Spatial Variability of Western Bean Cutworm (Lepidoptera: Noctuidae) Pheromone Trap Captures in Sprinkler Irrigated Corn in Eastern Colorado

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ABSTRACT   Strategies for controlling pests are an integral part of any agricultural management plan. Most field crops, such as wheat (*Triticum* spp.) and corn (*Zea mays* L.) are managed as if they are homogeneous units. However, pests within fields are rarely homogenous. Development of plans that use targeted pest control tactics requires knowledge of the ecological drivers of the pest species. That is, by understanding the spatio–temporal factors influencing pest populations, we can develop management strategy to prevent or reduce pest damage. This study was conducted to quantify variables influencing the spatial variability of adult male western bean cutworm, *Striacosta albicosta* (Smith). *Striacosta albicosta* moths were collected in pheromone traps in two center pivot, irrigated corn fields near Wiggins, CO. We hypothesized that moth abundance would be influenced by the distance from the edge of the field, distance to nearest alternative corn crop and affected by anisotropic effects, such as prevailing wind direction. Greater trap catches of *S. albicosta* in each of the fields were found with increased proximity to the edge of the field, if the nearest neighboring crop was corn. Prevailing wind direction and directional effects were found to influence abundance. Results serve as a first step toward building a precision pest management system for controlling *S. albicosta*.

KEY WORDS   *Striacosta albicosta*, western bean cutworm, spatial, pheromone, precision pest management

Agricultural management strategy for pest control is dependent upon three overarching principles: 1) an understanding of pest-crop agroecosystems and phenology will help determine vulnerabilities in crop and insect life stages, and may suggest ways to misalign vulnerable crop stages with pest incidence; 2) Strategy must include economically feasible pest detection to inform the timing and location for use of control tactics or confirm the efficacy of control efforts; and 3) costs of control tactics need to be less than costs associated with uncontrolled pest damage. A multitude of strategies exist ranging from organic farming to integrated pest management.

Typically, crops are managed as if they are homogenous. Crop managers commonly understand the fallacy of managing their fields as if they are each homogenous units. Yet routinely, nitrogen is applied to areas of the field at levels greater than can be taken up by the crop and pesticides are sprayed on areas without pests. One potentially dramatic way to reduce direct and indirect costs would be to use the heterogeneity that exists within our cropping systems. The

Precision Agriculture management strategy advocates using within-field, spatially-explicit characteristics to target management tactics such as using variable seeding and fertilization rates to maximize yield potential.

One underused aspect of Precision Agriculture is precision pest management. Like many aspects of cropping systems, spatial dynamics of pest densities are heterogeneous (Taylor 1984). Spatial patterns may be caused by numerous factors including aggregation pheromones or landscape covariates such as field slope (Merrill et al. 2009). Precision pest management is defined as the use of spatially-explicit pest ecology to directed scouting efforts and inform precision agricultural strategy. For example, Merrill et al. (2009) estimated that adequate control of the Russian wheat aphid could be achieved by only spraying within-site locations modeled to have medium to high aphid incidence thereby reducing pesticide inputs by 30%. In Pennsylvania, treating only the infested portions of potato (*Solanum tuberosum* L.) fields reduced the amount of pesticide needed to control the Colorado potato beetle by 30–40% (Weisz et al. 1996). Finally, Davidson et al. (2007) found differing levels of western bean cutworm, *Striacosta albicosta* (Smith), larvae survival in yield based site-specific management zones, which could have implications for directed scouting. Thus, research describing spatio-temporal

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agroecosystem dynamics has been shown to effectively delineate pest vulnerabilities.

However, even with spatio–temporal pest dynamic models found to be highly accurate and precise, models should be used as tools for assisting in planning and pest detection and should not be used as a substitute for observations. Moreover, the economic feasibility of many precision spatio–temporal modeling efforts have yet to be demonstrated because of the potential costs of pest sampling. That is, sampling costs need to be balanced against benefits provided by precision pest management. Moreover, the ability to produce adequate density maps for arthropod pests in a manner timely enough to be relevant for management purposes has been identified as a serious constraint to the development of precision pest management (NRC 1997). Thus, development of spatio–temporal models that use inexpensive inputs, such as pheromone traps combined with inexpensive remotely sensed data, may have substantial value for assisting in the development of pest management strategy.

One opportunity for increasing our understanding of spatio-temporal structure of a damaging pest of corn (*Zea Mays* L.) arises with *S. albicosta,* sampled using economically feasible pheromone trapping. *S. albicosta* has been recognized as a serious pest of corn and beans (*Phaseolus vulgaris* L.) for over 50 yr (Douglass et al. 1955, 1957; Hagen 1962, Blickenstaff and Jolley 1982). Damage to corn is primarily caused by larvae feeding on the ear and indirectly from access to the corn plant provided by the entrance holes (e.g., access for pathogens) (Douglass et al. 1957, Hagen 1962). Unlike many other corn pests, *S. albicosta* are not cannibalistic and, under infestation conditions resulting in economical losses, more than five larvae can be expected per plant (Appel et al. 1993). Natural infestations have been found to reduce kernel yield by as much as 40% (Hagen 1962). Moreover, additional losses caused by ear rots have been found in association with *S. albicosta* feeding (Hagen 1962). Damage has been estimated at 3.7 bu/acre per larvae when corn is at the dent stage (Appel et al. 1993).

Many variables are likely correlate with the spatial distribution of *S. albicosta* adults within corn fields. Prevailing wind direction, as a vector for pheromone dispersal, likely plays an important role in determining within-field distribution (Mahrt et al. 1987). For example, if prevailing winds were from the east, pheromone traps along the western edge of the field would have their pheromone blown away from the field. Thus, prevailing wind along with other directional effects may influence moth behavior. Population dynamics may be affected by edge effects. For example, insect population density may be affected by temperature gradients from crop edge to crop interior (Chen et al. 1995), differences in predator abundance and predator diversity may exist within field margins (Bolger et al. 2000), or simply because once a suitable location is found, the need to disperse is reduced.

In addition, distance to the nearest alternative population source may influence population dynamics by assuming immigration from locations at greater distances is less likely (Hanski and Gilpin 1991). Mahrt et al. (1987) found 18% greater catch numbers in traps located adjacent to beans (an important alternative food source).

We hypothesized that spatial variability within the *S. albicosta* flight, as monitored by pheromone traps, would be correlated to directional variables in addition to the distance from nearby corn crops from the previous year (i.e., locations of previous year corn crops would act as a source for emerging adult moths) and the distance from the edge of the field. We used an information-theoretic approach to link model inference and model selection to spatially-explicit pest dynamics, allowing for the examination of multiple candidate models and variables within each of the candidate models (Burnham and Anderson 2002, 2004).

Materials and Methods

S. albicosta flights were monitored during the 1997 and 1998 growing seasons in two center pivot-irrigated corn fields near Wiggins, CO in Morgan County (field 1, 40.332104° N, 104.02997° W; field 2, 40.30156° N, 103.946976° W). Pivot irrigated field sites, each measuring ≈220 acres, and adjacent corn fields were planted as part of a continuous corn cropping system. Traps were placed in field 1 and field 2 on 17 July 1997 and removed on 20 August 1997, after the flight had ceased. In 1998, traps were placed in field 1 and field 2 on 25 June 1998 and removed from the field on 26 August 1998. The sex pheromone used to attract male *S. albicosta* moths was identified by Klun et al. (1983) and the use of pheromone traps for *S. albicosta* monitoring was described by Mahrt et al. (1987).

S. albicosta samples were collected weekly at each trapping location. Moths were identified, then discarded within the field. Roughly half of the traps were arranged in a 76.2- by 76.2-m (250- by 250-ft) grid overlaying the field, with one trap located at the center of each grid square. Traps were placed within the corn row. Traps were located in the same positions in both fields in both years. In 1997, samples were collected at 91 grid points on field 1 and at 100 grid points on field 2. In 1998, samples were collected at 86 grid points on field 1 and at 100 grid points on field 2.

Because the scale of spatial autocorrelation of *S. albicosta* flight activity is unknown, additional traps were placed at random distances between grid points. That is, to determine if spatial autocorrelation of *S. albicosta* moths occurs, and with what spatial distribution, a range of distances between traps was needed (Turner et al. 2001). Grid-based sampling was augmented with additional traps as follows: Two additional traps were added to each grid square within one quadrant in each field (the high trap density quadrant), and one trap was added to each grid square in the remaining three quadrants in both fields. A restriction on the random location of these traps was that they were at least 30 m apart to reduce intertrap interference. Sufficiency of intertrap interference reduction was tested by determining if moth abundance

per trap in the high trap density quadrant was lower than in the low trap density quadrants. Field 1 had 98 and 95 additional traps in 1997 and 1998, respectively. Field 2 had 86 and 78 additional traps in 1997 and 1998, respectively. The use of additional traps allowed for more accurate analysis of spatial autocorrelation at distances <76.2 m (250 feet). There were 375 trapping locations, in total, on the two fields in 1997. In 1998, because of planting differences, the number of trapping locations was reduced to 359.

Pheromone traps were similar to those described by Thompson et al. (1987) and consisted of a 3,785-ml (1-gal) plastic milk jug with a pheromone lure attached to the cap. The plastic milk jug was modified by cutting a 7.5-cm circle out of the side to the right of the jug's handle. Two small holes were drilled approximately 1 cm apart through the cap. Pheromone lures were attached to paperclips which had been bent into a 'J' shape. The paperclips then were inserted through the holes in the cap. Lures consisted of rubber septa to which had been added 10 μl of a 5:5:1 mixture of (Z)5-, 11- and (Z)-7-docenyl acetates (Klun et al. 1983).

Traps were attached to electric fence posts placed in the aforementioned augmented grid-based pattern. An 'X' $\approx$2.5 cm long was cut in the base of the milk jug's handle though which the post was inserted. Traps then were filled with $\approx$1500 ml of soapy water (mixed at a rate of two drops liquid dish soap to 1 liter water [Doyle 1994]), which was replenished weekly. Trapped *S. albicosta* moths were counted weekly, recorded, and discarded in the field.

Traps initially were placed on the ground. After cultivation operations were complete, traps were placed on the electric fence posts. Pheromone lures were not replaced during the trapping period in either year because previous field experience with this pheromone indicated that a single lure was sufficient to monitor the flight period (Peairs et al. 2006).

All sampling points were referenced with Global Positioning System (GPS) technology by using OmniStar 6300 or OmniStar 7000 differential (OmniStar Inc., Houston, TX). Coordinates were collected in latitude and longitude with MapInfo (MapInfo Corp., Troy, NY) and FarmGPS (Agri-Tech Solutions, Onawa, IA) and then converted to Universal Transverse Mercator (UTM) coordinates.

Data analysis was completed in R(R Development Core Team 2008). Multiple regression models were used for all analyses. Weekly trap data were averaged by sampling point across each field season. Average weekly *S. albicosta* abundance data were skewed. Transformed abundance data were used as the dependent variable. The Box-Cox method (Box and Cox 1964) was used to find the most appropriate transformation of the dependent variable. Specifically, a -0.34 power transformation was used to normalize the data (i.e., (average weekly abundance data $+ 1$) -0.34).

The variable distance from edge of field was calculated in meters. To examine the effect of the distance of the trap to an alternative population source, we used a binary variable labeled Corn Adjacent. Specif-

ically, the Corn Adjacent variable indicated whether the nearest adjacent crop was corn (i.e., a likely population source) or other. If the nearest neighboring crop was corn, the Corn Adjacent variable was delineated as 1. If the nearest neighboring crop to the trap was other than corn (e.g., fallow, alfalfa, etcetera), it was delineated as 0. The directional variables: North–South component, East–West component, and the interaction term between North–South and East–West Components were calculated in meters by using UTM coordinates. The directional variable prevailing wind direction was calculated using hourly CoAgMet (http://www.coagmet.com/) wind direction data (in degrees) collected at each site during the sampling period for each year. Hourly wind direction data were binned by increments of 5°. For each site and each year, the bin with the largest count was considered the prevailing wind direction. Prevailing wind direction in 1997 was found to be 100° for field 1 in 1997 (i.e., wind was blowing primarily easterly with some northerly wind) and 90° (easterly wind) for field 2. In 1998, prevailing wind was found to be 110° on field 1 and 105° on field 2. Therefore, formulas for calculating prevailing wind effect at each trap location were as follows:

Field 1 in 1997: prevailing wind at 100°; EW-0.173 * NS

Field 1 in 1998: prevailing wind at 110°; EW-0.336 * NS

Field 2 in 1997: prevailing wind at 90°; EW

Field 2 in 1998: Prevailing wind at 105°; EW-0.256 * NS

where EW and NS are the variables east–west and north–south components. For example, within field 2 in 1997, the prevailing wind effect increased with increased easterly trap location.

In addition, substantial year-to-year variability as well as field-to-field variability in moth density likely exists. Although understanding between-year and between-field variability in *S. albicosta* density is very important, this understanding is beyond the scope of this study. That is, we sought for relative spatial differences in moth abundance within field, within year. Thus, we standardized moth density across years and between fields, thus allowing for examination of the within-field spatial structure of the moth flight.

A set of a priori candidate models was developed using all subsets of the variables of interest (distance from edge of field, corn adjacent, prevailing wind direction, north-south component, east-west component, and the interaction between the north-south and east-west components). An information-theoretic approach to model selection and multimodel inference was used (Burnham and Anderson 2001, 2002, 2004). That is, values for Akaike's Information Criterion (AIC), ΔAIC (ΔAIC measures the distance between the best AIC model and the model of interest), and AIC weight (AIC w_r, provides a measure of the probability that the selected model is the best candidate model given the data) were calculated for each candidate model (Burnham and Anderson 2002, 2004). Models with strong likelihoods of being the best ap-

Table 1.   Models included in the Model Averaging Procedure

Model	Variables[a]	AIC	ΔAIC	$L(g_r/\text{data})$	AIC w_r normalized	Adjusted R²
No. 1	SY, DistanceEdge, Wind, AdjCorn, East-West, North-South, East-West*North-South	−667.48	0	1	0.280	0.214
No. 2	SY, DistanceEdge, Wind, East-West, North-South, East-West*North-South	−667.36	0.12	0.94	0.264	0.213
No. 3	SY, DistanceEdge, East-West, North-South, East-West*North-South	−667.13	0.35	0.84	0.234	0.211
No. 4	SY, DistanceEdge, AdjCorn, East-West, North-South, East-West*North-South	−667.01	0.47	0.79	0.222	0.213

$L(g_r/\text{data})$ is the likelihood of the model (g_r) given the data.

[a] where SY is the categorical variable sampling date per site per year, DistanceEdge is Distance from edge of field, Wind is Prevailing Wind Direction, AdjCorn is the variable Adjacent Corn, East-West is the East-West component of the field, and North-South is the North-South component of the field.

proximating model (AIC $w_r > 0.05$) were used for multimodel inference. That is, all candidate models selected as good models (AIC $w_r > 0.05$) were averaged using a weighted average based on the value of the standardized AIC w_r.

Variable relative importance weight is the sum of the AIC w_rs over all models in which a predictor variable occurs (e.g., if variable X occurs in three of the top five models, with AIC w_rs of 0.3, 0.2 and 0.16, then variable X's relative importance weight would equal 0.66 and would be compared with the relative importance weight of the other tested variables) (Burnham and Anderson 2002, 2004). The resulting weight can range from 0 to 1. The more important predictor variables have weights with higher values. Because variable weights are derived from AIC w_rs, they can be interpreted as the likelihood of the predictor variable being an important predictor variable for understanding variation in *S. albicosta* density.

Results and Discussion

Five weekly *S. albicosta* samples were collected in both fields from 23 July 1997 to 20 August 1997, and nine weekly samples were collected in both fields from 2 July to 26 August 1998.

In 1997, field 1 total weekly trap catch peaked on 23 July with 2,189 moths and then diminished through 20 August, totaling 2,854 *S. albicosta* moths for the season summed across all plots within the field. In 1998, field 1 total weekly trap catch peaked on 15 July with 934 moths and then diminished through 26 August, total-

ing 2,489 moths collected at all sites within the field. In 1997, field 2 total weekly trap catch peaked on 23 July with 5,808 moths and then diminished through 20 August, totaling 9,602 moths. In 1998, field 2 total weekly trap catch peaked on 23 July with 2,550 moths and then diminished through 26 August, totaling 5,170 moths. Total trap catch per plot per season was averaged to obtain the dependent variable: average weekly trap catch per sample site.

Within the high trap density quadrant within each field, one extra trap was placed within each grid cell within one quadrant of each field. We tested that reduced distances between traps and the overall increase in trap density within one quadrant would not create bias from intertrap interference. On average, traps in the high density quadrant showed lower trap counts than those in the low density quadrants. However, the trap catches on average were ≈0.01 *S. albicosta* per trap fewer (i.e., ≈0.4% fewer moths). Because of this low value, variation attributed to intertrap density was not included in model selection.

Like studying many insect species, substantial variation in trap counts was observed throughout our test sites. However, we were able to discern strong structural components within the moth flight. Four models had high likelihoods for being the best approximating model (Table 1), and thus, were averaged by their model-specific AIC weight. Table 2 dictates parameter estimates, confidence intervals for the model with the lowest AIC value. Small parameter estimates are an artifact of the normalization transformation of the dependent variable combined with relatively large

Table 2.   Parameter estimates and confidence intervals for Model #1, plus effect direction and AIC variable wt for variables included in modeling efforts

Variables[a]	Parameter estimates (Model 1)	Lower confidence interval (Model 1)	Upper confidence interval(Model 1)	Back-transformed effect direction	Model averaged variable AIC wt
DistanceEdge	−0.0002967	−0.0004041	−0.0001894	+	1
East-West	−0.0004765	−0.0009159	−3.704E-05	+	1
North-South	−0.0001095	−0.0002549	3.597E-05	+	1
East-West*North-South	4.894E-07	2.179E-07	7.609E-07	−	1
Wind	−0.0003167	−0.0007237	9.044E-05	+	0.544
AdjCorn	−0.01969	−0.04639	0.007001	−	0.501

[a] where DistanceEdge is Distance from edge of field, Wind is Prevailing Wind Direction, AdjCorn is the variable Corn Adjacent, East-West is the East-West component of the field, and North-South is the North-South component of the field.

values of many of the variables (EW, NS, EW*NS, distance from edge of the field and prevailing wind direction). It is important to note that back-transformed parameter values will switch effect direction. That is, as transformed moth counts decrease, the corresponding back-transformed modeled values will increase. For example, the adjacent corn variable was parameterized as having a negative effect on the transformed *S. albicosta* moth abundance, which means that adjacent corn will have a positive effect on moth incidence when back-transformed.

As expected, broad-scale spatial and temporal variability were noted for pheromone trap catches in both fields in both years (i.e., there was a year*field effect in each of the four selected models). This variation was addressed and removed using a categorical field by year variable.

Striacosta albicosta average trap counts were influenced by their distance from the edge of the field (AIC variable weight = 1), with more moths caught closer to field margins (i.e., moth density decreasing toward the center of the pivot), indicative of an edge effect. Distance from field edge was included in all of the models selected for model averaging indicating that it is a good variable for spatial delineation of *S. albicosta.* Because of the layout of our grid-based pheromone traps, this edge effect may result from males being attracted to the closest trap, or closest available mate and thus, not traveling into the interior past perceived mates.

The directional variables EW, NS, and the interaction term between EW and NS were included in all of the selected for model averaging, indicating that these variables influenced *S. albicosta* spatial dynamics (each of these variables had an AIC variable weight = 1). Directional variation may be because of differences in insolation or other unexamined directional factors.

The prevailing wind direction variable was only found in two of the four models (AIC variable weight = 0.544). Interestingly, prevailing wind direction influenced moth abundance in the opposite direction as expected. Two mechanisms could explain this result: 1) prevailing wind direction in all years at both sites was primarily or entirely the variable EW (i.e., primarily an easterly wind). The variable EW has a large effect size in the opposite direction as the prevailing wind variable and may be assuming some of the variation associated with prevailing wind. 2) In each year at both field sites, there was wind blowing in the opposite direction (approximately westerly) for a substantial proportion of the sampling time. Moth behavior interacting with the timing of wind may affect spatial distribution. That is, moth trap catches may be more closely associated with night time prevailing wind direction (e.g., because of higher nocturnal moth activity) as compared with average prevailing wind direction. Recalculating prevailing wind direction solely during nocturnal hours may provide a different value as that calculated from the observed daily average prevailing wind direction. However, little is known about the hourly timing of peak *S. albi-*
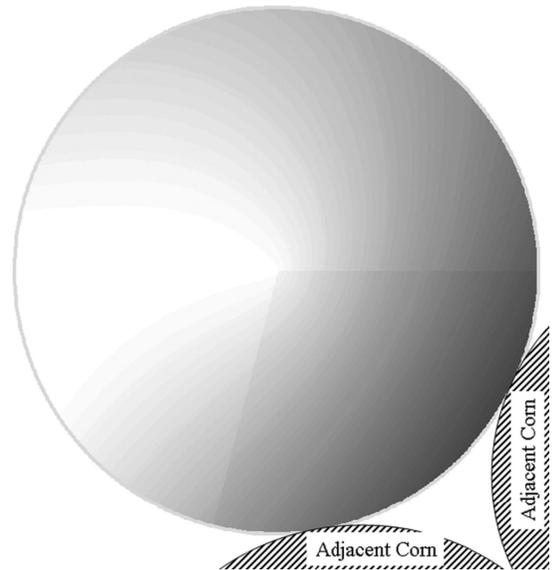

Fig. 1. Modeled results of a pivot-irrigated corn field (Field 2) in 1998. Average *S. albicosta* trap catch density is depicted with darker areas indicating higher moth incidence with modeled results showing a high of 2.35 moths per trap and lighter gray areas have low to zero moth incidence.

costa moth activity. Thus, a posteriori recalculations were not completed based on wind direction during nocturnal hours or a set of hours selected for high moth activity because reanalysis with multiple additional prevailing wind variables verged upon data mining.

The adjacent corn variable was included in two of four models (AIC variable weight equals 0.501) as a variable for elucidating location and abundance of *S. albicosta* moths. This effect was parameterized in the direction as expected from our hypothesis (Table 2). Because of the variable's AIC weight, adjacent corn is the least likely of the selected variables to be an important variable for elucidating variation in this system. Potential reasons that adjacent corn was not selected highly by this data set as a top predictor of the spatial dynamics of *S. albicosta* moths include: 1) The signal correlating moth variability associated with adjacent corn fields was detected more strongly by another variable (e.g., distance from edge of field). 2) The scale at which adjacent corn influences moth distribution was not captured by this trap pattern, 3) There is a threshold distance after which corn adjacency becomes irrelevant, and 4) The data were biased, reducing the effect size of nearby corn fields.

Fig. 1 depicts the predicted *S. albicosta* moth relative abundance map by using the model-averaged result for field 2 in 1998. Figure 1 was created using model results in combination with GIS layers for each of the covariates (e.g., prevailing wind direction) by using the raster calculator tool (spatial analyst) in ARCGIS 9.1 (ESRI 1995–2007). Maps, such as Fig. 1,

could be used to as a first step toward developing spatial explicit management strategy. For example, Fig. 1 depicts areas expected to have high and low moth incidence. Results depicting structured moth abundance, if found to be associated with ovipositioning females, could be used to help pesticide application patterns or for resistance management. Alternatively, information on spatial structure of male flight may be used to optimize releases of sterile males if a sterile insect tactic is found to be economically viable. Model results and the derivative maps should influence future research. For example, research efforts may prove more enlightening by concentrating on areas of the field that consistently showed higher unexplained variability in trap counts. Moreover, because directional variables were found to have such power in elucidating spatial population structure, addition research could explore mechanism creating this direction structure.

Pest agroecosystem dynamics are not economically valuable unless they are recorded in a timely and cost efficient manner, thus allowing for the development of precision pest management strategy. Our results reflect *S. albicosta* moth dispersal in an irrigated continuous corn production system in a region commonly observed to relatively contiguous corn (and bean) moth emergence sites. Our work should be considered a first step toward directed scouting efforts and to focus future research efforts. Future research should emphasis reduced sampling costs and the development of pest density maps that are relevant for use in precision pest management. Moreover, additional research is needed to assess how spatial relationships developed in this work hold for nonirrigated regions of corn and soybean production especially given the recent expansion of *S. albicosta's* habitat range into the eastern midwest of the United States (DiFonzo and Hammond 2008). Continued research in this field could allow growers to enjoy the potential benefits of precision agriculture approaches for pest management inputs, as well as those benefits already being realized for nutrients and water.

Acknowledgments

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