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Incidence-Severity Relationships for Sclerotinia Stem Rot of Canola

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ABSTRACT

Sclerotinia stem rot is one of the most damaging diseases of canola in many areas of the world, including Iran. The relationship between disease incidence (I) and severity (S) is important because incidence is quicker and easier to measure than severity. The I-S relationship of SSR of canola was studied in Mazandaran and Golestan provinces, northern Iran. Statistical analyses were performed on data collected from 80 fields in four different regions (Galogah, Ali Abad, Dashte Naz, and Gonbad) during two consecutive years (2010 and 2011). Results of linear regression analyses using raw and ln, complementary log-log, and sqrt transformed data showed that all of four models could appropriately describe the *I-S* relationships in this pathosystem. Comparisons of parameters showed that slope of linear and sqrt models for Gonbad region was significantly ($P < 0.05$) different from other regions. Based on residual plots and lack of fit tests, allometric (ln of I and S) model had the best fit with evaluated disease intensities. SSR severity can be calculated with equations $S = (0.526)\ I^{(1.2)}$ and $S = (0.819)\ I^{(1.07)}$ for Gonbad and other three regions, respectively.
KEYWORDS*:* *Sclerotinia sclerotiorum, Brassica napus*, Sclerotinia stem rot, epidemiology, *I-S* relationships

INTRODUCTION

Sclerotinia stem rot (SSR), caused by *Sclerotinia sclerotiorum*, is one of the most damaging diseases of canola (*Brassica napus*) in the world [1, 2]. In Iran, SSR is observed mostly in canola growing areas in the northern provinces, especially Mazandaran and Golestan. Barari et al [3] surveyed the areas of Mazandaran province and found the disease was present in all canola growing areas, with an average incidence of 12.3 to 54.4%. SSR incidence in the Golestan province ranged from 1 to 82% and from 3 to 78 % in 2010 and 2011, respectively. Yield loss of canola in the province due to SSR was assessed as 0.3 to 34.7% [4].

Disease incidence is defined as the proportion (0 to 1) or percentage (0 to 100) diseased entities within a sampling unit, whereas, severity is the quantity of disease affecting entities within a sampling unit. Severity is defined as the area (or volume) of plant tissue affected by disease [5]. Incidence is generally perceived to be quicker and easier to assess than severity, and assessments for incidence are often more accurate, precise, and reproducible than measures of severity [6]. Assessment of disease severity under field conditions is tedious, costly, and time-consuming, and may be prone to bias and experimental error [7]. Even when standard area diagrams and other types of severity assessment keys and scales are used to facilitate disease assessment, inaccurate severity assessments may still occur [8]. Despite these drawbacks, disease severity is often considered to be a more important and useful measure of disease intensity than disease incidence for quantification of yield loss and for determining the effectiveness of disease management strategies. Therefore, a model of the quantitative relationship between incidence and severity could greatly facilitate the evaluation of disease intensity when the accuracy of disease severity assessments is questionable or not available [9, 5,10].

Models quantifying the relationships between incidence and severity [11,12,13,9,10,14] and relationships between these measures of disease intensity at different spatial scale hierarchies [15,16 ,17,18,14,19] have been developed in several pathosystems. These relationships differ from one pathosystem to another and may be influenced by the cultivar and plant organ (sampling unit) assessed, time of disease assessment during an epidemic, growing season, location and treatments applied to the assessed plots (experimental units) [5]. Thus, it would be important to use these models to quantify and understand the relationship between incidence and severity of diseases prior to applying them over multiple years and locations under a range of cropping/management scenarios to ascertain which model best provides consistently strong relationships between incidence and severity of diseases [20].

Relationships between disease incidence (I) and disease severity (S) are described by several different types of models, including the allometric family [$I = aS^b$], restricted exponential family [$I = b\ (1-e^{-aS})$], polynomial family [$I = a + bS^{1/2}$], linear relationship [$S = \alpha + \beta I$] and trigonometrical family [$I = tanh\ (aS)$]. These models point out some limitations in the practical use of incidence-severity relationships. Most limitations derive from the lack of consistency of the model with reference to location, season, stage of epidemic and host genotypes [20].

James and Shih [21] used an exponential equation to describe the incidence-severity relationship in the powdery mildew system of wheat. A linear regression was shown to be appropriate to estimate severity from incidence data, but only until incidence reached 65% within the season; thus the model was not geographically independent, but was dependent on crop cycle.

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Severity estimates can be reliable when made by trained persons who are supported by pictorialized keys and who regularly compare results [7]. The reproducibility of severity estimates among observers is generally poor. Severity estimates as a means to establish damage thresholds for foliar diseases cannot be recommended. For example, a farmer concerned about his crop readily overestimates severity. In practice, there is little objectivity in severity estimates [8,22].

Counting is more precise than estimation, and many studies have relied upon incidence counts rather than on severity estimation. Incidence is determined by following a clear and rigid sampling and counting protocol. The results have been reproducible among researchers, although instruction and training is needed here, as well. At low disease intensity levels, there is often a good correlation between severity and incidence, however, at high disease intensity levels, the relationship between incidence and severity becomes less clear. Much of the early work on incidence-severity relationships was ill-spent because it was aimed at high severities, when it was too late to affect disease dynamics, instead of at low severities to generate more timely disease warnings [22].

Incidence data are binary values which measured by counting. Severity can be measured as an area or proportions of diseased tissues. Both of these data can be analyzed by so-called parametric statistical methods (e.g. analysis of variance [ANOVA] and *t* tests) [23]. Plant pathologists assess severity of most diseases by an ordinal scale (pictorial or descriptive). It is easy to see that, with ordinal scales, differences between the measured values are not interpretable, at least in a quantitative sense. Parametric methods of analysis using statistics based on means, or differences between means (such as ANOVA), and thus, strictly speaking, inappropriate for analyzing data on an ordinal scale. It is possible to transform rating data to develop a disease score (commonly called a disease severity index = DSI) that is analogous to a continuous scale variable with a normal distribution [24].

Relationships between incidence and severity have not studied for SSR diseases on any crops, yet, and for most studies involving SSR, only incidence have been used as a measure of disease intensity. The objectives of this study were to: (i) determine if there is a significant and consistent relationship between incidence and severity of SSR of canola in the Mazandaran and Golestan provinces in north of Iran, and (ii) determine whether severity can be reliably predicted from disease incidence data.

MATERIAL AND METHODS

Disease assessment location

Data used in this study were obtained from 80 canola fields (cv. Hyola 401) in four different regions (Galogah, Ali Abad, Gonbad and Dashte Naz) of the Mazandaran and Golestan provinces in north of Iran (10 fields per region) during two growing seasons (2010 and 2011).

Disease quantification and data analysis

After flowering (during March), canola fields were scouted in a regular program (every week) and disease intensity was recorded. Approximately 500-600 plants per field were randomly selected and assessed for recording SSR intensity. Disease incidence (I) was determined using formula $I = \sum[x/N]$ where x is the number of diseased plants and N is the total number of evaluated plants (Cardoso et al. 2004)[11]. Disease severity (S), which is known sometimes as disease severity index, [20] was estimated as $S = \sum(x_i n_i)/5N$ [11], in which x_i represented disease severity grade based on a descriptive scale (0: no disease, 1: small branch infected, 2: large branch infected, 3: stem at least 50% girdled, 4: plant dead, but some yield is harvested, 5: plant dead, poor yield) [24], and n_i indicates the number of diseased plants on the ith grade of the disease scale [11]. The data were edited to remove observations with no diseased plants (i.e., I = 0 and S = 0), since the I-S relationship is only defined when disease is present.

Modeling the I-S relationship

Disease incidence and severity assessments were first plotted against one another to visually display overall trends. Linear regression analysis was performed to find the mathematical association between incidence and severity of SSR of canola. Four different models (linear, natural logarithm, complementary log-log (abbreviated by CLL), and square root) were used to explain the *I-S* relationships in different years and locations (Campbell & Madden 1990, McRoberts et al. 2003)[6,20]. In the other words, linear regression analyses were performed on the pairs of data as: *I-S*, ln(*I*)-ln(*S*), ln[-ln(1-*I*)]- ln[-ln(1-*S*)], and sqrt(*I*)-sqrt(*S*) for mentioned models, respectively. Regression models evaluated were as follows:

$$S = a + bI \quad (1)$$

$$\ln(S) = a + b\ln(I) \quad (2)$$

$$\mathrm{CLL}(S) = a + b\,\mathrm{CLL}(I) \quad (3)$$

$$\mathrm{Sqrt}(S) = a + b\,\mathrm{Sqrt}(I) \quad (4)$$

Model fit was evaluated based on criteria recommended by Cornell & Berger [25] and Campbell & Madden [6], and their corresponding statistics. All statistical analyses and plotting were performed by StatGraphics Centurion XV Version 15.2.05 (StatPoint Inc.) software. To compare models using different transformations of the dependent variables for goodness-of-fit, predicted transformed S was back-transformed and coefficient of determination (R^2) calculated based on these values (R^{*2}) [6].

RESULTS

Disease intensity

SSR intensity varied across regions and years and within each data set (Fig. 1). Overall, final disease incidence ranged from 0.01 to 0.81, and 0.03 to 0.78 for 2010 and 2011, respectively, and final disease severity ranged from 0.006 to 0.668, and 0.017 to 0.63 for 2010 and 2011, respectively. Averaged final disease incidence ranged from 0.107 to 0.221, for Dashte Naz and Ali Abad regions, respectively, while averaged final disease severity ranged from 0.056 to 0.172, for Gonbad and Ali Abad regions, respectively (Fig. 1).

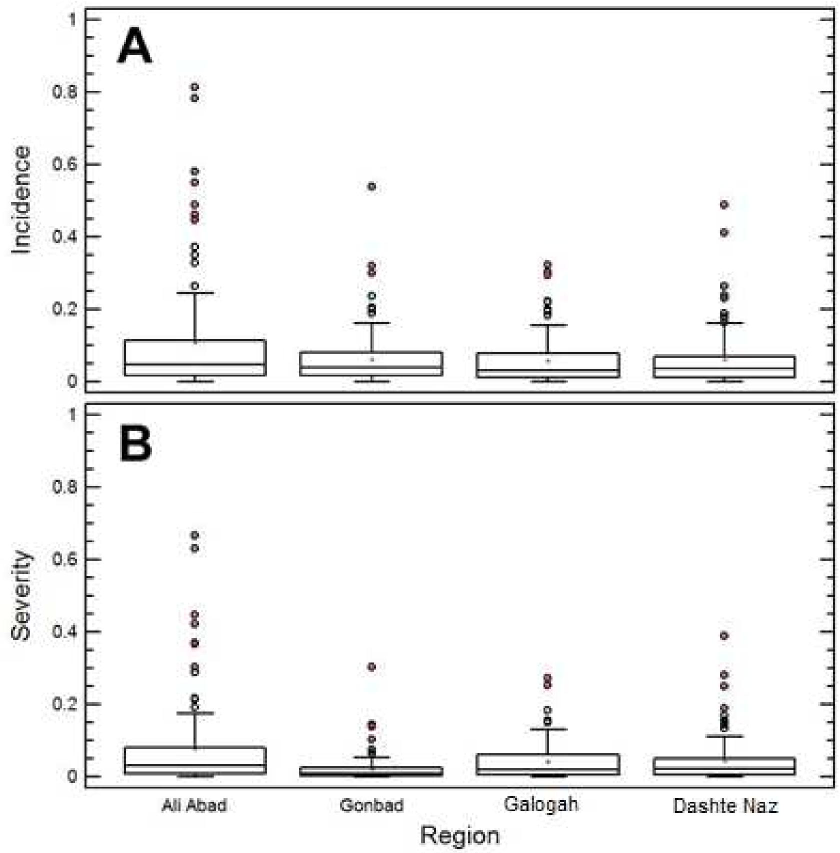

Fig. 1. Box plots summarizing the distribution of A, incidence and B, severity of Sclerotinia stem rot of canola for four regions of Mazandaran and Golestan provinces in Iran during 2010 to 2011. The solid lines within the box represent the median, while the top and bottom lines of the box represent the 75th and 25th percentiles of the data, respectively. Vertical bars extending the boxes represent the 10th and 90the percentiles, and circles indicate outliers.

Modeling the I-S relationship

Based on the value of adjusted coefficient of determination (R_a^2), the linear relationship between raw and three type-transformed disease incidence and severity could appropriately describe the *I-S* relationships in this pathosystem (Table 1). Except for two cases in Gonbad-2010 data set, the R_a^2 values for all regions in two years was greater than 90 percent (Fig. 2).

Both parameter estimates for all of four models were highly significant ($P < 0.0001$) for all data sets (Table 1). Estimated slopes (*b*) and intercepts (*a*) varied somewhat from one data set to another, suggesting a variation in the relationship between *I* and *S* among the regions. Estimated intercepts were -0.013 to -0.002, -0.996 to -0.032, -1.122 to -0.052, and -0.032 to -0.010 for linear, Allometric, CLL and Sqrt models, respectively. Estimated slopes of linear and Sqrt models were significantly ($P < 0.05$) different among the regions (Table 2). In both of cases, estimated *b* values of the mentioned models in Gonbad region were lower than three other regions (Fig. 3). Based on this difference, another series of analyses were performed for Gonbad data during 2010-2011 and for pooled data of other three regions during 2010-2011. In this case, all four mentioned models could appropriately describe the relationships between *I* and *S* (Table 3). Based on *F*-value, R_a^2, and R^{*2}, all four models were acceptable, but based on residual plots and lack-of-fit test, only Allometric and complementary log-log models were accepted (Table 3). Overall, Allometric model (ln transformation of *I* and *S* values) was selected as the best fit model for describing *I-S* relationship in this pathosystem under the conditions of Mazandaran and Golestan provinces of Iran, based on the mentioned statistics and simplicity (Fig. 4).

Table 1. Summary of the regression analyses of the relationship between raw and three different type-transformed disease incidence and severity of Sclerotinia stem rot of canola in four regions of Mazandaran and Golestan provinces, north of Iran, during 2010 and 2011

Region	Year	Obs.	Model[b]	Statistics[c]								
				a	se (*a*)	*b*	se (*b*)	R_a^2	R^{*2}	MSE	*F* value	Residual plot
Galogah	2010	38	Linear	-0.002	0.001	0.803	0.028	0.955	0.956	0.000	790.6	Not OK
			Ln	-0.032	0.170	1.089	0.042	0.948	0.961	0.047	680.5	OK
			CLL	-0.052	0.168	1.085	0.041	0.949	0.961	0.047	683.8	OK
			Sqrt	-0.010	0.005	0.910	0.031	0.959	0.956	0.000	847.0	Not OK
	2011	55	Linear	-0.008	0.002	0.836	0.015	0.982	0.983	0.000	3046.0	Not OK
			Ln	-0.087	0.067	1.112	0.021	0.982	0.987	0.036	2925.2	OK
			CLL	-0.131	0.065	1.103	0.020	0.982	0.988	0.037	2978.0	OK
			Sqrt	-0.024	0.005	0.934	0.016	0.980	0.983	0.000	2716.2	OK
Ali Abad	2010	36	Linear	-0.005	0.004	0.775	0.018	0.980	0.981	0.000	1752.2	Not OK
			Ln	-0.290	0.084	1.035	0.026	0.979	0.983	0.041	1638.6	OK
			CLL	-0.387	0.080	1.011	0.025	0.980	0.987	0.043	1693.9	OK
			Sqrt	-0.011	0.007	0.875	0.020	0.982	0.981	0.000	1868.4	Not OK
	2011	49	Linear	-0.010	0.003	0.778	0.013	0.987	0.987	0.000	3687.1	Not OK
			Ln	-0.158	0.071	1.139	0.023	0.980	0.991	0.044	2356.6	OK
			CLL	-0.283	0.068	1.107	0.023	0.980	0.990	0.048	2363.9	OK
			Sqrt	-0.029	0.005	0.902	0.014	0.988	0.987	0.000	3943.1	OK
Dashte Naz	2010	28	Linear	-0.004	0.002	0.877	0.021	0.984	0.985	0.000	1699.2	Not OK
			Ln	-0.039	0.104	1.078	0.029	0.981	0.988	0.032	1387.0	OK
			CLL	-0.066	0.101	1.072	0.028	0.981	0.988	0.032	1413.1	OK
			Sqrt	-0.015	0.005	0.952	0.022	0.986	0.985	0.000	1935.8	OK
	2011	37	Linear	-0.003	0.002	0.767	0.018	0.980	0.981	0.000	1787.3	Not OK
			Ln	-0.304	0.140	1.029	0.046	0.934	0.981	0.067	507.3	OK
			CLL	-0.364	0.132	1.014	0.044	0.937	0.980	0.068	540.1	OK
			Sqrt	-0.015	0.008	0.894	0.026	0.970	0.981	0.000	1180.8	OK
Gonbad	2010	32	Linear	-0.013	0.004	0.517	0.025	0.934	0.936	0.000	441	Not OK
			Ln	-0.996	0.215	1.035	0.077	0.853	0.942	0.132	181.0	OK
			CLL	-1.122	0.197	1.002	0.071	0.863	0.961	0.130	196.5	OK
			Sqrt	-0.032	0.013	0.708	0.041	0.904	0.936	0.001	293.9	OK
	2011	59	Linear	-0.004	0.001	0.405	0.009	0.974	0.974	0.000	2103.9	Not OK
			Ln	-0.569	0.068	1.234	0.019	0.986	0.984	0.017	4125.9	OK
			CLL	-0.667	0.066	1.212	0.019	0.986	0.984	0.017	4244.4	OK
			Sqrt	-0.028	0.002	0.677	0.011	0.984	0.974	0.000	3619.5	Not OK

a Total number of observations (pairs of incidence and mean severity) used to fit regression models. Observations with 0% omitted from all data sets because then severity is also 0, by definition

b Equations of the models: Linear $\{Y = \beta.I + \alpha\}$, Ln $\{\ln(S) = \beta\ln(I) + \ln(\alpha)\}$, CLL $\{\ln[-\ln(1\text{-}S)] = \beta\ln[-\ln(1\text{-}I)] + \alpha\}$, and Sqrt $\{\mathrm{Sqrt}(S) = \beta\mathrm{Sqrt}(I) + \alpha\}$.

c Estimates of the intercept (*a*) and slope (*b*) of the regression lines; se = standard error of the estimate; R_a^2 = adjusted coefficient of determination; R^{*2} = squared correlation between actual severity and back-transformed predicted severity; MSE = mean square error; and *F* value = *F* statistics from the regression analysis of variance. All *F* values were highly significant ($P < 0.001$), meaning that *b* was different from 0.

Table 2. Analysis of variation for the slope of four models describing the relationship between disease incidence and severity of Sclerotinia stem rot of canola in four regions of Golestan province, north of Iran, during 2010 and 2011

S.O.V.	Df	Mean Square[a]			
		Linear	Ln	CLL	Sqrt
Region	3	0.062 *	0.002 n.s.	0.002 n.s.	0.029 **
Year	1	0.004 n.s.	0.009 n.s.	0.009 n.s.	0.000 n.s.
Residual	3	0.002 n.s.	0.006 n.s.	0.006 n.s.	0.000 n.s.
Total	7				

[a] n.s., *, and ** = nonsignificant and significant at $P < 0.05$ and 0.01, respectively

Table 3. Summary of the regression analyses of the relationship between raw and three different type-transformed disease incidence and severity of Sclerotinia stem rot of canola in four regions of Golestan province (Galogah, AliAbad and Dashte Naz, HAK; Gonbad, G)

Region	Obs.[a]	Model[b]	Statistics[c]									
			a	se (*a*)	*b*	se (*b*)	R_a^2	R^{*2}	MSE	*F* value	Residual plot	Lack of fit[d]
HAK	243	Linear	-0.004	0.001	0.779	0.007	0.982	0.985	0.000	13190.4	Not OK	0.000
		Ln	-0.199	0.042	1.069	0.013	0.968	0.986	0.055	7244.7	OK	0.998
		CLL	-0.273	0.040	1.051	0.012	0.969	0.987	0.057	7402.9	OK	0.999
		Sqrt	-0.015	0.002	0.894	0.009	0.978	0.984	0.000	10594.0	Not OK	0.155
G	91	Linear	-0.008	0.001	0.484	0.013	0.938	0.91	0.000	1362.7	Not OK	0.000
		Ln	-0.642	0.095	1.200	0.029	0.951	0.915	0.067	1753.6	OK	0.078
		CLL	-0.769	0.091	1.169	0.028	0.952	0.908	0.068	1777.2	OK	0.081
		Sqrt	-0.032	0.004	0.699	0.017	0.948	0.892	0.000	1646.1	Not OK	0.000

a Total number of observations (pairs of incidence and mean severity) used to fit regression models. Observations with 0% omitted from all data sets because then severity is also 0, by definition.

b Equations of the models: Linear {$Y = \beta.I + \alpha$}, Ln {$\ln(S) = \beta\ln(I) + \ln(\alpha)$}, CLL {$\ln[-\ln(1-S)] = \beta\ln[-\ln(1-I)] + \alpha$}, and Sqrt {$\mathrm{Sqrt}(S) = \beta\mathrm{Sqrt}(I) + \alpha$}.

c Estimates of the intercept (*a*) and slope (*b*) of the regression lines; se = standard error of the estimate; R_a^2 = adjusted coefficient of determination; R^{*2} = squared correlation between actual severity and back-transformed predicted severity; MSE = mean square error; and *F* value = *F* statistics from the regression analysis of variance. All *F* values were highly significant ($P < 0.001$), meaning that *b* was different from 0.

d *P*-value of Lack of fit test.

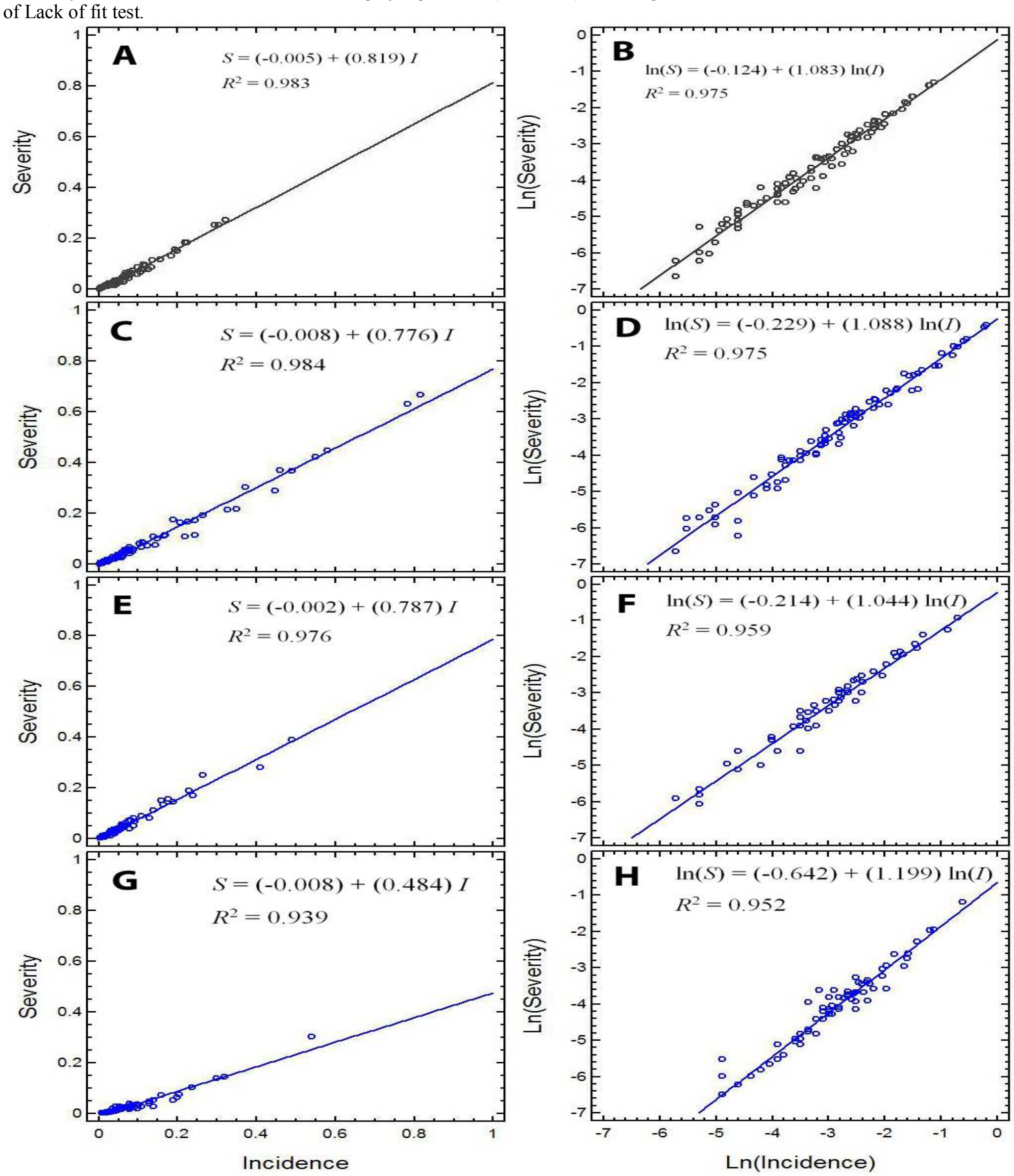

Fig. 2. Relationship between incidence and severity of Sclerotinia stem rot of canola for untransformed (A, C, E, G) and ln transformed (B, D, F, H) data from 40 fields in four regions of Mazandaran and Golestan provinces, in northern Iran during 2010-2011: Galogah (A, B); Ali Abad (C, D); Dashte Naz (E, F); and Gonbad (G, H).

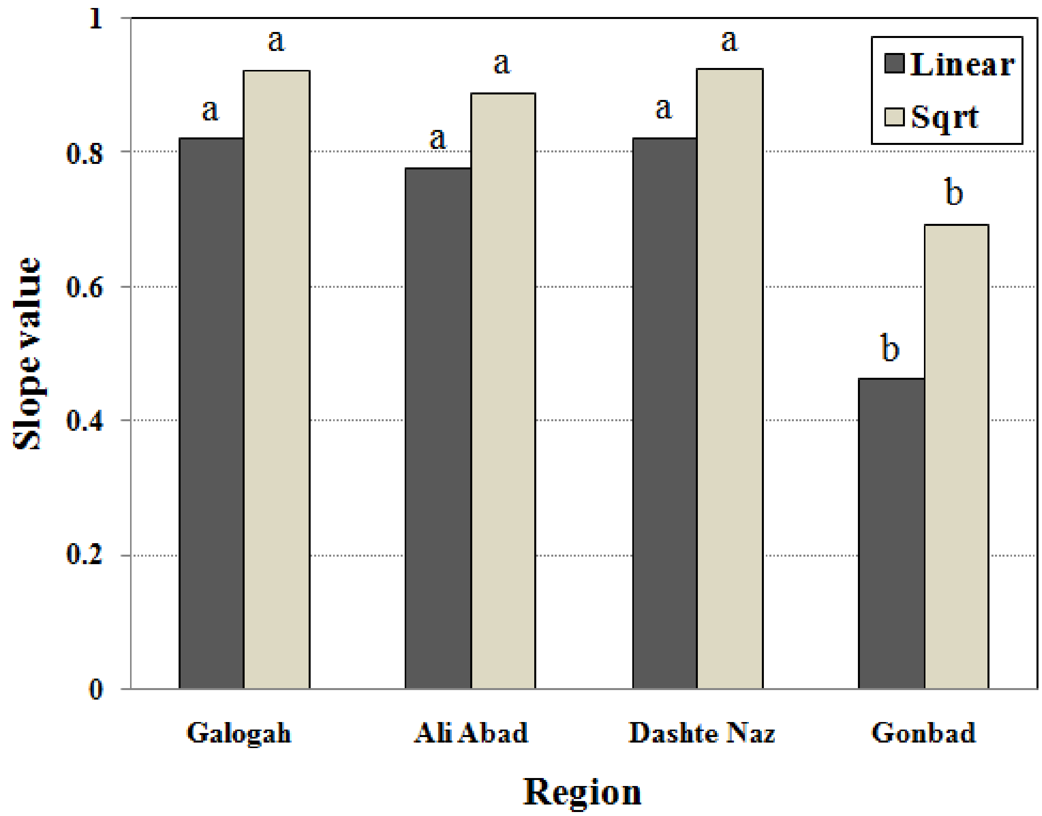

Fig. 3. Comparison of slope of linear and sqrt models for *I-S* relationships in SSR of canola between four regions of Mazandaran and Golestan provinces in Iran during 2010 to 2011

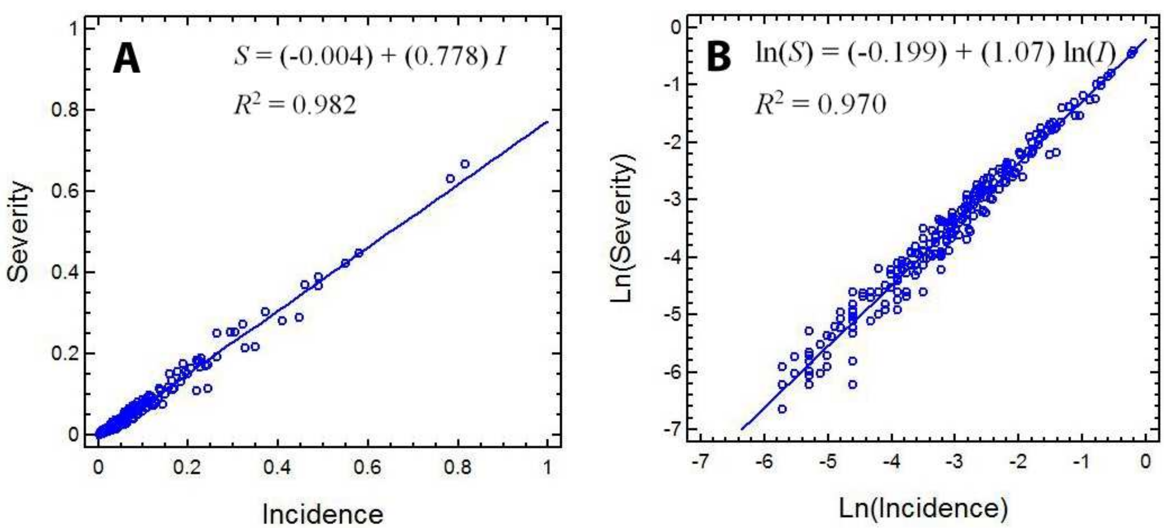

Fig. 4. Relationship between incidence and severity of Sclerotinia stem rot of canola for untransformed (A) and ln transformed (B) data from 60 fields in three regions (Galogah, Ali Abad and Dashte Naz) of Mazandaran and Golestan provinces, in northern Iran during 2010-2011

DISCUSSION

A highly significant ($P < 0.0001$) relationship between incidence and severity of Sclerotinia stem rot of canola was observed for all data sets at each region in each year (Table 1). Despite the variation in severity at a given incidence, the relationship was fairly consistent among data sets. The model based on ln-transformation of incidence and severity (equation 2) performed consistently well on all data sets, explaining between 85 and 99% of the variation in severity on a ln scale. The squared correlation between S and predicted S was between 0.94 and 0.99. As expected, severity was estimated more precisely at lower incidence values than at higher values (Fig. 2 and 4).

It should be noted that a significant relationship does not necessarily mean that precision is high enough for a model to be used for predictions, since achieved significance level is highly influenced by the number of observations (Paul et al. 2005)[9]. In order for the regression evaluation to be useful, the calculated (i.e., achieved) F value statistic from a model fit (Table 1 and 3) needs to be at least four to five times larger than the critical F value (F^*) for a significant result at the chosen probability value (such as $P = 0.05$). With the number of observations being analyzed here (Table 3), $F^* = 3.90$ and 3.96 for a significant fit at $P = 0.05$ for HAK (Galogah, Ali Abad and Dashte Naz regions) and G (Gonbad region) data sets, respectively. The achieved F value were 7244.7 and 1753.6, which were 1857.6 and 442.8 times larger than F^* for HAK and G data sets, respectively. Clearly, by this standard, the fitted ln(S)-ln(I) models had sufficient precision for predictions as well as for describing the relationship between severity and incidence. Based on the statistics (Table 3), final models for estimating SSR severity using incidence are:

$$S = (0.819)\, I^{(1.07)} \quad (5)$$

$$S = (0.526)\, I^{(1.2)} \quad (6)$$

for HAK (Galogah, Ali Abad and Dashte Naz regions) and G (Gonbad region) data sets, respectively.

Other models evaluated in this study, provided satisfactory fit for all of data sets. In particular, model based on CLL transformation of S and I resulted in R_a^2 and R^{*2} values comparable to those resulting from the fit of the ln(S)-ln(I) model. Paul et al. [9] after evaluating several transformations of Fusarium head blight of wheat values concluded that the CLL is the most appropriate model for describing I-S relationships in this pathosystem. They rejected the other models because none of those models constrains predicted severity to be ≤1 (100%), but in this study, all of four evaluated models showed this activity and are acceptable, based on this criterion.

Three basic interrelated approaches for study of relationships between incidence and severity of plant diseases are (i) correlation and regression methods; (ii) multiple infection methods; and (iii) measurement of aggregation and representative discrete distribution (Madden and Hughes, 1995)[16]. We used the first approach and data transformation minimized the problem of non-uniform variances associated with the use of regression methods. The key step in modeling I-S relationships is using the parameters of the distribution to estimates the probability of a zero (i.e., the probability of being disease free [26]. It is suggested that when severity is considered to be a continuous variable, as was done in this study (because of transforming mean severity of diseased plants [discrete data] to DSI [= S, which is a continuous data]), the use of an empirical curve-fitting approach is appropriate to establish a functional relationship between the two measures of disease intensity. This is because there is inadequate knowledge of the statistical distribution of severity as a continuous random variable [26, 27].

Although empirical, beside the Allometric model, equation 3 provided a biologically meaningful representation of disease incidence and severity in a field (Table 1 and 3). This can be seen by expressing equation 3 in nonlinear form:

$$S = 1 - \exp(-q(-\ln(1-I))^b \quad (7)$$

in which $q = \exp(a)$. When $b = 1$, equation 7 reduces to $S = 1 - (1 - I)^q$, a common model for discrete disease data at multiple hierarchical scales in a canopy (Groth et al. 1999)[28], with $q < 1$ (or $a < 0$). Hughes et al.[26]explain how, when $b = 1$, q is an empirical metric related to the magnitude of severity at a given incidence and also a parameter of the incomplete beta function related to the relative area of SSR severity per plant. Treating b as an unknown constant (to be estimated) adds to the flexibility of equation 5. The parameters q and b jointly control both the shape and steepness of the severity–incidence curve, although only the latter affects the steepness of the CLL-CLL line. Equation 5 and its special case ($b = 1$) describe a relationship where S initially increases slowly with increasing I, followed by more rapid increase in S with I at high I. This agrees with our results for SSR. More formally, this relationship of the two disease intensities can be characterized by using the rate of increase in S with unit increase in I (dS/dI) at a fixed time, which is given by

$$\frac{dS}{dI} = \frac{qb(-\ln(1-I))^b}{(I-1)\ln(1-I)} \exp(-q(-\ln(1-I))^b) \quad (8)$$

dS/dI was <1 over most of the range of incidence for the 8 data sets; with the parameter estimates in this study, dS/dI only exceeded 1 at an incidence of ≈0.8 or higher for Ali Abad region (Fig. 5). Figure 6 shows the estimated dS/dI for different regions of this study, which was significantly ($P < 0.05$) different.

Equation 7 is undefined at both severities and incidences of 0 and 1. More formally, S goes to 0 as I approaches 0 in the limit, and S goes to 1 as I approaches 1 in the limit, which completes the range specification for I-S. In a sample, however, it is possible to obtain 0 or 1 for incidence (or severity), which can present complications in data analysis. As mentioned previously, observations with $I = 0$ (and thus, $S = 0$) should be removed before data analysis, since the I-S relationship is defined when disease is present. In cases of $I = 1$, some analytical methods presented [9], but we do not have such data.

For the CLL(S)-CLL(I) model, there was a remarkable similarity of the slopes (on the transformed scale), with the absolute values of estimated b being slightly (and frequently significantly) above 1 for two of the data sets (Fig. 5). These results were similar to those reported by Xu et al. [19] and Paul et al. [9] for the relationship between CLL-transformed spikelet and spike incidence levels of Fusarium head blight in Europe and Iowa, respectively. They reported a slope of 1.156 and 0.833-1.497 and an intercept of –2.313 and -1.73, similar to our results in Table 3. The variation among the data sets primarily was in terms of the estimated intercepts, reflecting height differences in the CLL(S)-CLL(I) lines.

The low value of dS/dI over most of the incidence range (Fig. 5) has important consequences for temporal progress of severity and incidence. Using the arguments in Hughes et al. [26], if dI/dt is the rate of increase in incidence, then the rate of increase in severity is given by

$$\frac{dS}{dt} = \left(\frac{dI}{dt}\right) \cdot \left(\frac{dS}{dI}\right) \tag{7}$$

Whenever dS/dI is <1, the temporal rate dS/dt must be less than dI/dt, no matter what equation is used for dI/dt. Ultimately, dS/dt will exceed dI/dt when most plants are already infected but there is still a substantial area of each plant unaffected by the disease (low severity scales). Differences in the rates of increase in incidence and severity have been attributed to the occurrence of two distinct types of infection, allo- and auto-infection [11,5] for polycyclic diseases. An increase in incidence results from allo-infection (spread among plant units), whereas an increase in mean severity within a sampling unit results from both allo- and auto-infection (spread within infected plants – increasing severity scales) [9,29, 22]. Using simulation models, Willocquet & Savary [30] demonstrated that the time taken for maximum disease incidence (I = 1) to occur decreased with increasing allo-infection. However, in the case of SSR, which normally functions as a monocyclic disease, the infection of new healthy plants from primary inoculums (analogous to allo-infection) was probably higher than the spread within infected plants (analogous to auto-infection), at least until most plants were infected, resulting in a lower severity than incidence (and dS/dI < 1). Jeger et al. (1983) [27] suggested that increase in disease incidence over time was related to the availability of inoculum. Pataky & Headrick [13] reported that the relationship between incidence and severity for common rust of sweet corn varied with distance from a source of inoculum. Paul *et al.* [9] reported an initially high incidence (relative to severity) of Fusarium head blight due to high inoculum density and misting in the wheat nurseries.

Primary infection of canola by *S. sclerotiorum* occurs by ascospores produced in apothecia. Mycelial germination from sclerotia contributes minimally, if at all, to the development of epidemics [31, 32]. In our field studies, however, we observed that secondary spread of disease occurred in the field mainly via contacts between healthy and diseased plants. By this manner, secondary infection through mycelium (and increase of disease incidence) continued up to a short time before harvesting. This period is critical in some fields that have favorable conditions for disease development such as dense canopy, high N fertilizer input and varieties with massive vegetative growth. These conditions may cause lodging in some fields which in turn, increase dramatically the disease incidence [33,34].

The estimation of mean severity from incidence would substantially reduce the work load in disease quantification in field surveys and treatment comparisons [35]. It is less time-consuming than direct assessment of severity and generally requires less training of assessors [36]. Once assessors can distinguish between diseased and healthy plants, incidence can be quantified reliably at multiple locations, and large data sets can be acquired in relatively little time. This should greatly facilitate the comparison of epidemics in treatment evaluations, field surveys, and some resistance screening. In breeding programs where potentially thousands of varieties are assessed for SSR reaction, the estimation of incidence, and not severity, would save considerable resources [3, 37,17, 38]. These advantages of incidence are rational when the *I-S* relationships for the specific locations and/or climates established [3, 39]. In this study, in three locations including Galogah, Ali Abad and Dashte Naz, for each one percent increase in SSR incidence, there was a 0.8-0.9 percent increase in severity. In Gonbad (which has a hotter and drier climate), however, had a less favorable conditions for disease spread, and for each 1 percent increase in disease incidence, there was approximately 0.5 percent increase in disease severity. It is suggested to determine *I-S* relationship in each geographical and climatologically “zone” before conducting other epidemiological studies such as crop loss assessment, because in lack of this relationship (and converting I values to S values), these studies and their results will not have enough validity. As a practical result, characterizing the functional relationship between incidence and severity is still critically important, because through this relationship researchers can identify the genotypes or locations (with a specific climate) with unusually large or small severities for a given incidence [20].

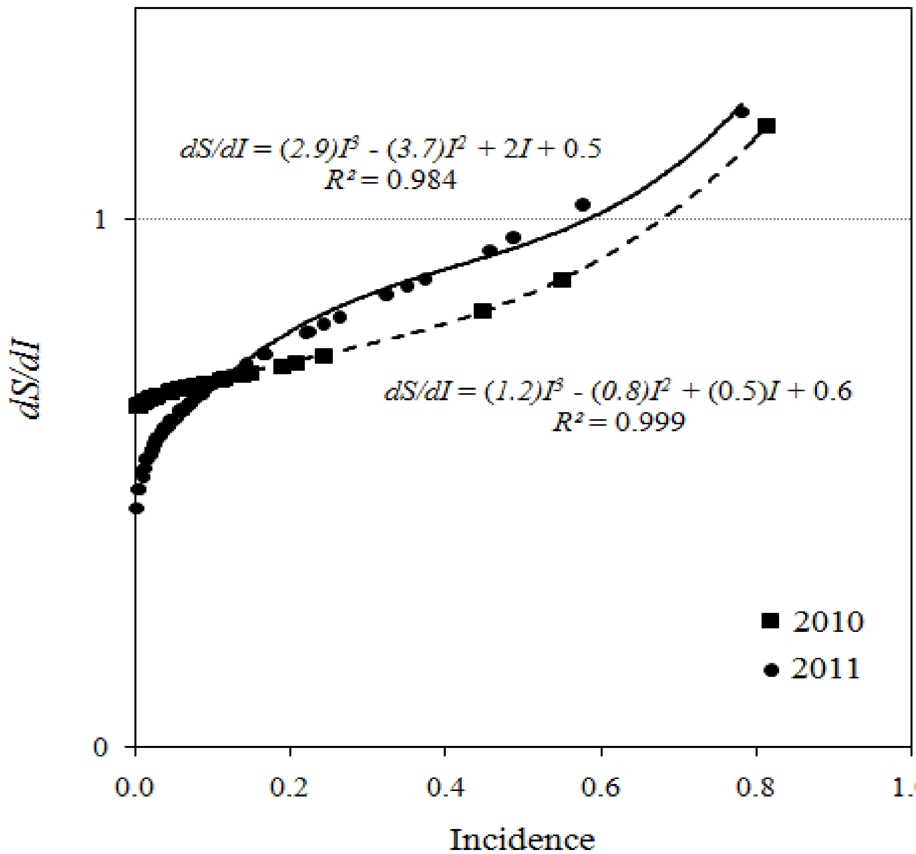

Fig. 5. Rate of increase in severity (*S*) with unit increase in incidence (*I*) (*dS/dI*) of Sclerotinia stem rot of canola in region Ali Abad of Golestan province, in northern Iran during 2010-2011. Curves based on equation 6, with parameter estimates in Table 1 (and *q* calculated as exp(*a*)).

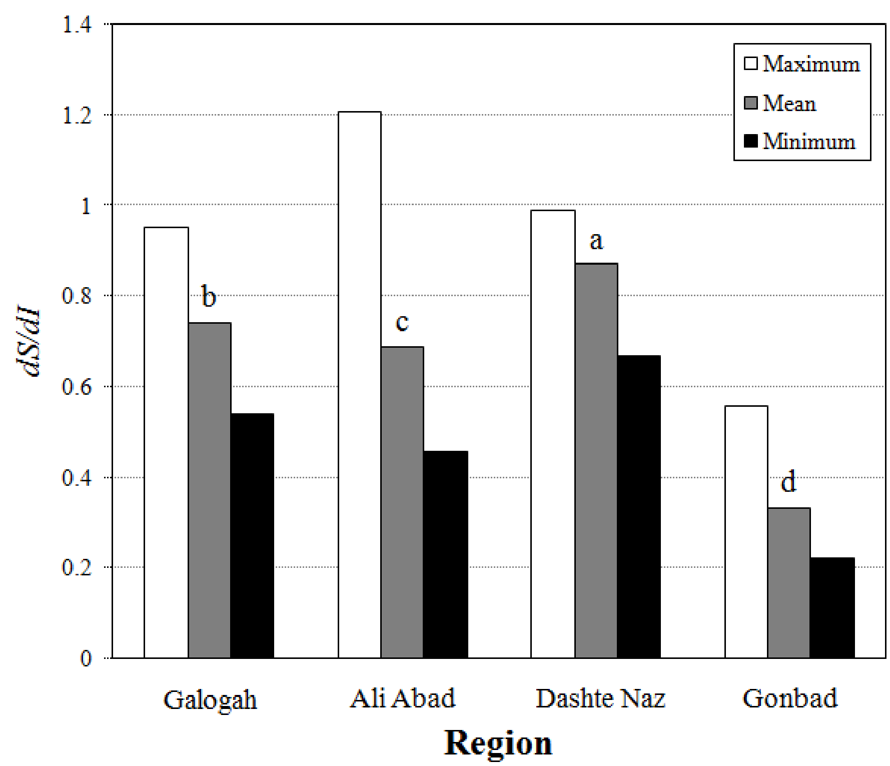

Fig. 6. Rate of increase in severity (*S*) with unit increase in incidence (*I*) (*dS/dI*) of Sclerotinia stem rot of canola in four regions of Mazandaran and Golestan provinces, in northern Iran during 2010-2011

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