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Abstract

The Russian wheat aphid, *Diuraphis noxia* (Kurdjumov), is a serious pest of small grain production with damage estimated in excess of a billion dollars since its introduction into the United States in the mid-1980s. Typically, *D. noxia* densities decrease during the winter, resulting in densities being low or locally extinct by late winter or early spring. As spring populations of *D. noxia* rebound from the harsh overwintering period, large variation in aphid density is frequently observed. One component thought to be important for understanding heterogeneity of *D. noxia* density in the spring is the density of *D. noxia* after fall flight (i.e., pre-winter aphid density). Using a spatially-explicit framework, we examined the correlation between heterogeneous *D. noxia* population density measured in the late fall to *D. noxia* density in the spring. Our analysis revealed that fall density of *D. noxia* correlated significantly with spring density ($p < 0.0001$, F-statistic 23.69, $R^2 = 0.038$), with the variability in spring *D. noxia* density explained by fall density decreasing as the spring progressed. Results may be used to inform pest management regarding the timing of scouting efforts for this important small-grain pest.

Introduction

The Russian wheat aphid, *Diuraphis noxia* (Kurdjumov), is a serious pest of small grain production in areas west of the 100th meridian with crop damage estimates in excess of a billion dollars since its introduction into the United States in the mid-1980s (Webster et al. 1994, Morrison and Peairs 1998). Effective management tactics for control of *D. noxia* are limited and chemical control plays an important role, especially since the development of *D. noxia* biotypes that have overcome resistance in all commercially available winter wheat cultivars (Haley et al. 2004). Because management currently relies primarily on pesticide applications, scouting efforts, which are used to inform insecticide timing and placement, are essential to reduce pesticide application errors. However, even though scouting fields for *D. noxia* infestations is a proven integrated pest management tool, dryland wheat producers are reluctant to invest in routine field scouting, likely due to the relatively low value of these crops (Holtzer et al. 1996). That is, the economic benefit of scouting needs to be weighed against the management value of information provided by the effort. Therefore, information that helps direct scouting efforts to maximize knowledge of infestations may have substantial value. In essence, greater understanding of spatial and temporal *D. noxia* population dynamics within small grain agroecosystems would be beneficial for limiting direct (e.g., pesticide inputs and costs of supportive scouting efforts to guide insecticide use) and indirect costs (e.g., increased pesticide resistance and environmental contamination attributable to pesticide usage) associated with *D. noxia* management.

Past research suggests that fall infestation levels likely affect spring aphid abundance and crop damage. For example, Dewar and Carter (1984) found that summer outbreak of *Sitobion avenae* (F.) was primarily determined by fall infestation levels (i.e., abundance of

fall flight), winter severity, spring abundance of natural enemies, crop planting date, and size of the spring infestation or spring migration. Moreover, fall aphid abundance can influence the degree of winterkill of infested plants resulting in reduced yield (Thomas and Butts 1990).

The spatial distribution of *D. noxia* in fall populations was found to be highly aggregated, especially where local aphid densities were low (Butts and Schaalje 1994). Fall aggregations of *D. noxia* may manifest as aphid hot spots in the spring (areas with a high degree of spatially autocorrelation in aphid population densities) with associated yield losses.

Conversely, fall *D. noxia* density and variations in density may be of limited importance in predicting spring *D. noxia* density and yield loss caused by aphid feeding. Girma et al. (1993) and Archer et al. (1998) found that sensitivity of wheat yield components to *D. noxia* infestations in the fall is less than to spring infestations. Therefore, if fall densities are not strongly correlated with spring densities, determining the factors influencing successful fall infestations would be of low importance from a management perspective.

Within-field heterogeneity of spring *D. noxia* density has been found to be correlated to topography and Landsat 7 Enhanced Thematic Mapper Imagery (Merrill et al. 2009b). These variables may be important determinants of micro-habitat difference. Because we are interested in determining the correlation between fall density and spring density, variation associated with these within-field micro-habitat covariates will be modeled and removed. Thus, we will be able to quantify the correlation between *D. noxia* density in the fall and spring *D. noxia* density in wheat-fallow agroecosystems.

Methods

Two field sites, Last Chance, CO (39°44' N 103°48' W) and Lamar, CO (37°58' N 102°30' W), were established based on disparate topographic and climatic variables, and were located representatively for Colorado dryland wheat harvested acreage.

From 2001-2004 (three overwintering periods), ca. 80 plots were established in the fall at each field site. All plots were georeferenced using a GPS device (Garmin GPSmap76S, Garmin International, Olathe, KS). For the first two years, plots were selected based on a stratified random grid design. The third year plots were stratified across soil type because preliminary analysis indicated that soil type was an important variable for determining spring abundances. Plots consisted of three consecutive, 1-meter rows (subplots) of dryland winter wheat. Each year, subplots were infested in the fall (ca. November 15th) with aphids from the *D. noxia* Biotype 1 colony (maintained at Colorado State University) using a Davis Inoculator (Davis and Oswalt 1979) at a rate of ca. 300 aphids per meter row. *Diuraphis noxia* densities were measured once in the late fall (after infestation, ca. December 10th) and measured twice the following spring. Fall and spring data were collected at both sites for three overwintering periods (i.e., winters of 2001-2002, 2002-2003, and 2003-2004). At the Lamar field site in 2002, a combination of snowfall and rainfall created logistically prohibitive sampling conditions. Thus, samples were not obtained during this time period. To determine *D. noxia* densities, wheat tillers were removed from subplots. Sample design was for tillers to be removed at a rate of six tillers per subplot. If tiller density was low (e.g., from low wheat emergence), tillers were removed to maximize tillers obtained over both sample periods. For example, if only eight tillers existed on a subplot during the first spring sample period, half of the tillers would be removed allowing the second four tillers to be removed

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during the second spring sample period. Tillers were placed into Ziploc bags, and transported to Colorado State University's Agricultural Research Development and Education Center, Fort Collins, CO. Tillers were then removed from the Ziploc bags and placed into Berlese funnels for approximately 24 hours to extract the aphids for counting under a dissecting microscope and expressed on an aphid per tiller basis. Subplot densities were averaged to obtain a plot average. The distribution of *D. noxia* densities at the plot level was skewed. Therefore, a log transformation (ln (*D. noxia*/tiller + 0.1)) was used to approximate a normal distribution. Due to various factors including poor emergence and crop destruction, not all plots were sampled during every sample period.

Twenty six GIS layers were developed and used as independent variables for fall *D. noxia* density. All GIS data layers were projected to the NAD 84 (North American Datum of 1984) projection using ArcGIS 9.1 (ESRI 1995-2007). The GIS data layers used were Landsat 7 ETM+ Band imagery (nine data layers: Bands 1-5, Thermal Bands 6.1 and 6.2, Band 7, and the panchromatic Band 8) from images taken ca. December 15th of each year, categorical soil data layers (nine data layers, specifically the soil types: Weld Series, Wiley Series, Baca Series, Colby Series, Samsil Series, Arvada Series, Shingle Series, Adena Series, Loamy Alluvial Lands, and Gullied Land), topographic data layers (five data layers: Relative Elevation, Landshape, Aspect, North-South aspect, and Slope). Topography layers were developed from a United States Geological Survey 30-meter digital elevation map (DEM). All topography data layers were generated with a 30-meter grid resolution. Topography layers tested are as follows: Relative Elevation - Relative elevation is the measure of the elevational distance (in meters) from the mean elevation at the field site. A Slope layer was developed (measured in degrees) from the USGS 30-meter DEM using the

ArcGIS 9.1 (ESRI 1995-2007) slope tool. An Aspect layer (measured in degrees from 0° to 360°) was derived from the USGS 30-meter DEM using the ArcGIS 9.1 (ESRI 1995-2007) aspect tool. A North-South Aspect layer was derived from the Aspect layer using the Raster Calculator function in ArcGIS 9.1 (ESRI 1995-2007) with the function: Float(Abs(180-[Aspect])). This function creates a continuous variable from 0-180 with 0 directly north and 180 directly south. A Landshape data layer was created by the ArcGIS 9.1 (ESRI 1995-2007) Raster Calculator function: Focalmean ([DEM],Circle,3,nodata) − [DEM]. This function calculates the mean elevation value (i.e., from the DEM) in a circle with a 3-cell (90 meter) radius around the georeferenced plot, then subtracts that value from the elevation at the plot. The resulting value describes the relative elevation of the georeferenced plot to its local surroundings.

Data values were extracted from the GIS layers associated with each independent variable in association with the GPS coordinates for each *D. noxia* density measurement. All independent variable parameters (GIS layers) were standardized across all data using the formula (X_i − Minimum(X) / (Maximum(X) − Minimum(X))) for all data points i. Landsat imagery bands were standardized within each image to observe relatively high and low reflective data within-field instead of between fields. Parameters for the Relative Elevation variable were standardized by site to correct for the large relative elevation differences between sites.

To develop fall *D. noxia* density surfaces, we analyzed and parameterized variance components associated with both the large-scale covariance structure (i.e., using GIS layer data) and the small-scale variance associated with the error structure (i.e., the residuals). Trend surface analyses, developed from GIS layers, were used to determine large-scale

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variance with extensive efforts made to analyze accessible covariates (Cressie 1993). Variance associated with the covariance structure residuals was examined for spatial autocorrelation. If additional signals, besides signals in the covariance structure, were detected, they were used to develop a more accurate interpolated *D. noxia* density surface.

Models were developed to quantify each fall infestation *D. noxia* density trend surface. We used an Information Theoretic approach to develop a set of candidate models and selected among these candidate models using Akaike's Information Criterion (AIC) with an adjustment for small sample sizes (AICc) (Burnham and Anderson 2002, 2004). Candidate models were generated using an AICc based, forward selection procedure (e.g., Twombly et al. 2007, Merrill et al. 2009b). All models were developed using a linear regression of predictor variables against the log transformed fall *D. noxia* density data. AICc based, forward selection was undertaken as follows: At each step of the model selection process, we computed the AICc of the candidate model as compared to the lowest AICc from any previous steps. Specifically, we added each of the 26 predictor variables to the null model (i.e., intercept only) to build 26 single-variable models. These were fit to measured fall *D. noxia* density data using SAS Proc GLM (SAS 2002-2003), and AICc values were computed for each single-variable model. If the AICc values for every single-variable model were higher than the AICc of the null model, model selection was finished and the null model was selected. Otherwise, we selected the model with the lowest AICc as the best single-variable model (B1VM). Then, we iteratively added each of the remaining 25 predictor variables to the B1VM to build 25 two-variable models. If the AICc values of the two-variable models were higher than the B1VM, then model selection was finished and the B1VM was selected as the best approximating model. If not, we selected the best candidate

model (i.e., the model with the lowest AICc) from the set of two-variable candidate models (defined it as the best two-variable model, B2VM). After which, we iteratively added each of the remaining 24 predictor variables to the B2VM to build candidate three-variable models. As before, three-variable models were compared using AICc. If the AICc values of the three-variables models were higher than the B2VM then model selection was complete, resulting in the B2VM being selected as the best approximating model. Else, the three-variable model with the lowest AICc was selected as the best three-variable candidate model. This process was repeated to build four-variable candidate models, etc., until an overall best approximating candidate model (i.e., with the lowest overall AICc) was selected. This iterative process was repeated for each of the five fall data sets. The best approximating models for each of the five fall data sets were then used to develop GIS-based trend surfaces.

Spatial autocorrelation between best approximating model residuals was tested for using Moran's contiguity ratio (1948) (also known as Moran's i) (S-Plus 2005). If spatial autocorrelation was found, it was quantified using a variogram. The variogram was used to develop an interpolated surface (kriged surface (Cressie 1993)) between spatially delineated points. The kriged surface was then added as a layer to the GIS-based trend surface resulting in a fall *D. noxia* density interpolated surface.

After the fall *D. noxia* density interpolated surfaces were developed for each fall data set, data values were extracted from the interpolated density surfaces in association with the GPS positions of the *D. noxia* spring density data. That is, when model development for fall density was complete, modeled values were extracted to correlate with measured spring D. *noxia* density, which allowed for quantification of correlation between fall density and spring density of *D. noxia*.

Results and Discussion

During this study, fall *D. noxia* density averaged 0.97 aphids per tiller at the Last Chance, CO field site, and 1.67 aphids per tiller at the Lamar, CO field site. Spring *D. noxia* density averaged 0.85 aphids per tiller at the Last Chance site, and 3.61 aphids per tiller at the Lamar site. Mean density and standard deviations of *D. noxia* sample sets are listed in Table 1. Linear models were developed using the AICc based, forward selection (Twombly et al. 2007), with a single best approximating model selected for each fall data set (i.e. the model with the lowest AICc). The variables selected by the AICc based, forward selection procedure for each fall regression equation are listed in Table 2. Trend surfaces depicting log transformed *D. noxia* densities were developed for each fall data set using selected candidate models (Table 2).

Residuals from the best approximating model were tested for spatial autocorrelation. Only model residuals from the model created for the Last Chance field site during the 2001-2002 winter were spatially autocorrelated (i.e., Moran's i = -0.056, SD = 0.023, p = 0.08). Therefore, these model residuals (Last Chance 2001-2002 fall data) were kriged and added to the Last Chance 2001-2002 model.

Once trend surface models were developed for each set of fall density data, values were extracted from each model at the spatial location of each spring *D. noxia* density measurement. Fall interpolated surface density data (i.e., modeled data) were then regressed against spring density measurements (Proc GLM, SAS 2002-2003). Figure 1 depicts spring plot locations for the Last Chance field site in 2002 overlaid on top of the fall interpolated trend surface for the Last Chance Field site in 2001.

Fall densities were correlated significantly to aphid densities in the spring ($p < 0.0001$, F-statistic = 23.69, $R^2 = 0.038$). Fall density surfaces predicted spring density during late February through March time period ($p < 0.0001$, F-stat = 20.26, $R^2 = 0.061$) better than they predicted aphid densities in April ($p = 0.0018$, F-stat = 9.91, $R^2 = 0.034$). These results are difficult to compare because within-field variance during April sharply increased. However, results show that less variation in spring *D. noxia* density is less associated with fall density as the season progresses.

Diuraphis noxia fall density distributions were significantly correlated with spring density distributions. The relatively small R^2 values result from a combination of fall density modeling error and limited spring density field variability associated with fall density. While fall infestation level is an important variable, other variables may elucidate more heterogeneity in spring *D. noxia* density. For example, variables such as winter weather severity could potentially mask and overwhelm the influence of fall *D. noxia* density on the density of aphids in the spring.

It is unsurprising that density in the fall is correlated to spring density. Exceptionally low or locally extinct populations can be expected to result in locally extinct spring populations. In contrast to the above example, our study examines relatively high fall density values and their correlation to spring density values. The correlation found here, while appearing low, is an important result given the high variability associated with insect populations with exceptional high intrinsic rates of increase such as found in *D. noxia* populations (e.g., Merrill et al. 2009a). Our results could provide an important phenological link from a management perspective. Establishing that fall infestations are correlated, albeit with a low R^2, provides an essential base for future modeling work and will help inform pest

management strategy. That is, scouting efforts in the fall will likely provide some information about spring densities of this pest, but extensive scouting efforts in the fall are unlikely to be cost effective.

Acknowledgements

Figure 1. The fall 2001 interpolated *D. noxia* density surface for the Last Chance field site. Data were extracted from the fall density surface at each georeferenced spring plot (green circles) and were regressed against *D. noxia* density measurements obtained in the spring of 2002 from the Last Chance field site.
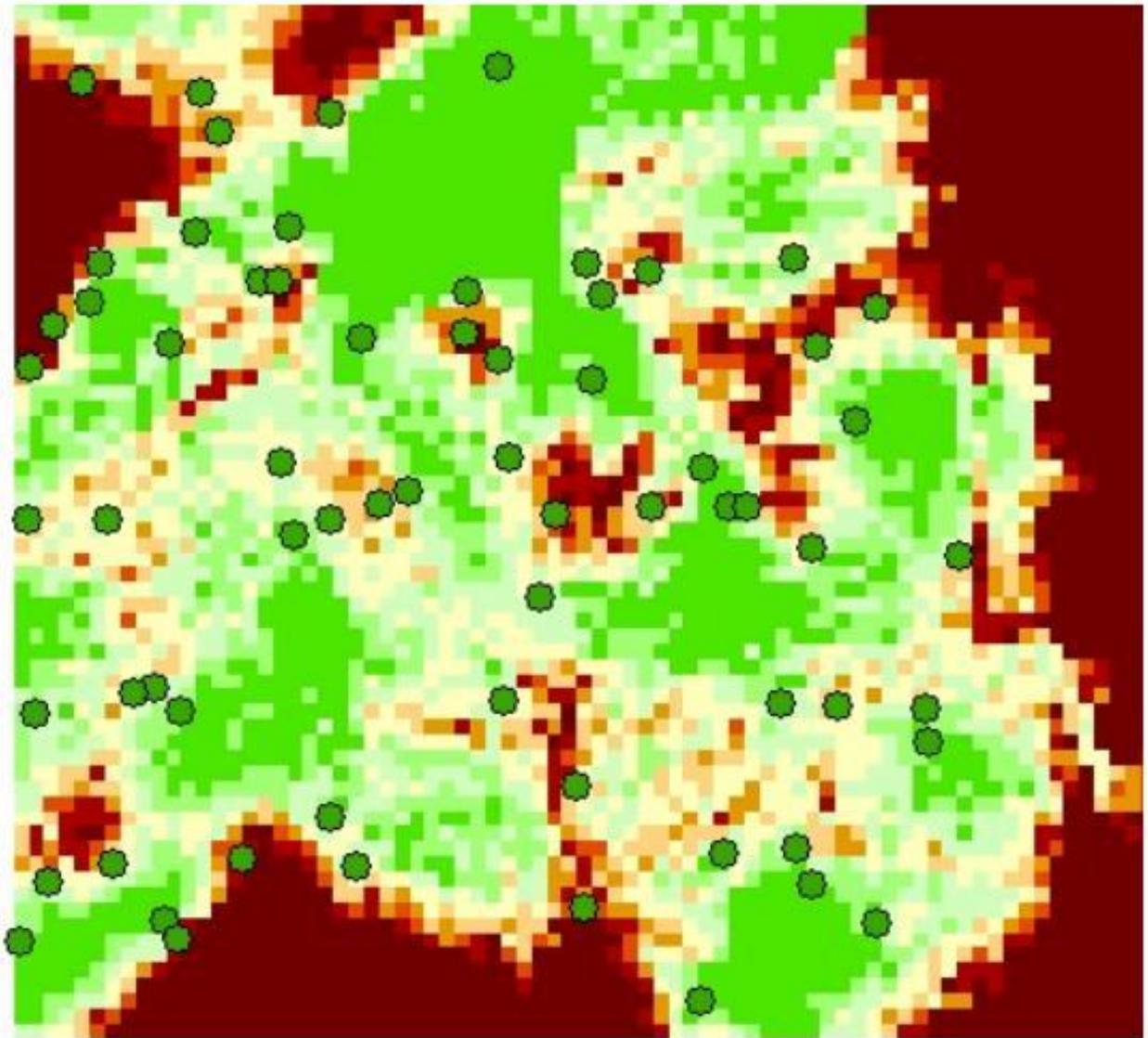
Table 1: Means and standard deviations for *Diuraphis noxia* samples sets from two locations in Colorado during three winter wheat production cycles.

Location	Sample Date	Number of plot measurements	Average *D. noxia* / Tiller	St Dev
Lamar	11/30/2001	65	0.60	0.62
Lamar	02/23/2002	72	0.49	1.44
Lamar	04/12/2002	66	4.06	5.17
Lamar	04/11/2003	43	1.59	1.45
Lamar	12/11/2003	55	1.33	1.53
Lamar	03/25/2004	60	3.35	5.13
Lamar	04/25/2004	51	8.56	11.65
Last Chance	11/16/2001	66	2.93	3.60
Last Chance	03/23/2002	65	0.56	0.68
Last Chance	04/06/2002	40	0.58	0.62
Last Chance	12/10/2002	81	0.71	0.59
Last Chance	03/30/2003	54	0.45	0.62
Last Chance	04/25/2003	64	1.26	1.55
Last Chance	12/06/2003	62	1.38	1.56
Last Chance	03/19/2004	65	0.54	1.02
Last Chance	04/13/2004	61	1.69	2.22

Table 2: Table of data layers for interpolated surfaces for each fall period from two locations in Colorado during 2001 to 2003*

Site	Fall Date	Variables in GIS-Based, Trend Surface for Modeling Fall *Diuraphis noxia* Density	Moran's i of the Residuals, SD, (p-value)	Kriged Residual Layer added?
Last Chance	2001 Fall	Band 6.2, Relative Elevation, Band 1, Band 3, Landshape, Soil types: Wiley, LAL, AcC, Weld, Adena, Kriged Residual Surface layer	-0.056, 0.023, (p = 0.08)	Yes
Last Chance	2002 Fall	Relative Elevation, Band 1, Band 2, Band 3, and the soil types Samsil and Wiley	0.078, 0.208, (p = 0.664)	No
Last Chance	2003 Fall	Slope, North-South Aspect, Band 2, Band 8 and the soil type Weld	0.064, 0.187, (p = 0.667)	No
Lamar	2001 Fall	Band 3, Band 4, and the soil type Baca	-0.213, 0.197, (p = 0.32)	No
Lamar	2003 Fall	Relative Elevation, Slope, North-South Aspect, Band 1, Band 6.1, Band 7 and the soil type Baca	-0.102, 0.061, (p = 0.17)	No

* Data were not collected from the Lamar field site in 2002 due to severe weather.

References Cited

Archer, T. L., G. D. Johnson, F. B. Peairs, K. S. Pike, and M. K. Kroening. 1998. Effect of plant phenology and climate on Russian wheat aphid (Homoptera : Aphididae) damage to winter wheat. Environmental Entomology 27: 221-231.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: the practical information theoretic approach. Springer, New York, USA.

Burnham, K. P., and D. R. Anderson. 2004. Multimodel inference - understanding AIC and BIC in model selection. Sociological Methods & Research 33: 261-304.

Butts, R. A., and G. B. Schaalje. 1994. Spatial-distribution of fall populations of Russian wheat aphid (Homoptera, Aphididae) in winter-wheat. Journal of Economic Entomology 87: 1230-1236.

Cressie, N. A. C. 1993. Statistics for spatial data. J. Wiley, New York.

Davis, F. M., and T. G. Oswalt. 1979. Hand inoculator for dispensing lepidopterous larvae. U.S. Dept. Agric. Sci. and Edu, New Orleans, LA, USA.

Dewar, A. M., and N. Carter. 1984. Decision trees to assess the risk of cereal aphid (Hemiptera, Aphididae) outbreaks in summer in England. Bulletin of Entomological Research 74: 387-398.

ESRI, A. 1995-2007. ArcGIS 9.1 computer program, version By ESRI, A., Redlands, CA.

Girma, M., G. E. Wilde, and T. L. Harvey. 1993. Russian wheat aphid (Homoptera, Aphididae) affects yield and quality of wheat. Journal of Economic Entomology 86: 594-601.

Haley, S. D., F. B. Peairs, C. B. Walker, J. B. Rudolph, and T. L. Randolph. 2004. Occurrence of a new Russian wheat aphid biotype in Colorado. Crop Science 44: 1589-1592.

Holtzer, T. O., R. L. Anderson, M. P. McMullen, and F. B. Peairs. 1996. Integrated Pest Management of insects, plant pathogens, and weeds in dryland cropping systems of the great plains. Journal of Production Agriculture 9: 200-208.

Merrill, S. C., T. O. Holtzer, and F. B. Peairs. 2009a. *Diuraphis noxia* reproduction and development with a comparison of intrinsic rates of increase to other important small grain aphids: a meta-analysis. Environmental Entomology 38: 1061-1068.

Merrill, S. C., T. O. Holtzer, F. B. Peairs, and P. J. Lester. 2009b. Modeling spatial variation of Russian wheat aphid overwintering population densities in Colorado winter wheat. Journal of Economic Entomology 102: 533-541.

Moran, P. A. P. 1948. The interpretation of statistical maps. Journal of the Royal Statistical Society Series B-Statistical Methodology 10: 243-251.

Morrison, W. P., and F. B. Peairs. 1998. Response model concept and economic impact, pp. 1-11. *In* S. S. Quisenberry and F. B. Peairs [eds.], Response model for an introduced pest- the Russian wheat aphid. Thomas Say Publications in Entomology, Lanham, Maryland.

S-Plus 2005. S-Plus 7 for Windows. Users guide computer program, version By S-Plus, Seattle, WA.

SAS. 2002-2003. SAS version 9.1, SAS User's Guide: Statistics. SAS Institute Inc, Cary, NC.

Thomas, J. B., and R. A. Butts. 1990. Effect of Russian wheat aphid on cold hardiness and winterkill of overwintering winter-wheat. Canadian Journal of Plant Science 70: 1033-1041.

Twombly, S., G. M. Wang, and N. T. Hobbs. 2007. Composite forces shape population dynamics of copepod crustaceans. Ecology 88: 658-670.

Webster, J. A., S. Amosson, L. Brooks, G. L. Hein, G. D. Johnson, D. E. Legg, W. Massey, P. Morrison, F. B. Peairs, and M. Weiss. 1994. Economic impact of the Russian wheat aphid in the western United States: 1992-1993. Russian Wheat Aphid Task Force to the Great Plains Agricultural Council, Stillwater, OK.