates that most Scottish spring barley farmers estimated the yield benefit from applying fungicides to be between 1 and 2 t/ha (Stetkiewicz et al. 2018), suggesting that if this yield difference is representative, farmers are overestimating the effect of fungicide.

Preliminary economic analysis suggests that increased profit from sprayed fields is in the range of 4.5% for malting barley, considering only the difference between mean treated and untreated yields, and the cost of applying fungicides. When additional factors, such as labour and machinery costs are taken into account, this figure may decrease further. This analysis assumes that all untreated barley in the Field Trials was of sufficient quality for malting, which may be inaccurate. There are, however, instances where fungicide treated yields were substantially (up to 2.01 t/ha) greater than those for untreated plots. In these situations, for example where varietal disease resistance scores are low, or in years of particularly wet weather, the scope for fungicide reduction or elimination is likely limited. Similarly, Wiik and Rosenqvist (2010) found that mean net return from fungicide use on winter wheat in Sweden was 12 euro/ha over the 25 years studied, with mean net return being negative in 10 years and with fewer than half of trials in 11 years being profitable to treat. Recent work on winter wheat in Sweden found that rain, disease severity, soil type and previous crop were able to identify situations where fungicide treatment gave a positive marginal return, and that profitability varied with wheat prices (Djurle, Twengström, and

Andersson 2018). Additional information about the costs, risks, and potential benefits would give farmers more confidence when deciding whether or not to reduce fungicide inputs.

Approximately half of the 2011 – 2014 trials showed a significant impact of fungicide treatment on Rhynchosporium, Ramularia, mildew, and Total AUDPC levels. Fungicide treatment therefore appears to impact disease severity in a large number of trials, but this impact does not translate directly into a significant impact on yield. Disease tolerance, whereby the yield of some genotypes is less affected by a given level of disease than other genotypes (Bingham et al. 2009 working on barley and wheat), may explain some of this variation. Treatment significance varied across year and location, suggesting other factors also impact yield difference, such as, perhaps, soil type and quality. Further, 2013, the driest year, and therefore a year which was not conducive to fungal growth, was also the only year with no trials showing a significant impact of treatment on yield. Previous work on long-term databases of winter wheat has found precipitation, along with temperature, to be a significant factor in predicting yield and disease severity (Wiik & Ewaldz, 2009).

b) Key factors influencing impact of fungicides on yield

The results from the 1996 – 2014 regression model suggest that using season rainfall (perhaps via a model using within-season weather to identify periods of high risk, as done for Sclerotinia stem rot in oil seed rape by Yuen et al. (1996), a project which falls beyond the scope of this paper) as an indicator for likely need to spray fungicide, in conjunction with varietal disease resistance, has the potential to reduce the need for fungicide use while maintaining high yields. In all stepwise and individual factor regression models, regardless of the dataset tested, Total AUDPC was identified as an important factor in terms of yield difference between treated and untreated trials, suggesting that where fungicide use is effective at increasing yields, this may be related to its reduction of disease severity.

High levels of resistance to one or more of the three diseases was also important in both stepwise and individual factor regression models developed for the full 1996 – 2014 dataset. In all cases disease resistance was linked with lower yield differences between treated and untreated trials. That disease resistance buffers the effect of not spraying fungicide is well established in the field trial literature for wheat diseases (Berry et al., 2008; Cook & Thomas, 1990; Martens et al., 2014).

Dry conditions have previously been seen to lower the impact of fungicide use on wheat yields in long-term experiments (Wiik & Ewaldz, 2009), and to be crucial to high yields in Scottish barley (Brown, 2013). Meanwhile, wet periods have been proposed as one of the risk factors for Ramularia (Havis et al., 2015) and Rhynchosporium (Ryan & Clare, 1975; Xue & Hall, 1992) to flourish, as has humidity for mildew development (Channon, 1981), conclusions which are supported by this analysis.

Final stepwise regression models were related to individual factor regressions, following a similar method used to assess risk factors for sclerotinia in oilseed rape using logistic regressions (Yuen et al., 1996). For both datasets, the Total AUDPC stepwise regressions fitted the individual factor regression results well, with five out of the six factors which were significant when tested individually also being retained in the relevant stepwise model (those retained in the 1996 – 2014 dataset analysis: growing season rainfall, Any Resistance and Total AUDPC; those retained in the 2011 – 2014 dataset analysis: growing season temperature, Total AUDPC; season rainfall was significant individually for the 2011-2014 data, but not retained in the model).

c) Parallels and differences in results from the two datasets

The final stepwise models for both datasets using Total AUDPC were similar: each included Total AUDPC and one weather variable (season temperature for the 2011 – 2014 plot level data, and season rainfall for the full 1996 – 2014 dataset), though Any Resistance was only included in the full 1996 – 2014 dataset model. As the only stepwise model for Total AUDPC which contained a factor not significant when tested in an individual regression (season temperature) was that created for the 2011 – 2014 plot level data, it is not clear that plot level information provides a more accurate representation of the factors influencing yield difference than mean, trial-level information. In this instance, means level long-term data seems to provide more useful results for understanding the impact of management and weather factors on yield differences, due to the larger amounts of variation than are seen in the short term database. In future, comparing results from a long-term plot level database and its means counterpart could provide useful data about which is more important in modelling factor impacts on yield.

d) Limitations

A number of limitations to this study exist which are, in large part, due to the difficulties inherent in using a large database which has been collected for other purposes. Few conclusions can be drawn from this work regarding the potential influence of sowing date and preceding crop on disease and yield impacts of fungicide application, due to a lack of variation in the database for these factors. An attempt was made to include early season disease measurements (between GS 24 - 34) as a way of considering disease which provides farmers with a measure to act upon within season, as recommended in previous decision making tools (Burke & Dunne, 2008), however a lack of sufficient data prevented this from inclusion in the regressions analysis. More information regarding these factors, as well as more detailed weather data, linked to each individual farm or county, rather than data compiled at regional level, could provide more insight into the factors of interest.

In addition, the small size of plots included in the Field Trials database (typically 20 x 2m), as compared to the size of a commercial barley field, combined with the fact that the single untreated plot in any given trial block is surrounded by treated plots, may reduce the yield difference between treated and untreated plots by buffering the plot from disease pressure. Within the models themselves, being unable to include random terms, or interactions between terms such as rainfall and temperature (which are unlikely to be fully independent) also restricts the robustness of the results. Assessing diseases at an individual, rather than aggregate level could also provide more precise results, which may be of value in management decisions.

The use of large datasets such as the Field Trials database provides opportunities for analysing variation across a wider range of conditions, but, as many of these long-term data sources were not designed with such analysis in mind, the lack of potentially useful detail is an important trade-off of using such data. Despite these limitations, and though finer detail could no doubt be revealed with additional data, important patterns regarding the impact of fungicide use on yield were detected.

V. Conclusion

Fungicide treatment impacted yield levels significantly in just over one third of the trials assessed from 2011 – 2014, though disease levels were significantly reduced in many cases. The lack of a constant influence on yield, and the minimal cost benefit from fungicide treatment, estimated at less than 5% on average, suggests there may be an opportunity to reduce fungicide use in this sector with little negative impact on yield or profit.

In addition, the yield differences seen in these field trials (on average: 0.62 t/ha for commercially relevant varieties grown from 2011 – 2014 and 0.74 t/ha for all trials in the 1996 – 2014 database) were well below those expected by Scottish spring barley farmers and agronomists (Stetkiewicz et al. 2018). Stetkiewicz et al. (2018) report 71.8% of surveyed farmers and 75% of agronomists estimating the impact of fungicide application to spring barley to be between 1 and 2 tonnes per hectare – well above the impacts reported here. Farmers and agronomists therefore appear to be substantially overestimating the impact of fungicide use on yield.

Using the final stepwise regression model developed for the full 1996 – 2014 dataset testing Total AUDPC, and the individual regressions for this data, three factors appear to be crucial in determining the impact of fungicide treatment on yield in the Field Trials database: season rainfall, disease resistance, and Total AUDPC. Ranked by R^2, season rainfall explains the most variation in yield difference, followed by Any Resistance, and Total AUDPC. As fungicide use did not always result in increased yield, and the increases which did occur were often minimal, forecasting disease severity for the season and acting upon this, e.g. planning to spray when the season is forecast to be wet and reducing spraying when dry, may help to rationalise fungicide use, given that the alternative of waiting until a disease appears before treating would preclude the use of preventative fungicides, and restrict available products to those with curative action. Similarly, sowing only spring barley varieties which are highly resistant to one or more key diseases may reduce the need for fungicides. The inclusion of Total AUDPC as a key factor highlights the fact that disease severity is important in yield dynamics; this may be managed within season through a combination of techniques, including fungicide applications. Other IPM measures, such as rotation and sowing date, may play a role in determining yield impacts of fungicides, but could not be fully assessed here, due to lack of variation. These models provide a useful tool for assessing the relative merits of different IPM techniques on yield and allow farmers and decision makers to prioritise acting on those which have a significant explanatory effect, such as sowing highly disease resistant varieties.

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VII. References

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