Crop Protection 99 (2017) 17–25

Contents lists available at ScienceDirect

Crop Protection

journal homepage: www.elsevier.com/locate/cropro

Predicting potential winter wheat yield losses caused by multiple disease systems and climatic conditions

Radivoje Jevtić [a, *], Vesna Župunski [a], Mirjana Lalošević [a], Ljubica Župunski [b]

[a] *Institute of Field and Vegetable Crops, Maksima Gorkog 30, 21000 Novi Sad, Serbia*
[b] *University of Novi Sad, Faculty of Technical Sciences, Trg Dositeja Obradovića 6, 21000 Novi Sad, Serbia*

ARTICLE INFO

Article history:
Received 5 December 2016
Received in revised form
11 April 2017
Accepted 3 May 2017

Keywords:
Puccinia
Blumeria
Zymoseptoria
Regression models
Yield loss
Winter wheat

ABSTRACT

Yield losses in field crops are most commonly predicted by using regression models that include either biotic or abiotic factors as predictor variables. Knowing that yield loss is a complex trait, the potential capability of regression models for predicting yield losses by using models containing both biotic and abiotic factors as predictors were estimated in this study. Biotic factors considered in regression models were: leaf rust, powdery mildew, septoria tritici blotch and tan spot occurrence on the varieties Barbee and Durumko known to have various degrees of susceptibility to obligate parasites and leaf blotch diseases. Among abiotic factors, monthly averages of temperature, relative humidity and total rainfall taken from November to June for growing seasons 2006–2013 were used as predictors. In 2014, yellow rust became the predominant pathogen over leaf rust, thus 2014 and 2015 were excluded from regression models and analyzed separately. Since a high correlation was found between abiotic and biotic factors, partial least squares regression, stepwise regression and best subsets regression were applied. Best subsets regression revealed that models consisted of both biotic and abiotic factors were more precise in estimating regression coefficients and predicting future responses. The potential yield loss predictions, conducted using these models, were regressed with actual yield losses, and high coefficients of determination ($R^2 = 79\%$ for Barbee; and $R^2 = 63\%$ for Durumko) were obtained. It was also evident that using more predictors in regression models does not necessarily mean that the model would have a higher potential in making yield loss predictions. This study confirms that the relationship between a disease scoring scale and yield loss is not straightforward and higher potentials for yield loss predictions were given due to the regression models using abiotic and biotic predictor variables.

1. Introduction

Wheat (mainly common/soft wheat *Triticum aestivum* but also durum/hard wheat *T. turgidum*) is the world's largest crop in terms of harvested area and ranks third in the global annual production of commodities (FAO, 2012).

Significant concerns have been raised by the scientific community about the impacts of climate change on future yield potentials of wheat. However, in spite of the fact that climatic changes have been emphasized to have impact on wheat yield and quality, not only directly but also due to the interactions with biotic factors, the effects of biotic factors on yield losses have been neglected in recently reported studies (White et al., 2011; Juroszek and Von Tiedemann, 2013).

Among the economically most important diseases affecting winter wheat are obligate parasites (*Blumeria graminis* f. sp. *tritici*, *Puccinia graminis* f. sp. *tritici*, *Puccinia triticina*, *Puccina striiformis* f. sp. *tritici*) and crop residue-borne necrotrophic pathogens (*Pyrenophora tritici-repentis*, *Zymoseptoria tritici*, *Parastagonospora nodorum*, *Cochliobolus sativus*, *Fusarium* species). Although chemical treatment is a very powerful disease-control tool, followed by increases in yield, the main imperative of integrated pest management is environmental protection and reduced fungicide input. Thus, many efforts have been directed on determining damage thresholds and developing mathematical models that can be used to forecast yield losses caused by pathogenic infection. Typically, these experiments are conducted in a few locations during a two or three - year period, but only some of them raise the question about disease dynamics and yield over longer time periods (Wiik, 2009).

* Corresponding author.
E-mail addresses: radivoje.jevtic@ifvcns.ns.ac.rs (R. Jevtić), vesna.zupunski@ifvcns.ns.ac.rs (V. Župunski), mirjana.lalosevic@ifvcns.ns.ac.rs (M. Lalošević), ljubicaz@uns.ac.rs (L. Župunski).

http://dx.doi.org/10.1016/j.cropro.2017.05.005
0261-2194/

In literature, adversarial reports appear regarding correlation between diseased leaf area or any disease scoring scale and yield. For instance, some authors reported linear regression as suitable for describing relationship between disease rating scale and yield loss (Wegulo et al., 2009; Green et al., 2014; Budka et al., 2015), whereas there are also reports that the relationship between the two is not straightforward (Duveiller et al., 2007).

The objective of this study was to evaluate the potential of regression models for predicting yield losses in winter wheat if both biotic (leaf rust, powdery mildew, septoria tritici blotch, and tan spot) and abiotic factors (climatic conditions from November to June) are subjected to the same regression model. The data collected from 2006 to 2015 were analyzed and characterized in terms of agro-ecological conditions of Serbia.

2. Materials and methods

Data were obtained from fungicide efficacy trials which were conducted in the locality of Rimski Šančevi (Vojvodina, north province of Serbia) under the direction of the Institute of Field and Vegetable Crops, Novi Sad, Serbia, over the period of 2006–2015 using soft wheat variety Barbee (*Triticum aestivum* ssp. *compactum*), and hard wheat variety Durumko (*Triticum turgidum* subsp. *durum*). The Barbee variety has shown increased susceptibility to obligate parasites (*Blumeria* and *Puccinia*) while Durumko showed increased susceptibility to leaf blotch diseases (LBDs) such as *Pyrenophora tritici-repentis*, *Zymoseptoria tritici*, and *Phaeosphaeria nodorum* in agro-ecological conditions of Serbia.

2.1. Field trial

Field trials were set up under naturally occurring inoculum and were arranged in a randomized block design comprising four replicates. The plot size of each replicate was 10 m^2. A trial usually included 10 fungicide-sprayed and non-sprayed check treatments. Fungicides were applied at growth stage BBCH 36–37 (flag leaf just visible, rolled) and BBCH 51–59 (inflorescence emergence, heading). Different types of active ingredients such as amides, aromatics, azoles, benzimidazoles, morpholines, oxazoles, strobilurins, pyrazoles and pyridines were applied with recommended dosage rates using calibrated field crop sprayers with fan nozzles, at 300 kPa pressure and 200 L of water per hectare. Mean sowing date for winter wheat was 20 October (optimal time of sowing) and the mean harvest date was 30 June (range 25 June- 07 July).

2.2. Disease assessment

Assessments of leaf disease severity were made at the growth stage 71–73 BBCH (kernel watery; early milk), known to be highly related to yield (Wegulo et al., 2009). Disease severity for leaf rust and powdery mildew was assessed using modified Cobb's scale (Peterson et al., 1948; Corazza and Islongo, 1987). Disease severity of septoria tritici blotch and tan spot were assessed using the disease rating keys devised by James 1971. The disease indices (%) of leaf rust, powdery mildew, septoria tritici blotch and tan spot were calculated by taking into consideration disease incidence and average disease severity (Cao et al., 2014).

2.3. Yield

Yield was measured for each plot after harvest at 15% water content. Yield loss (%) was determined as yield reduction in untreated plots compared with yield response to fungicide treatment which provided the best control of wheat diseases (Eq. (1)).

$$Y(\%) = ((Y_1 - Y_2)/Y_1) \times 100 \tag{1}$$

Y_1 - grain yield of fungicide treatment for the best wheat disease control.
Y_2 - grain yield of the non - sprayed check treatment.

2.4. Predictor variables for regression models

In regression models, the biotic factors regarded as potential predictive variables were disease indices of leaf rust, powdery mildew, septoria tritici blotch and tan spot. On the other hand, abiotic factors used as predictors comprised monthly averages of: temperatures, relative humidity and total rainfall taken from November to June for growing seasons 2006–2013 (http://www.hidmet.gov.rs/). The shift in predominant rust pathogen occurred in 2014, thus a period of 2014 and 2015 was excluded from regression models and analyzed separately.

2.5. Statistical methods

The effects of year, variety and fungicide treatment on yield were examined by analysis of variance (*ANOVA*). Further, multivariate regression models were used to estimate relationship between disease indices, abiotic factors and yield losses. Knowing that abiotic and biotic factors are correlated not just to the yield loss but also with each other (multicollinearity), partial least squares regression, stepwise regression and best subsets regression were applied to make predictions of yield losses in the Barbee and Durumko varieties. Multicollinearity is problematic because it can increase the variance of the regression coefficients, making it difficult to evaluate the individual impact that each of the correlated predictors has on the response. Partial least squares (PLS) is a biased regression procedure that reduces the number of predictors and extracts a set of components that describes maximum correlation among the predictors and response variables. The technique used is similar to principal component analysis because it gives the option of leave-one-out cross-validation, which is used to maximize the model's predictive ability.

In addition, the method that can also be used to analyze correlated predictors is the stepwise regression model. It is used in the exploratory stages of model building to identify a useful subset of predictors. The process systematically adds the most significant variable or removes the least significant variable during each step until it identifies variables that explain the maximum variation in yield loss. Best subsets regression was performed to identify the best-fitting regression models with predictors of choice as well as to compare regression models obtained by PLS and stepwise regression. The general approach was to select the smallest subset that fulfills certain statistical criteria. The reason for using a subset of variables instead of a complete set is because the subset model might actually estimate the regression coefficients and predict future responses with smaller variance than the full model using all predictors. Regression models were followed with coefficient of determination (R^2), coefficient of prediction (R^2_{pred}), variance inflation factor (VIF) and Mallows' Cp. Coefficient of determination (R^2) is the percentage of variation in the response that is explained by the model. Coefficient of prediction (R^2_{pred}) determines how well the model predicts the response for new observations. VIF indicates how much the variance of an estimated regression coefficient increases if predictors are correlated. The VIFs will all be 1 if there is no correlation between factors. Mallows' Cp is used for