

## Chamberlain, Anne

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**From:** Fish, Gary  
**Sent:** Friday, December 09, 2016 11:03 AM  
**To:** AF-Pesticides; Murray, Kathy; Lund, Jennifer  
**Subject:** Monarch decline not linked to loss of milkweed from herbicide resistant crop culture

I found this to be quite interesting...

<http://www.oikosjournal.org/search/content/linking%20the%20continental%20migratory%20cycle%20of%20the%20monarch%20butterfly%20to%20understand>

# OIKOS JOURNAL

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## LINKING THE CONTINENTAL MIGRATORY CYCLE OF THE MONARCH BUTTERFLY TO UNDERSTAND ITS POPULATION DECLINE

Threats to several of the world's great animal migrations necessitate a research agenda focused on identifying drivers of their population dynamics. The monarch butterfly is an iconic species whose continental migratory population in eastern North America has been declining precipitously. Recent analyses have linked the monarch decline to reduced abundance of milkweed host plants in the USA caused by increased use of genetically modified herbicide-resistant crops. To identify the most sensitive stages in the monarch's annual multi-generational migration, and to test the milkweed limitation hypothesis, we analyzed 22 years of citizen science records from four monitoring programs across North America. We analyzed the relationships between butterfly population indices at successive stages of the annual migratory cycle to assess the validity of these citizen-science data, and to address the roles of migrant population size versus temporal trends that reflect changes in habitat or resource quality. We find a sharp population decline in the first breeding generation in the southern USA, driven by the progressively smaller numbers of spring migrants from the overwintering grounds in Mexico. Monarch populations then build regionally during the summer generations.

**Contrary to the milkweed limitation hypothesis, we did not find statistically significant temporal trends in stage-to-stage population**

**relationships in the mid-western or northeastern USA.** In contrast, there are statistically significant negative temporal trends in monarch success during fall migration and re-establishment at the overwintering grounds in Mexico, suggesting that these stages contribute strongly to the decline of monarchs. **Lack of milkweed, the only host plant for monarch butterfly caterpillars, is unlikely to be driving the monarch's population decline.** Conservation efforts therefore require additional focus on the later phases in the monarch's annual migratory cycle. We hypothesize that a lack of nectar sources, habitat fragmentation, and continued degradation at the overwintering sites are critical factors.

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Inamine, H., Ellner, S. P., Springer, J. P. and Agrawal, A. A. 2016. Linking the continental migratory cycle of the monarch butterfly to understand its population decline. – Oikos doi: 10.1111/oik.03196

Documents  [oik-03196.pdf](#)

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[www.gotpests.org](http://www.gotpests.org)

Inamine, H., Ellner, S. P., Springer, J. P. and Agrawal, A. A. 2016. Linking the continental migratory cycle of the monarch butterfly to understand its population decline. – Oikos doi: 10.1111/oik.03196

## **Supplementary material**

**Table A1:** Summary of annual data used in analyses.

**Appendix 1:** Summary of analyses examining quality and potential biases in the NABA dataset.

**Appendix 2:** Summary of analyses to examine temporal change in the relationship between stages of the monarch's annual migratory cycle.

Table A1. A summary of the annual census data used in analyses. All data were compiled, normalized and smoothed from the raw data (see Methods, code provided in Dryad), except that of the last four columns beginning with Mexico.

YEAR	Spring		Truncated			Cape		Fall		Mexico <sup>1</sup>	Change in monarch population estimate (Mexico) <sup>2</sup>	Average adoption of HT corn & soybean <sup>3</sup>	Change in HT adoption <sup>2</sup>
	South	Midwest	Northwest	Midwest	Northwest	May	Point	South					
1993	NA	153.365	39.425	53.258	34.591	544.6	NA	NA	6.23	NA	0	0	
1994	NA	226.537	59.704	210.537	39.124	839.8	NA	NA	7.81	1.58	0	0	
1995	NA	35.737	43.021	34.37	35.147	248.5	NA	NA	12.61	4.8	0	0	
1996	NA	102.151	37.713	61.293	32.97	503.6	104.411	NA	18.19	5.58	5	5	
1997	NA	230.106	108.253	149.485	70.155	919.6	254.429	NA	5.77	-12.42	10.5	5.5	
1998	NA	104.858	40.951	47.686	25.308	403.1	63.514	NA	5.56	-0.21	26.5	15.95	
1999	NA	255.704	104.118	126.978	45.144	2849.2	287.665	NA	8.97	3.41	32	5.3	
2000	NA	149.817	80.296	73.162	32.814	250.7	259.48	NA	3.83	-5.14	30.5	-1.4	
2001	NA	307.803	90.546	141.428	34.372	658.4	421.751	NA	9.36	5.53	38	7.5	
2002	NA	166.007	21.381	62.175	8.54	276.8	317.842	35	7.54	-1.82	43	5	
2003	NA	193.017	41.897	103.476	17.272	392.3	466.94	110.833	11.12	3.58	48	5	
2004	NA	58.672	16.049	33.361	9.238	74	92.053	28.25	2.19	-8.93	52.5	4.5	
2005	44.629	163.33	58.997	89.566	20.206	538.2	401.245	56.734	5.91	3.72	56.5	4	
2006	77.268	338.107	265.467	162.687	120.702	1743.4	56.64	133.614	6.87	0.96	62.5	6	
2007	72.977	266.017	179.67	159.438	90.476	746	129.424	64.362	4.61	-2.26	71.5	9	
2008	51.261	170.119	132.027	76.062	57.147	265.8	320.048	24.262	5.06	0.45	77.5	6	
2009	75.296	185.16	88.072	84.44	43.095	281.2	177.383	183.774	1.92	-3.14	79.5	2	
2010	29.595	306.761	95.789	156.473	51.278	1026.5	624.553	58.829	4.02	2.1	81.5	2	
2011	34.3	140.353	80.143	76.412	35.492	681.73	108.428	171.66	2.89	-1.13	83	1.5	
2012	20.861	169.584	178.336	89.023	114.551	1222.26	121.686	62.798	1.19	-1.7	83	0	
2013	10.31	41.939	16.801	17.153	6.524	112.73	42.462	37.39	0.67	-0.52	89	6	
2014	21.129	99.009	46.367	64.998	16.011	393.9	652.844	53.21	1.13	0.46	91.5	1.5	

<sup>1</sup>[http://assets.worldwildlife.org/publications/768/files/original/REPORT\\_Monarch\\_Butterfly\\_colonies\\_Winter\\_2014.pdf?1422378439](http://assets.worldwildlife.org/publications/768/files/original/REPORT_Monarch_Butterfly_colonies_Winter_2014.pdf?1422378439). For a YEAR N, the Mexico population corresponds to the butterflies overwintering from N to N+1.

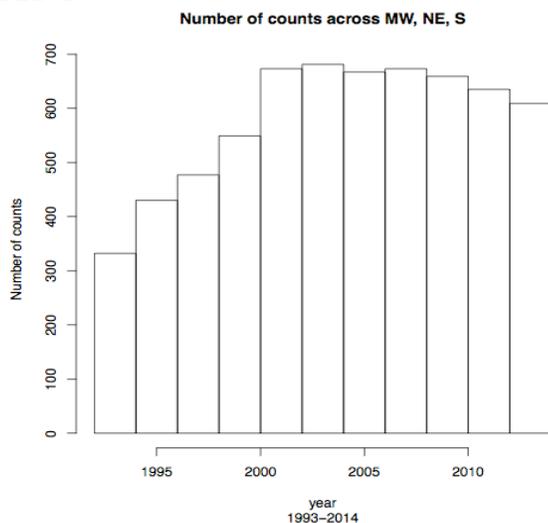
<sup>2</sup>the change given in year N represents the change from Year N-1 to N. <sup>3</sup>[http://www.ers.usda.gov/media/185551/biotechcrops\\_d.html](http://www.ers.usda.gov/media/185551/biotechcrops_d.html)

## Appendix 1

### Summary of analyses examining quality and potential biases in the NABA dataset.

Here we examine potential biases and quality issues common in citizen science datasets [1]. While there are some shortcomings, several lines of evidence and past studies [e.g. 2] suggest that this is a reliable dataset and it is appropriate for our analyses. First, we compared our complete population indices with truncated indices that only included sampling dates that had consistent data cross all years. The truncated dataset constitutes a very small portion (20-25%) of the original dataset, yet we see very high correlations between the two (Pearson's  $r$  in Midwest: 0.88; Northeast: 0.94). Second, to address the potential for missing data early in the season, we plotted the yearly counts for the Midwest and Northeast to ensure that censuses captured a temporal increase in butterfly abundance in late spring. Third, we addressed the relationship between sampling effort and butterfly counts by transforming party hours to test for sampling effort biases common in citizen science datasets [1]. Fourth, we used Ripley's  $K$  function [3] to assess whether the count data show a temporal bias of increased clustering over years. Finally, the potential for additional spatial biases in sampling are addressed in Results and Discussion in the main article.

#### A1.1



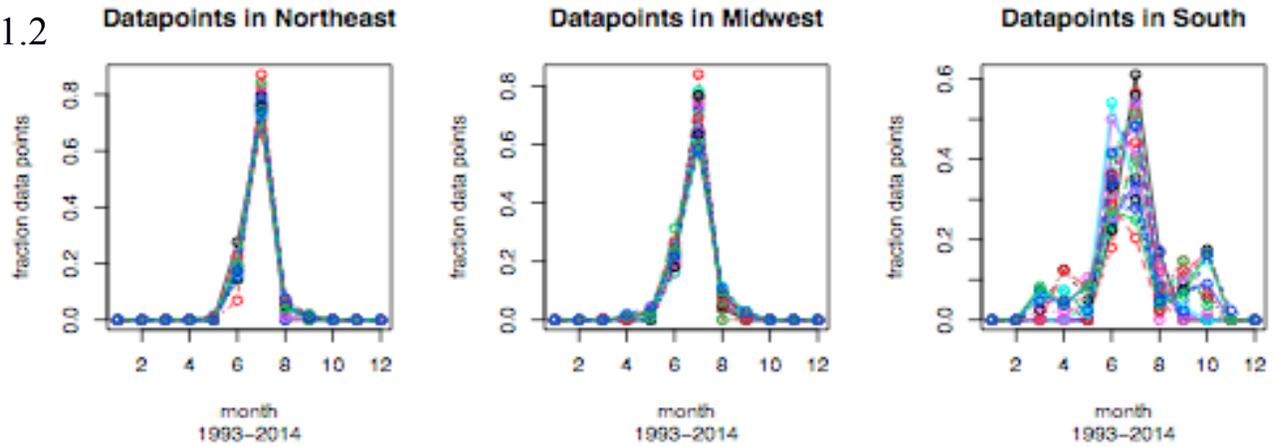
**Description of NABA dataset.** The North American Butterfly Association (NABA) has compiled butterfly counts from participating citizens across North America since 1975. The counts are taken from various locations throughout the year and the data includes the number of observed monarchs, the location (latitude and longitude), date, number of observers, number of parties (groups of observers), and the total hours spent.

The dataset goes back to 1975 initially as July 4<sup>th</sup> counts (led by the Xerces Society for Invertebrate Conservation, later acquired by NABA), but the number of sampling dates has been increasing every year, with samples taken more widely throughout the year. The number of counts gradually increased over the years and substantial number of counts were reported 1993-2014 (mean of 290 counts per year across the USA, see Fig A1.1). Furthermore, these years correspond to the data available on the overwintering population in Mexico from the surveys by the WWF.

While the counts originally took place on 4 July, participants started to collect data more widely throughout the year. Figure A1.2 shows the fraction of data points (each colored line represents a year) taken in each month. Northeast and Midwest are concentrated while South has wider sampling range. The two to three key breeding generations during the summer occur in the Midwest and Northeast regions. Although our earliest and latest NABA samples from these regions (across the 22 years in the dataset) were taken from 27 March and 3 October, respectively, on average there are ~74% of counts in July, with fewer samples in June (~20%) and August (~5%). These months correspond to the peak abundance and breeding period of monarchs [4] (also see Fig 3B). We used 27 March to 3 October to capture all the information

available on the breeding populations. While these intervals are large, they again capture the regional dynamics (Fig. 3B); a smaller subset of the dataset corresponding to the maximum of each peak (and with equal sampling effort across years) is highly correlated with the full dataset (see Section 1 below).

A1.2



It is important to note that intense sampling does not necessarily correspond to high butterfly counts. As a case in point, the mean relative population size index of the monarchs in the south is lower in the summer compared to spring and fall (Fig. 3B), even though the number of samples are much higher in the summer than either season. Below we address potential issues with varying sampling intensity.

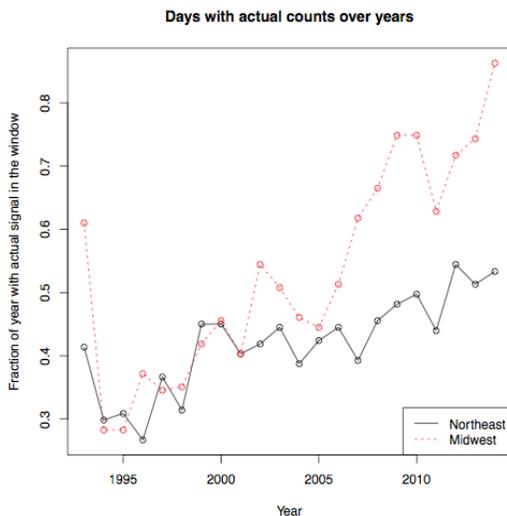
### 1. Moving average over large spatial and temporal scale: Will varying intensity cause bias in moving average?

NABA data points are collected in various locations throughout the USA, with different years of coverage. Furthermore, we see varying sampling intensity within a year. Not surprisingly, we see no obvious population dynamics pattern at fine spatial and temporal scales in the dataset. In order to focus on the appropriate scale that reflects continental population dynamics, we use a moving average (i.e., kernel estimation using uniform function) over 7-day windows. For each observed count within a region, let  $i$  be the day of year, and  $y_i$  the observed number of monarchs per party hour. Then, the averaged abundance assigned to day  $j$  for the specified region is

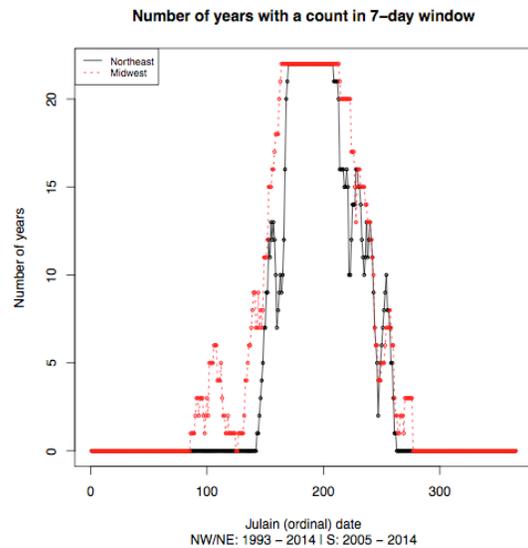
$$\bar{y}_j = \frac{1}{n_j} \left( \sum_{i=j-3}^{j+3} y_i \right)$$

where  $n_j$  is the number of counts that occurred during the 7-day window. If there are several counts on one day, they are both included in the sum. Conversely, a day without any counts within the 7-day window is assigned value 0.

A1.3



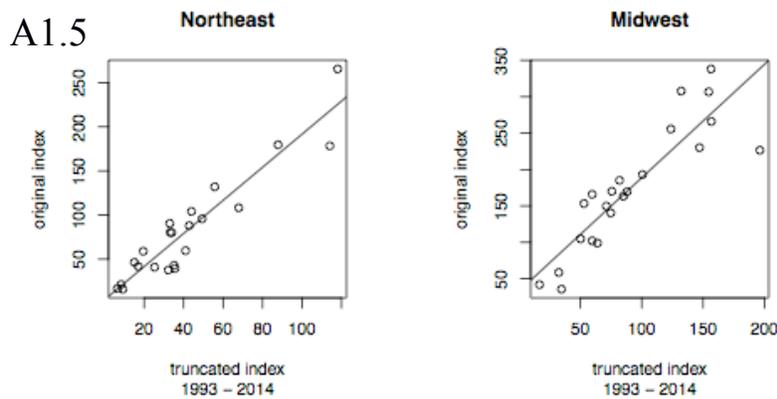
A1.4



Varying sampling intensity may bias our index, because clustered missing data results in 0, and therefore lowers the index compared to widely sampled years. For example, Figure A1.3

shows the fraction of days in NE and MW where there was at least one data point within each 7-day window; the number of samples increases over time. This varying sampling intensity could bias our results, leading to non-decreasing population index over years. We do not believe this is the case for Spring South, where the population index is decreasing over time; any increase in sampling effort over time would counteract the observed decline. The concern lies in Midwest and Northeast, however, where we see a largely stable population index across years despite decreasing abundance in Mexico. We therefore focus on these two regions for the rest of this Appendix.

To assess this potential bias, we constructed a truncated dataset for each region where the averaged days consistently included a count, across all 22 years; that is, we focused on days where  $n_j > 0$  across all years (See Fig A1.4 for corresponding dates; the figure shows, for each date, the number of years with a data point in the 7-day window). We summed the indices from these days and compared them to the total Midwest and Northeast population indices derived by our methods.



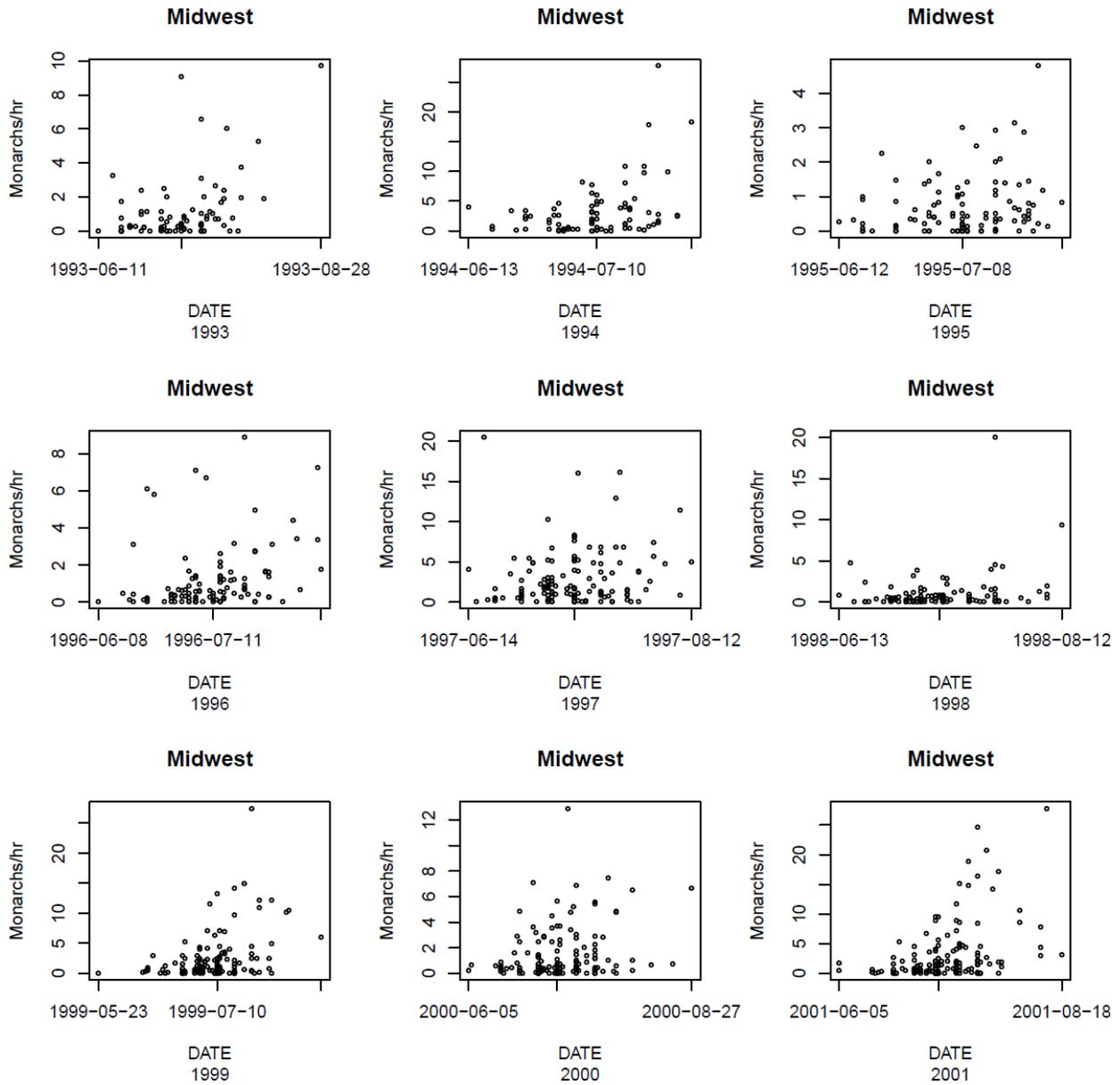
This reduced the dataset to samples taken from 13 June - 1 Aug. Importantly, this truncated index is not impacted by varying sampling intensity across years because sampling intensity has been fixed (no days without counts). Our complete yearly index was highly correlated with this truncated index ( $n = 22$ , Midwest Pearson's  $r = 0.88$ ,  $p < 0.001$ ; Northeast Pearson's  $r = 0.94$ ,  $p < 0.001$ ; see Fig. A1.5). Furthermore, analyses of linkages between regions and declines were qualitatively the same if we used the yearly index or the truncated index (data provided in Table A1). We therefore conclude that varying sampling intensity across years is not affecting the population indices. Accordingly, to utilize the most available information, we include the complete index from March through October for the main analyses.

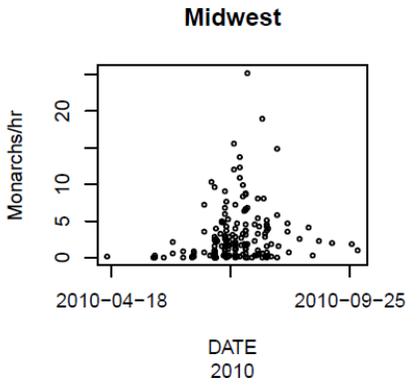
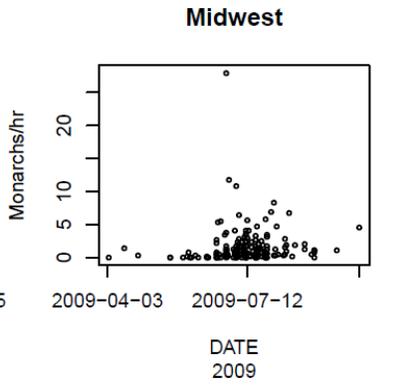
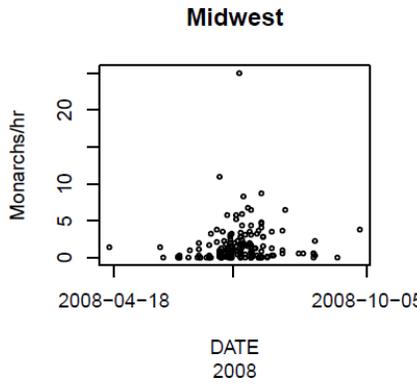
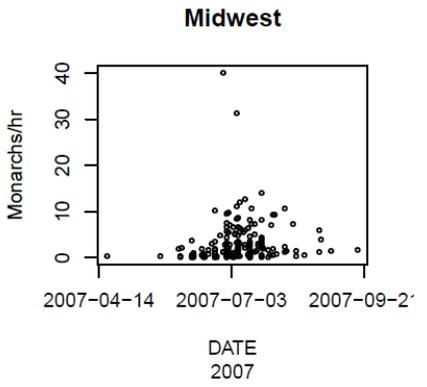
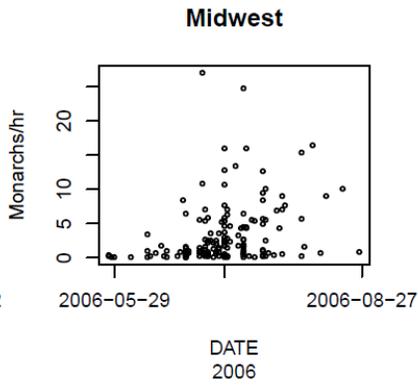
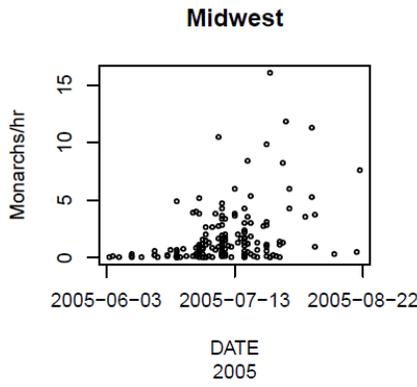
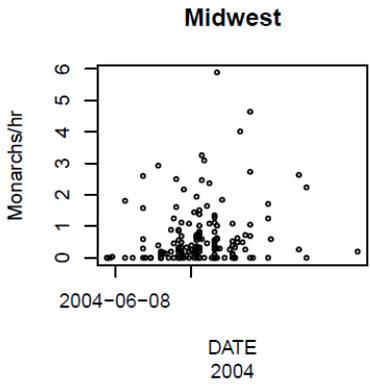
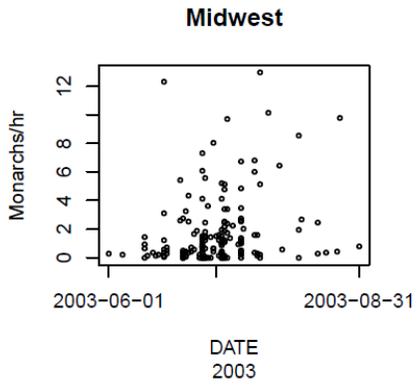
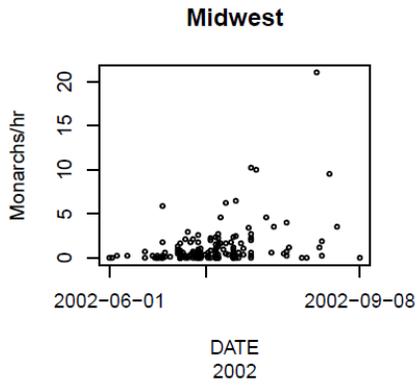
## 2. Census of early season butterflies

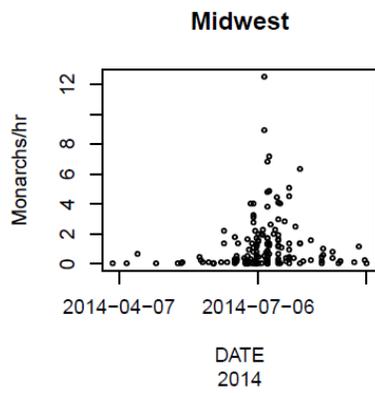
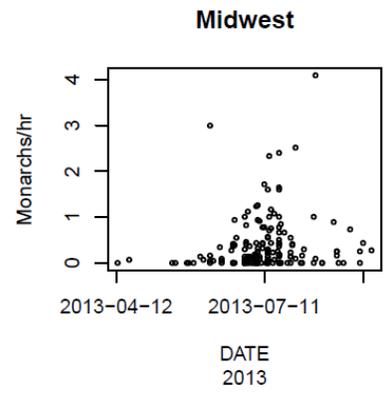
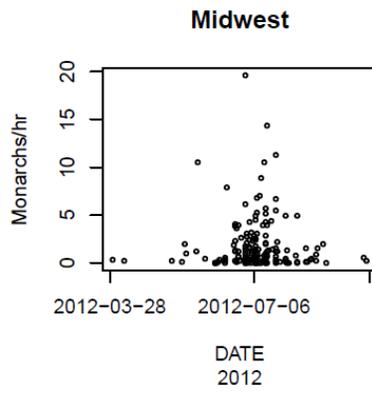
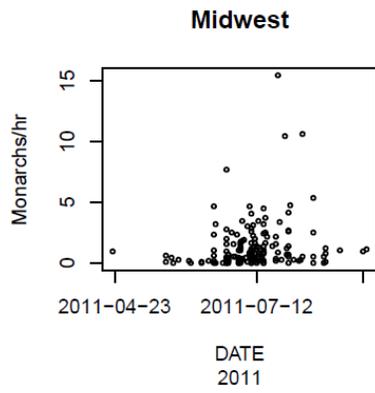
To address the potential for missing data early in the season, we plotted the yearly counts for the Midwest and Northeast to ensure that censuses captured a temporal increase in butterfly abundance in late spring. Namely, we were concerned that scarce sampling in some years could have missed some of the early migrating butterflies. In order to check that the incoming butterflies are all taken into account, we plotted the raw counts (i.e. before smoothing via moving average) for the Midwest and Northeast (Fig. A1.6). Throughout the panels, the seasonal data sets consistently begin with a low count ( $\sim 0$  monarchs per hour) early in the breeding

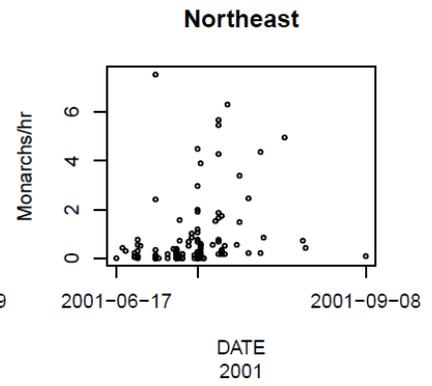
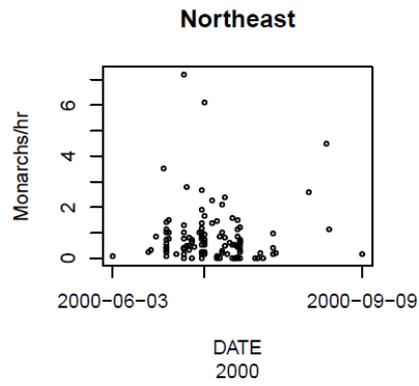
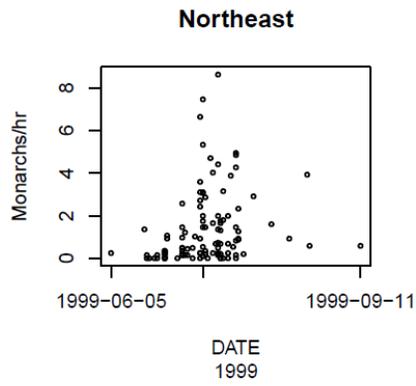
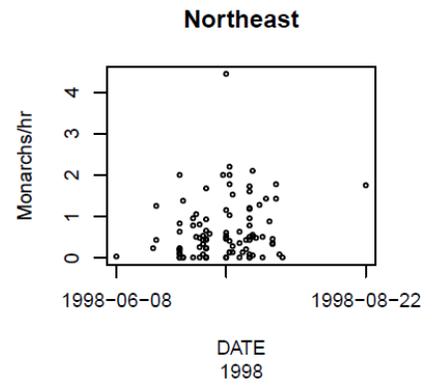
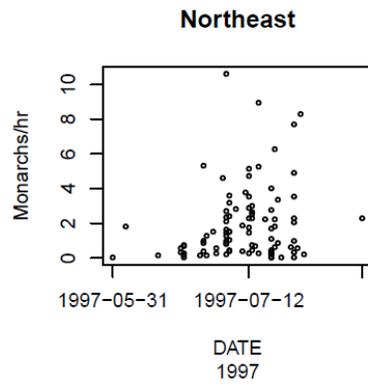
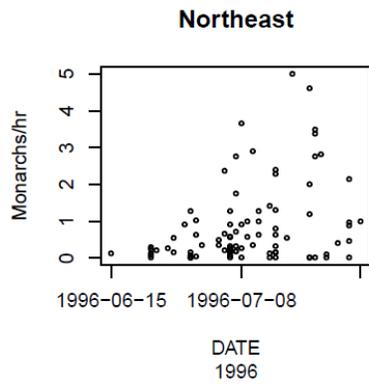
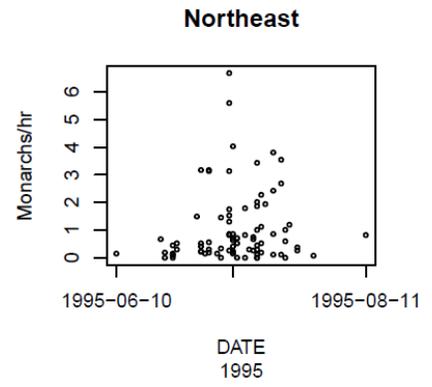
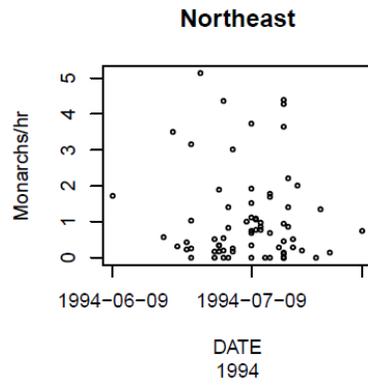
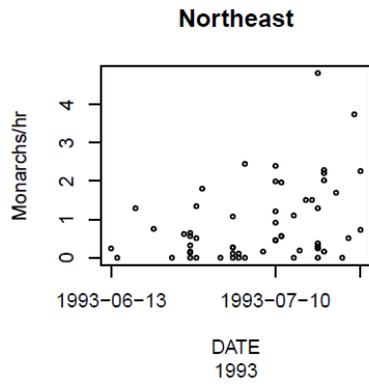
season, and the values typically increase over time. This suggests that counts began each year early enough to capture the timing of monarch arrival (which is somewhat variable across years). Given the consistent sampling coverage within the time of high monarch abundance each year, we are confident that our indices capture both the migrants and the breeding populations in Midwest and Northeast.

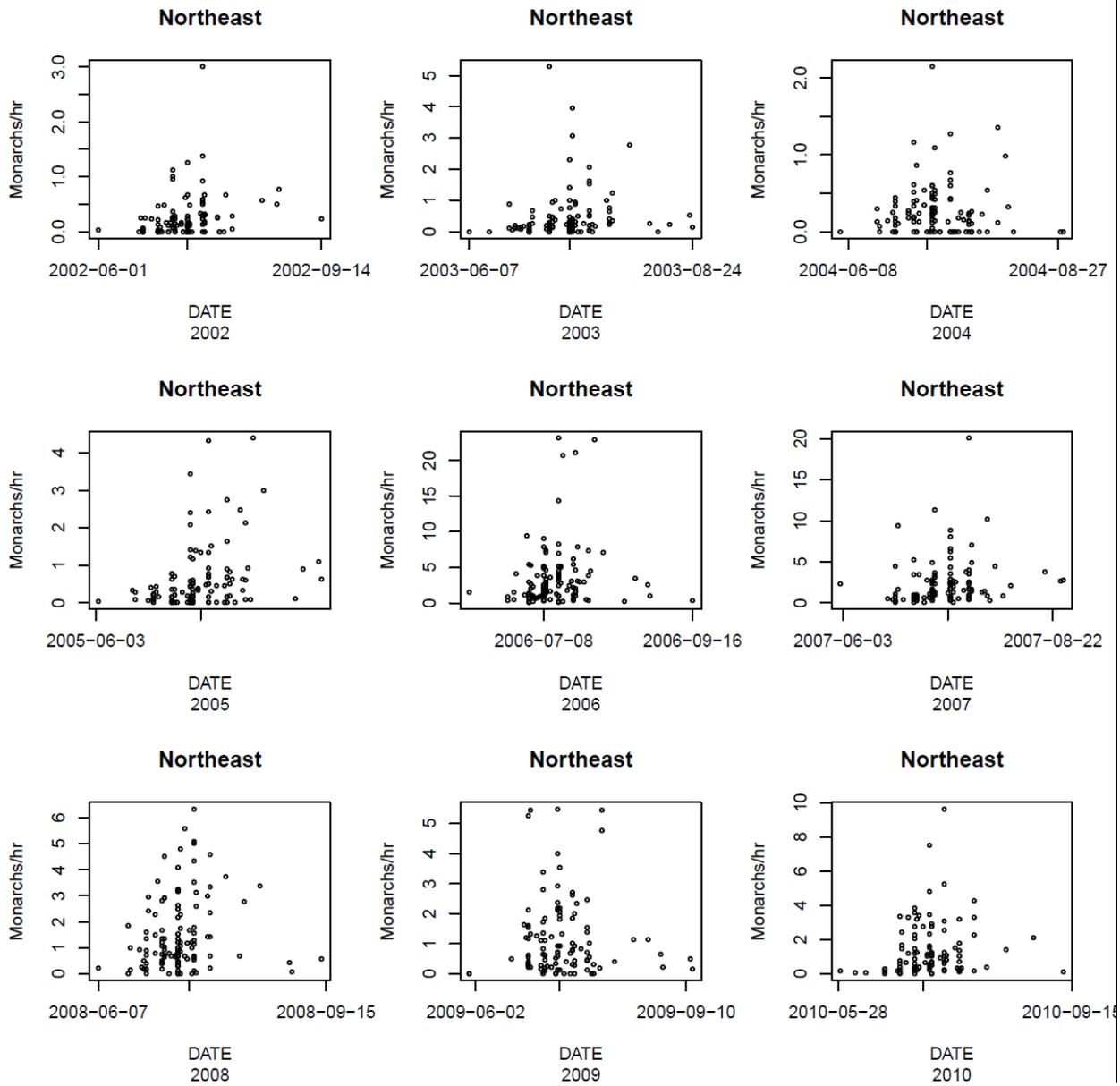
A1.6 (pages 8-13)

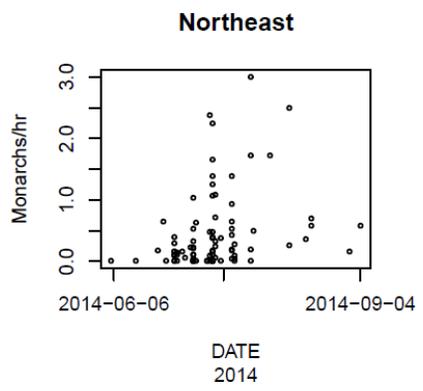
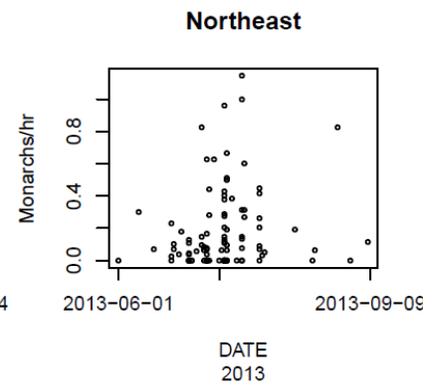
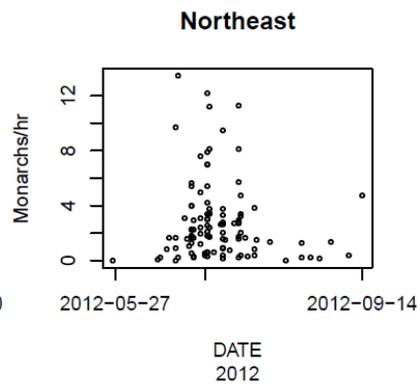
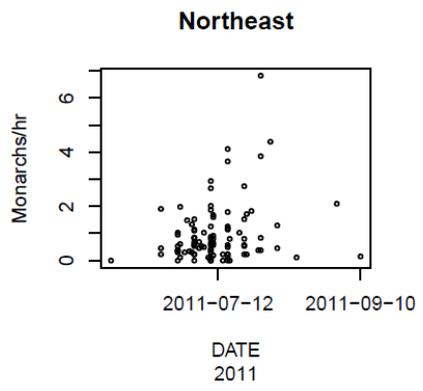










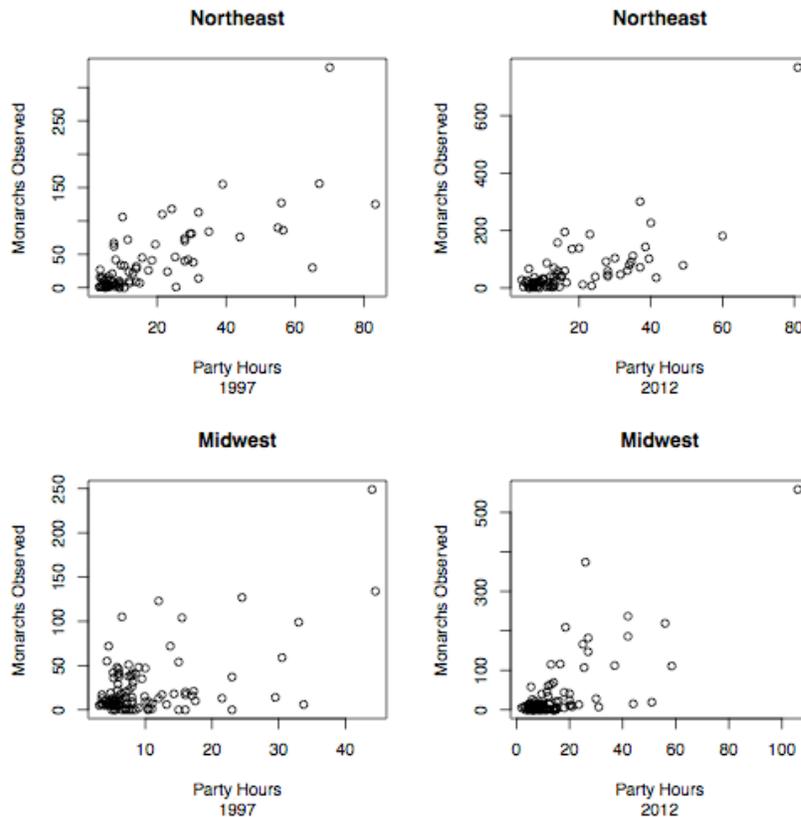


### 3. Are their biases in monarch censuses due to varying party hours?

A potential problem with citizen science datasets is variation in survey effort and its non-linear effect on counts (Link and Sauer 1999). As indicated in the Material and methods, each NABA count was normalized by dividing the number of observed monarchs by the party hours [5-7]. In some areas of citizen science analysis, as with Christmas bird counts, additional statistical methods have been used to account for potential spatial and temporal effort biases [1, 8]. For example, the number of organisms found may saturate with observation hours. These methods are used to correct for the saturating nature of count data with respect to hours spent. This bias would only appear when effort values are particularly high. Figure A1.7 shows representative graphs (from year 1997 and 2012) of how the number of observed monarchs changes with party hours for the count in both Northeast and Midwest. Specifically, we focused on July (the most intensely sampled month) under the assumption that the population size is more or less the same within a region over a month. We do not see a saturating relationship between sampling effort and butterfly observations. Similar results hold for other years.

In order to further test our dataset, we transformed our party hours to see if it affected the analyses [8, 9]. We re-ran our analyses using counts standardized by the square root of party hours (a simple method of transformation suggested by Link et al. 2006), and the patterns remain the same. Using  $\sqrt{\text{effort}}$  and re-calculating the annual indices, comparisons of the transformed to the original indices yielded  $R^2$  values of 0.95 to 0.99 (with the intercepts not being significantly different from zero). Thus, given the linear relationship between effort and monarch counts, the lack of an effect of further transforming the data, and to align with previous analyses [5-7], we maintain using the count data standardized by party hours.

A1.7

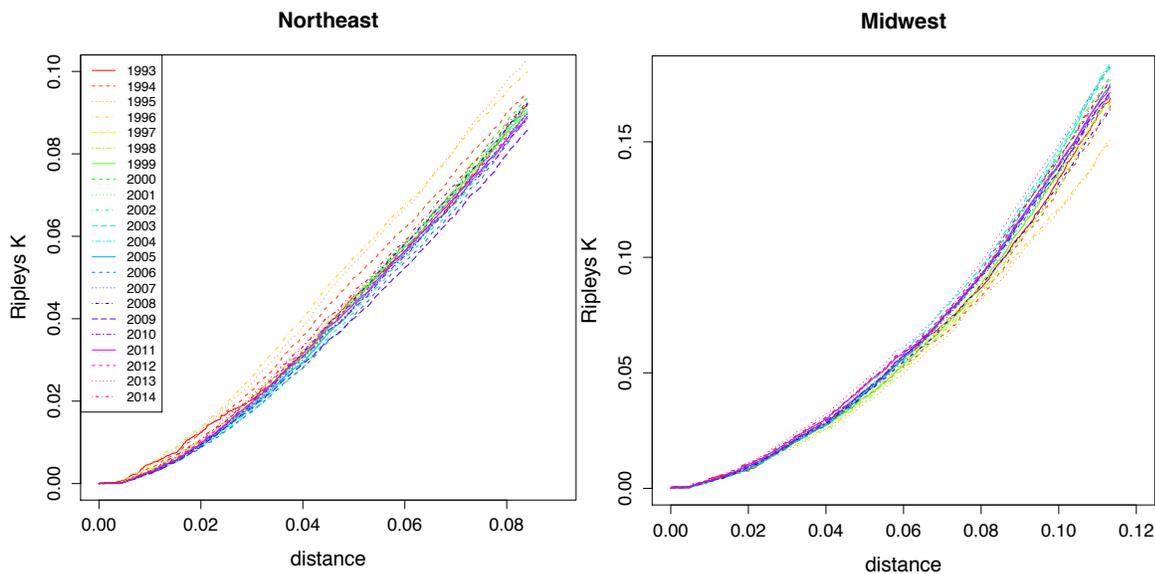


#### 4. Do census points cluster more over the years?

If patches of suitable monarch habitat are disappearing (in particular, due to loss of milkweed), then it is conceivable that NABA citizen science counts in later years were done in the few remaining patches, leading to an upward bias in population indices and masking a decline in the total regional population. To test for this possibility, we asked if NABA count locations show increasing spatial clustering in later years, which would occur if the counts are being done in a smaller number of locations. We used Ripley's  $K$  function [3], a standard measure of clustering in spatial statistics, to quantify the clustering of count locations in each year. Ripley's  $K$  function calculates the number of neighboring data points present within concentric circles around a focal sampling location, as the radius/distance increases. These values are averaged over all the sampling locations present in the data set for that year. We used Mercator projection (*mapproj* library in R) of sampling locations (given as latitude and longitude in the NABA data set) and Ripley's isotropic correction estimate of  $K$  (*spatstat* library in R).

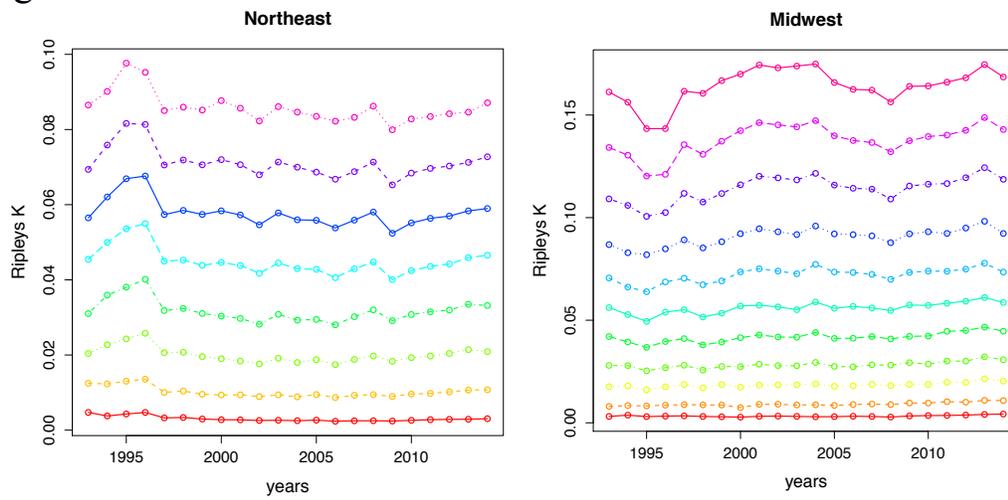
The patterns are consistent across years in both Northeast and Midwest regions (Fig. A1.8, different colors and lines correspond to different years), and do not differ substantially across years. More importantly, we do not see any trends in the  $K$  function with respect to year (Fig. A1.9) at any spatial scale. This implies that the count locations do not cluster more over time. We conclude that geographic clustering of monarch sampling is not increasing over time, and is therefore not a source of temporal bias in the NABA dataset.

Figure A1.8



**Figure A1.8.** Ripley's  $K$  function for the spatial locations of NABA population counts in each year.

Figure A1.9



**Figure A1.9.** Ripley's K function as a function of year for the Northeast and Midwest regions. The different colors and lines correspond to distances 0.01, 0.02, ..., 0.11 from bottom to top.

## Appendix 2

### Statistical analyses to examine temporal change in the relationship between stages of the annual migratory cycle

In the following series of analyses, we investigated the relationship between population size at one stage of the annual migratory cycle (DONOR region, independent variable) and the next time step (RECIPIENT region, dependent variable). To address temporal change in these relationships, we considered YEAR and the DONOR×YEAR interaction as additional covariates. YEAR was entered as a numerical covariate because we are interested in directional trends over time. Because the change in YEAR is small relative to its mean, DONOR and DONOR×YEAR are strongly collinear. To remove this, we centered YEAR about its mean. We considered the following models:

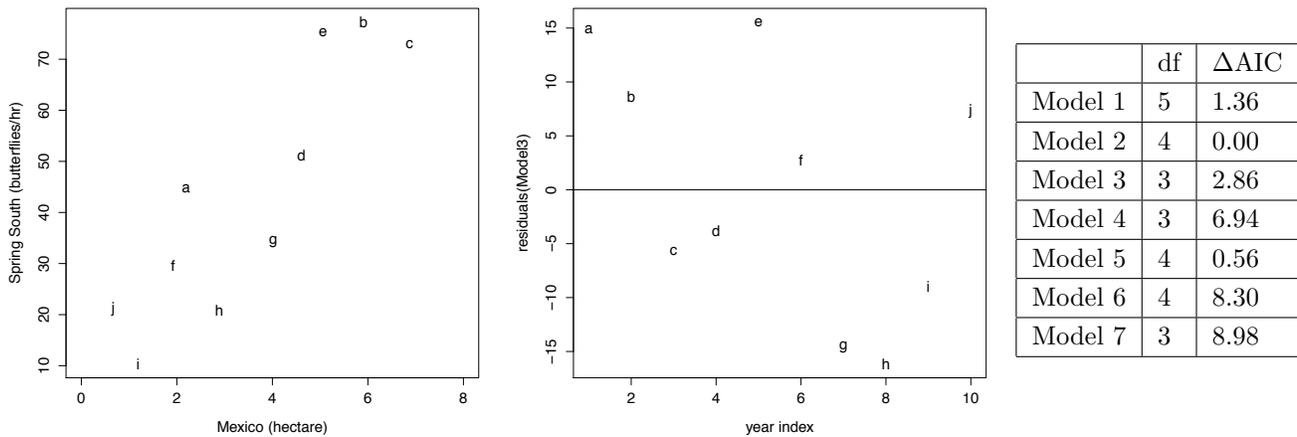
- Model 1: RECIPIENT  $\sim$  DONOR + YEAR + DONOR\*YEAR
- Model 2: RECIPIENT  $\sim$  DONOR + DONOR\*YEAR
- Model 3: RECIPIENT  $\sim$  DONOR
- Model 4: RECIPIENT  $\sim$  DONOR\*YEAR
- Model 5: RECIPIENT  $\sim$  DONOR + YEAR
- Model 6: RECIPIENT  $\sim$  YEAR + DONOR\*YEAR
- Model 7: RECIPIENT  $\sim$  YEAR

For each DONOR-RECIPIENT pair, we plot the relationship between regions or between region and year, with the letters on the plot indicating chronological order (a = first year of census, etc.). The table next to the graph shows the  $\Delta$ AIC value for each model, relative to the lowest AIC value.

We performed stepwise model selection based on AIC values [10], and also F-tests to evaluate the statistical significance of terms by a comparison of nested models with and without the term. We performed both backward and forward selection to check for consistency between these approaches. In backward selection, we started with the full model (Model 1) and sequentially eliminated the non-significant term (if any such exist) that resulted in the largest improvement in AIC, stopping when all terms are significant. In forward selection, we started with either DONOR (Model 3) or YEAR (Model 7), whichever had the stronger univariate correlation with the dependent variable, and sequentially added the term that gave the largest improvement in AIC, stopping when the added term was not statistically significant.

The table below each plot summarizes backward and forward model selection. The entries under **Model Comparison** in each row show the significance of that covariate, based on an  $F$ -test against a model with that term dropped (for Backward selection) or added (for Forward selection). The AIC of the modified model (with a term added or dropped) is also given. If an outlier was detected, the table reflects the analyses after it was removed.

# 1 Mexico to Spring South



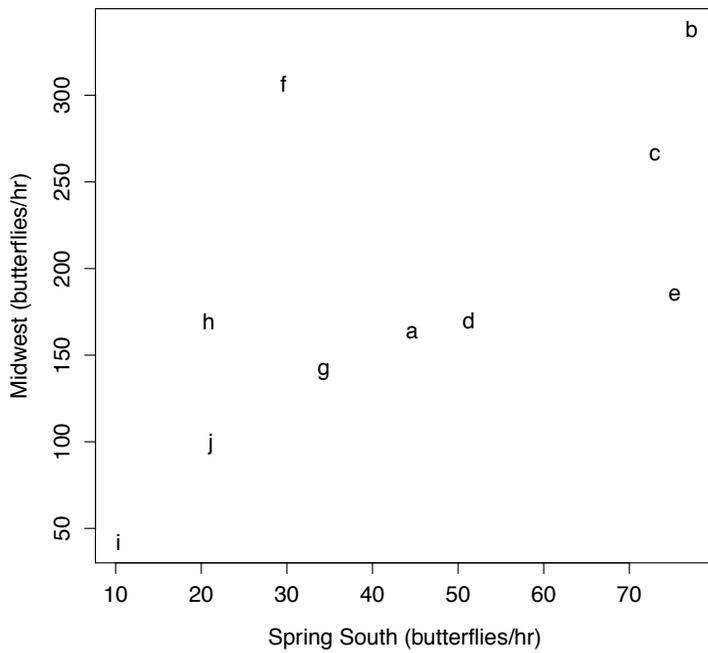
	Model	AIC	Model comparison		
			Mexico	YEAR	Mexico*YEAR
Backward					
1	Mexico + YEAR + Mexico*YEAR	50.38	<b>AIC=57.32, p=0.03</b>	AIC=49.02, p=0.55	AIC=49.58, p=0.42
2	<b>Mexico + Mexico*YEAR</b>	49.02	<b>AIC=55.95, p=0.02</b>		AIC=51.88, p=0.07
Forward					
3	Mexico	51.88		AIC=49.58, p=0.09	AIC=49.02, p=0.07
2	<b>Mexico + Mexico*YEAR</b>	49.02		AIC=50.38, p=0.55	

Backward and Forward model selection both lead to Model 3,  
 Spring South  $\sim$  Mexico

AIC favors the addition of Mexico\*YEAR (Model 2), but the  $F$ -test shows that this term is only marginal ( $p = 0.07$ ) and the residuals from Model 3 (plotted above) do not show any visible pattern over time.

*Conclusion:* The overwintering populations in Mexico predict Spring South populations. There is marginal evidence for a small decrease in the slope of this relationship over time.

## 2 Spring South to Midwest



	df	$\Delta$ AIC
Model1	5	3.32
Model2	4	1.43
Model3	3	0.00
Model4	3	0.70
Model5	4	1.35
Model6	4	2.40
Model7	3	0.54

	Model	AIC	Model comparison		
Backward			Spring South	YEAR	Spring South*YEAR
1	Spring South + YEAR + Spring South*YEAR	91.2	AIC=90.28, p=0.44	AIC=89.30, p=0.81	AIC=89.22, p=0.91
5	Spring South + YEAR	89.22	AIC=88.42, p=0.38	AIC=87.87, p=0.51	
3	<b>Spring South</b>	87.87	<b>AIC=91.30, p=0.04</b>		
Forward					
3	<b>Spring South</b>	87.87		AIC=89.22, p=0.51	AIC=89.30, p=0.54

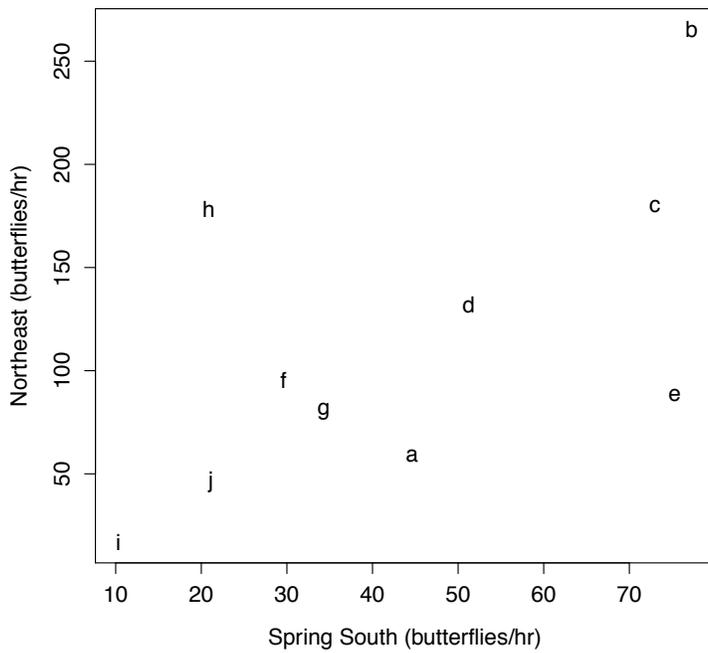
Forward selection, Backward selection, and AIC all lead to Model 3,

$$\text{Midwest} \sim \text{Spring South}$$

with the donor region as the only significant predictor ( $p < 0.05$ ).

*Conclusion:* Monarch populations in Spring South significantly predict those in the Midwest. There is no evidence for a temporal trend in this relationship.

### 3 Spring South to Northeast



	df	$\Delta$ AIC
Model1	5	2.29
Model2	4	1.35
Model3	3	0.00
Model4	3	0.24
Model5	4	1.98
Model6	4	1.70
Model7	3	1.87

	Model	AIC	Model comparison		
Backward			Spring South	YEAR	Spring South*YEAR
1	Spring South + YEAR + Spring South*YEAR	87.03	AIC=86.44, p=0.38	AIC=86.09, p=0.44	AIC=86.72, p=0.33
2	Spring South + Spring South*YEAR	86.09	AIC=84.98, p=0.45		AIC=84.74, p=0.52
3	<b>Spring South</b>	84.74	AIC=87.35, p=0.06		
Forward					
3	<b>Spring South</b>	84.74		AIC=86.72, p=0.92	AIC=86.09, p=0.52

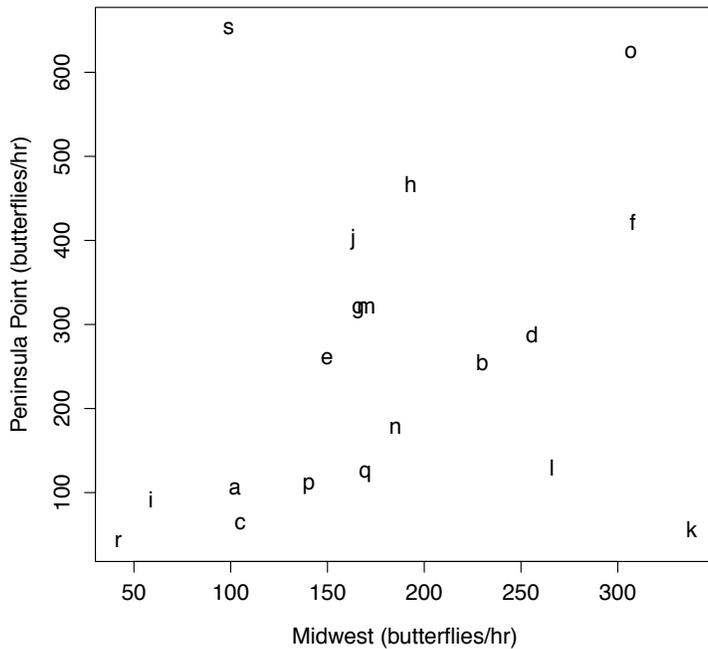
Forward selection, Backward selection, and AIC all lead to Model 3,

$$\text{Northeast} \sim \text{Spring South}$$

with the donor region as the marginally significant predictor ( $p = 0.06$ ).

*Conclusion:* Monarch populations in Spring South marginally predict that in the Northeast. There is no evidence for a temporal trend in this relationship.

## 4 Midwest to Peninsula Point



	df	$\Delta$ AIC
Model1	5	3.87
Model2	4	1.99
Model3	3	0.00
Model4	3	4.46
Model5	4	1.93
Model6	4	6.05
Model7	3	4.37

	Model	AIC	Model comparison		
Backward			Midwest	YEAR	Midwest*YEAR
1	Midwest + YEAR + Midwest*YEAR	186.29	AIC=188.47, p=0.08	AIC=184.40, p=0.77	AIC=184.35, p=0.83
5	Midwest + YEAR	184.35	AIC=186.78, p=0.06	AIC=182.41, p=0.82	
3	<b>Midwest</b>	182.41	<b>AIC=184.87, p&lt;0.05</b>		
Forward					
3	<b>Midwest</b>	182.41		AIC=184.35, p=0.82	AIC=184.40, p=0.91

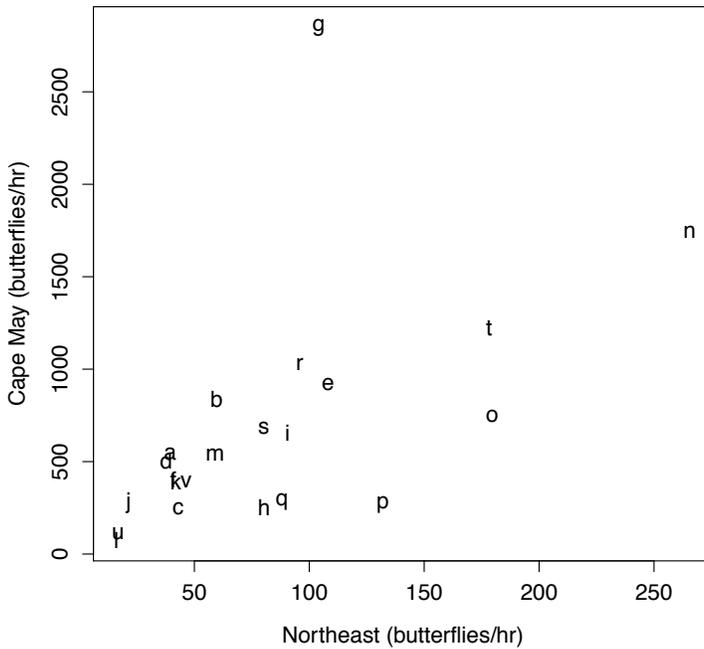
Forward selection, Backward selection, and AIC all lead to Model 3,

$$\text{Peninsula Point} \sim \text{Midwest}$$

With an outlier (2014: Midwest = 98.8, Peninsula Point = 652.8; Studentized residual >3.1) included, Midwest is not a significant predictor ( $p = 0.26$ ). However with an outlier removed, Midwest becomes a significant predictor ( $p < 0.05$ ). The model selection table reflects the analysis after the outlier was removed.

*Conclusion:* Without an outlier, Midwest monarch populations significantly predict fall migrants through Peninsula Point, and we do not see any signatures of change in the slope over time.

## 5 Northeast to Cape May



	df	$\Delta$ AIC
Model1	5	2.55
Model2	4	1.24
Model3	3	0.00
Model4	3	18.60
Model5	4	0.62
Model6	4	16.45
Model7	3	21.21

	Model	AIC	Model comparison		
			Northeast	YEAR	Northeast*YEAR
Backward					
1	Northeast + YEAR + Northeast*YEAR	236.29	<b>AIC=250.20, p&lt;0.001</b>	AIC=234.98, p=0.46	AIC=234.36, p=0.81
5	Northeast + YEAR	234.36	<b>AIC=254.96, p&lt;0.0001</b>	AIC=233.74, p=0.28	
3	<b>Northeast</b>	233.74	<b>AIC=253.10, p&lt;0.0001</b>		
Forward					
3	<b>Northeast</b>	233.74		AIC=234.36, p=0.28	AIC=234.98, p=0.43

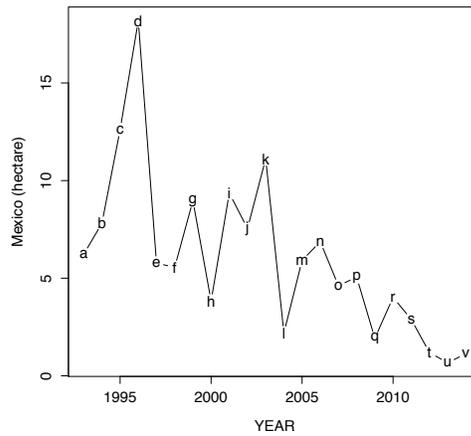
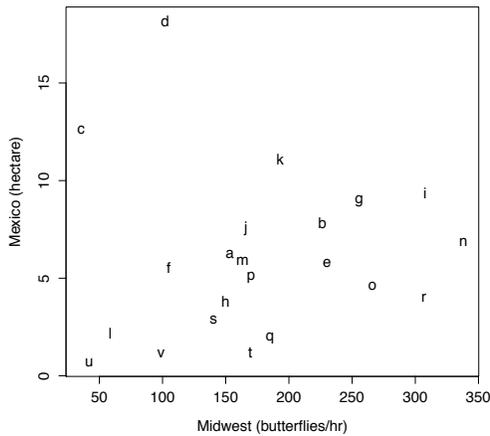
Without an outlier (1999: Northeast = 104.1, Cape May = 2849.2; Studentized residual 8.420), Forward selection, Backward selection, and AIC all lead to Model 3,

$$\text{Cape May} \sim \text{Northeast}$$

When the outlier is included, however, we see marginally significant effect ( $p = 0.09$ ) of the interaction term (Model 2) with negative slope. The model selection table reflects the analysis after the outlier was removed.

*Conclusion:* Northeast monarch populations predict Cape May, and the weak evidence for a temporal trend was due to a single outlier.

## 6 Midwest to Mexico



	df	$\Delta$ AIC
Model1	5	0.53
Model2	4	7.24
Model3	3	12.80
Model4	3	7.17
Model5	4	0.00
Model6	4	0.45
Model7	3	0.09

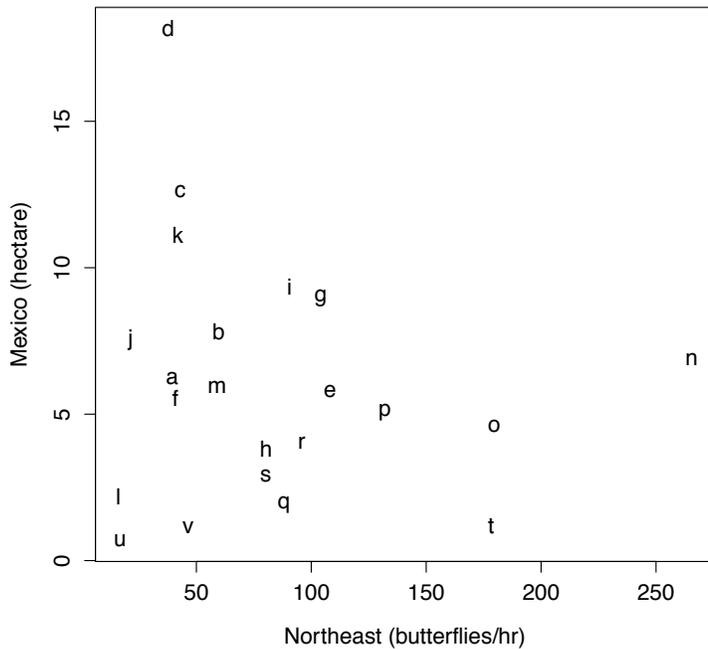
	Model	AIC	Model comparison		
Backward			Midwest	YEAR	Midwest*YEAR
1	Midwest + YEAR + Midwest*YEAR	39.56	AIC=39.49, p=0.22	<b>AIC=46.27, p&lt;0.01</b>	AIC=39.04, p=0.28
5	Midwest + YEAR	39.04	AIC=39.12, p=0.19	<b>AIC=51.84, p&lt;0.001</b>	
7	<b>YEAR</b>	39.12		<b>AIC=51.21, p&lt;0.001</b>	
Forward					
7	<b>YEAR</b>	39.12	AIC=39.04, p=0.19		AIC=39.49, p=0.24

Forward and Backward model selection both lead to Model 7,  
 $\text{Mexico} \sim \text{YEAR}$

AIC favors the addition of Midwest (Model 5), but this term is not significant ( $p = 0.19$ ). We had the same result with and without an outlier (1996: Midwest = 102.15, Mexico = 18.19; Studentized residual = 3.93). The model selection table reflects the analysis after the outlier was removed.

*Conclusion:* YEAR is an important predictor of the Mexican overwintering population, and neither Midwest nor the interaction shows statistical significance.

## 7 Northeast to Mexico



	df	$\Delta$ AIC
Model1	5	3.63
Model2	4	7.93
Model3	3	13.37
Model4	3	6.75
Model5	4	1.93
Model6	4	1.64
Model7	3	0.00

	Model	AIC	Model comparison		
Backward			Northeast	YEAR	Northeast*YEAR
1	Northeast + YEAR + Northeast*YEAR	56.05	AIC=54.06, p=0.91	<b>AIC=60.35, p=0.03</b>	AIC=54.35, p=0.62
6	YEAR + Northeast*YEAR	54.06		<b>AIC=59.16, p=0.01</b>	AIC=52.42, p=0.58
7	<b>YEAR</b>	52.42		<b>AIC=64.26, p&lt;0.001</b>	
Forward					
7	<b>YEAR</b>	52.42	AIC=54.35, p=0.81		AIC=54.06, p=0.58

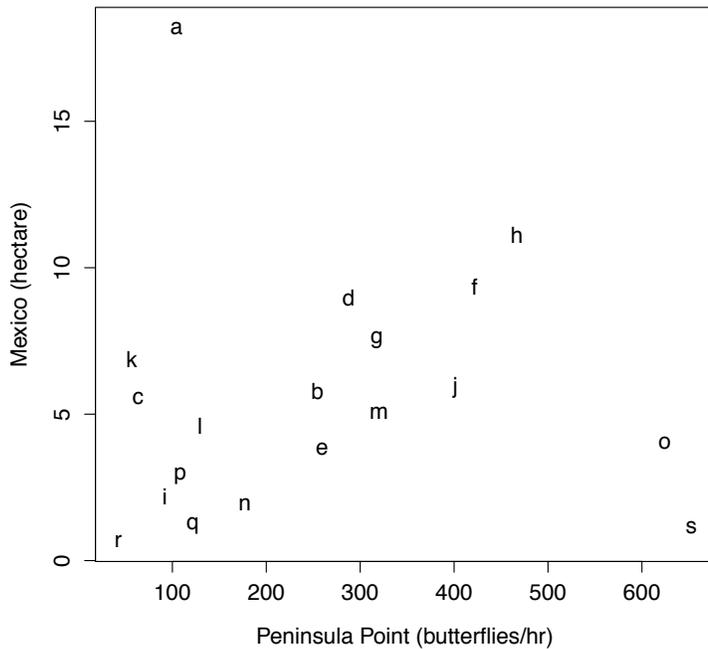
Forward selection, Backward selection, and AIC all lead to Model 7,

$$\text{Mexico} \sim \text{YEAR}$$

where YEAR is the only significant predictor ( $p < 0.001$ ).

*Conclusion:* YEAR is an important predictor of the Mexican overwintering population, and neither Northeast nor the interaction shows statistical significance.

## 8 Peninsula Point to Mexico



	df	$\Delta$ AIC
Model1	5	1.49
Model2	4	0.00
Model3	3	16.48
Model4	3	9.55
Model5	4	5.06
Model6	4	8.29
Model7	3	6.70

	Model	AIC	Model comparison		
Backward			Peninsula Point	YEAR	Peninsula Point*YEAR
1	Pen Point + YEAR + Pen Point*YEAR	26.63	<b>AIC=33.43, p=0.01</b>	AIC=25.14, p=0.54	<b>AIC=30.20, p=0.04</b>
2	<b>Pen Point + Pen Point*YEAR</b>	25.14	<b>AIC=34.69, p&lt;0.01</b>		<b>AIC=41.62, p&lt;0.001</b>
Forward					
3	Pen Point	41.62		<b>AIC=30.2, p&lt;0.001</b>	<b>AIC=25.14, p&lt;0.001</b>
2	<b>Pen Point + Pen Point*YEAR</b>	25.14		AIC=26.63, p=0.54	

With an outlier included, Forward selection, Backward selection, and AIC all lead to Model 7,  
 $Mexico \sim YEAR$

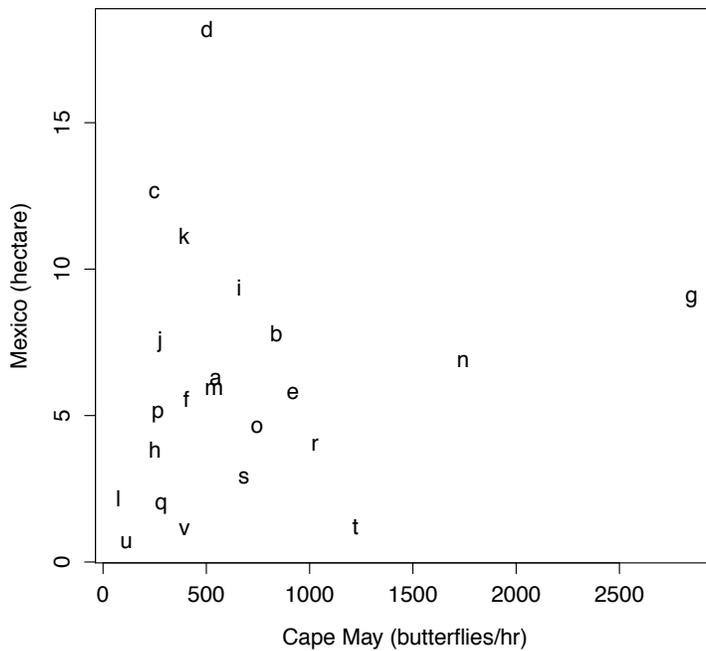
However when an outlier (1996: Peninsula Point = 104.4, Mexico = 18.19; Studentized residual = 4.41) is removed, Forward selection, Backward selection, and AIC all lead to Model 2,

$$Mexico \sim Pen\ Point + Pen\ Point*YEAR$$

with a negative coefficient for the interaction term ( $p < 0.001$ ) and significant donor region ( $p < 0.01$ ). The model selection table reflects the analysis after the outlier was removed.

*Conclusion:* With an outlier remove, Peninsula Point predicts Mexico and the relationship changes over time (i.e. the slope decreases over time). This effect cannot be explained by declining milkweed.

## 9 Cape May to Mexico



	df	$\Delta$ AIC
Model1	5	3.34
Model2	4	9.35
Model3	3	13.50
Model4	3	7.35
Model5	4	1.75
Model6	4	1.81
Model7	3	0.00

	Model	AIC	Model comparison		
Backward			Cape May	YEAR	Cape May*YEAR
1	Cape May + YEAR + Cape May*YEAR	55.76	AIC=54.23, p=0.54	<b>AIC=61.76, p=0.01</b>	AIC=54.17, p=0.57
5	Cape May + YEAR	54.17	AIC=52.42, p=0.65	<b>AIC=65.92, p&lt;0.001</b>	
7	<b>YEAR</b>	52.42		<b>AIC=64.26, p&lt;0.001</b>	
Forward					
7	<b>YEAR</b>	52.42	AIC=54.17, p=0.65		AIC=54.23, p=0.69

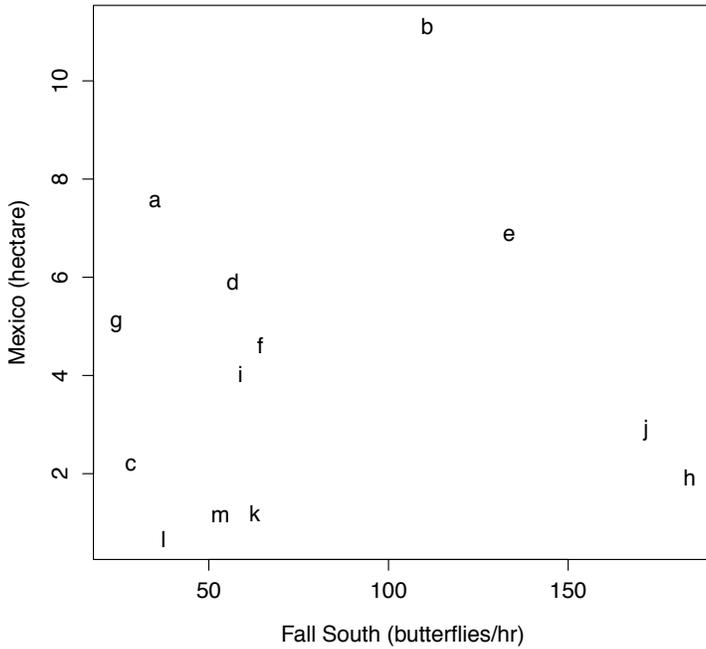
Forward selection, Backward selection, and AIC all lead to Model 7,

$$\text{Mexico} \sim \text{YEAR}$$

where YEAR is the only significant predictor ( $p < 0.001$ ).

*Conclusion:* YEAR is an important predictor of the Mexican overwintering population, and neither Cape May nor the interaction shows statistical significance.

## 10 Fall South to Mexico



	df	$\Delta$ AIC
Model1	5	1.55
Model2	4	0.00
Model3	3	16.90
Model4	3	0.58
Model5	4	5.83
Model6	4	1.91
Model7	3	4.48

	Model	AIC	Model comparison		
Backward			Fall South	YEAR	Fall South*YEAR
1	Fall South + YEAR + Fall South*YEAR	16.56	AIC=16.92, p=0.21	AIC=15.01, p=0.59	<b>AIC=20.84, p&lt;0.05</b>
2	Fall South + Fall South*YEAR	15.01	AIC=15.59, p=0.17		<b>AIC=31.90, p&lt;0.001</b>
4	<b>Fall South*YEAR</b>	15.59			<b>AIC=29.99, p&lt;0.001</b>
Forward					
7	YEAR	19.49	AIC=20.84, p=0.49		AIC=16.92, p=0.07
6	<b>YEAR + Fall South*YEAR</b>	16.92	AIC=16.56, p=0.21		

AIC leads to Model2, but backward selection shows that Fall South is not significant under the  $F$ -test. Forward selection shows that the interaction term is marginally significant even when YEAR is included in the model. Taken together, we infer that

$$\text{Mexico} \sim \text{Fall South} * \text{YEAR}$$

is the best model.

*Conclusion:* Interaction term is an important predictor of the Mexican overwintering population, and neither Fall South nor YEAR shows statistical significance.

## Additional references

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