ASSOCIATION BETWEEN SHRIMP CATCH PER UNIT EFFORT AND ENVIRONMENTAL VARIABLES IN THE GULF OF MEXICO

An Undergraduate Research Scholars Thesis

By

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ABSTRACT

Association between Shrimp Catch per Unit Effort and Environmental Variables in the Gulf of Mexico (May 2013)

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The commercial shrimp harvest is the second most important fishery in the United States, and eighty percent of this harvest by weight is caught in the Gulf of Mexico (GOM). Survival rate in the post larval stage in GOM estuaries is hypothesized to be the most important in determining cohort strength. Previous research has shown that salinity and temperature changes in estuaries during peak recruitment affect shrimp growth, which can affect their survival. If environmental conditions such as tide and discharge affect these conditions and accordingly affect shrimp growth, then these environmental factors could be used as a proxy for estimating shrimp populations. Our analysis was performed to test the idea that shrimp abundance is significantly affected by tidal fluctuations and/or river discharge. Tide height data were obtained from 6 NOAA stations within the GOM, river discharge data were obtained from 7 major rivers, and SEAMAP brown shrimp (*Farfantepenaeus aztecus)* and white shrimp (*Litopenaeus setiferus)* catch per unit effort (CPUE) data were obtained from 10 statistical zones within the GOM. Two analysis methods, correlation analysis and partial least square regression analysis (PLSR), were performed between both environmental factors and shrimp data. Correlation analysis results showed consistently positive correlations between SEAMAP shrimp trawl data and tide data and

consistently negative associations between SEAMAP shrimp trawl data and discharge data, both results are consistent with previous research. Results from both analytical methods indicate that the association between environmental variables and shrimp CPUE are small, but present and statistically significant, which is consistent with past research. Because PLSR analysis estimates effect size, these results can be viewed in terms of biological importance and used as a shrimp population management tool.

ACKNOWLEDGMENTS

It is with immense gratitude that I acknowledge the support and instruction of my research advisor, Dr. Masami Fujiwara, who spent countless hours guiding me through the research process. Without that guidance and support, this research would not have happened. I would also like to thank Drs. James Nance, Tom Minello and Rick Hart for constructive comments and advice that furthered my understanding of shrimp population dynamics. I am grateful to the researchers involved in SEAMAP data collection and management for providing the raw data used in this project. Additionally, this research would not have been possible without the funding provided by Texas Sea Grant in the form of an undergraduate fellowship as well as a research grant awarded to Dr. Masami Fujiwara. Finally, I am grateful to the Undergraduate Research Scholars Program for the feedback and funding provided to support my research.

CHAPTER I

INTRODUCTION

The commercial shrimp harvest is the second most important fishery in the United States, contributing 192,033 tons annually. Eighty percent of the total national shrimp harvest by weight is caught in the Gulf of Mexico (GOM) (Voorhees 2011). Shrimp caught in the GOM represent ninety seven percent of all brown shrimp *Farfantepenaeus aztecus* and almost ninety percent of all white shrimp *Litopenaeus setiferus* harvested in the United States (NOAA 2010). Shrimp are also the most important consumer seafood item, the average consumption per capita being 4.2 pounds annually (Voorhees 2011). Shrimp in 2011 contributed $517,697,000 in landings revenue (Voorhees 2011). Because of the economic importance of shrimp, particularly shrimp harvested in the GOM, it is important for us to understand how environmental factors affect shrimp population dynamics.

Estuaries are very important habitats for shrimp because they serve as “nurseries” for juveniles, when growth rate has the greatest effect on overall mortality (Diop et al. 2007). Shrimp spawn in the open water, and their larvae move into estuaries at about one month. Past research shows that white juvenile shrimp enter estuaries between May and November, with peak recruitment between June and September; brown shrimp enter estuaries all year, with peak recruitment occurring between February and April (Lassuy 1983, Muncy 1984). Survival and growth rate of this postlarvae stage in the estuaries is the most important in determining cohort strength (Diop et al. 2007). Thus measuring environmental factors in these estuaries can be used as a proxy for estimating shrimp populations.

Numerous studies have investigated the association between shrimp growth and environmental conditions in GOM estuaries (Diop et al. 2007, Rozas and Minello 2011, Adamack et al. 2012). These studies have found that shrimp growth rates are affected by temperature and salinity, which affect metabolic rates and food availability, respectively. Both of these factors are positively correlated with juvenile shrimp survival. Past research has also found substantial evidence that penaeid shrimp productivity is dependent on access to salt marshes (Minello et al. 2011). Minello et al. (2011) found evidence of a positive relationship between marsh selection and flooding duration. Even though Minello's research showed a relationship between tidal fluctuations and shrimp productivity, because of limited data, these results need to be viewed with caution (Minello et al. 2011).

Rozas and Minello (2011) found that shrimp growth was reduced in low salinity, this was attributed to less food availability and increased metabolic cost. Consequently, when river diversions reduce salinity for enough time during peak recruitment periods and over enough habitat, shrimp growth rates would decrease. In a subsequent study, Adamack et al. (2012) found that freshwater diversions in April and May, which dropped water temperature by 5°C, decreased juvenile brown shrimp productivity by 40 to 60 % while diversions in February and March had little effect.

If juvenile survival is affected by access to estuarine edge then we would expect tide to be positively correlated with adult abundance (Minello et al. 2011). We also expect that, if juvenile survival is affected by river discharge then there will be a negative correlation between freshwater discharge and adult abundance. Preliminary analysis was conducted between temporally coordinated environmental data and shrimp abundance data, after stationarizing the time series using maximum autocorrelation factor analysis, to look for significant relationships (Fujiwara and Mohr 2009). For the next analysis, environmental variables were spatially and temporally coordinated with shrimp CPUE so that only those tide and discharge data closest to each SEAMAP statistical zone were analyzed. For this analysis, partial least square regression was used to identify how much variation in the environmental variables could be used to explain the variation in shrimp CPUE.

CHAPTER II

METHODS

Data Collection

Three types of existing data were used from different sources; shrimp trawl data, river discharge data and tide height data. All data was collected for the time period of 1987 to 2010. Fishery independent summer and fall shrimp research trawl data were obtained from the Southeast Area Monitoring and Assessment Program (SEAMAP). Summer and fall samples for brown and white shrimp were obtained in catch per unit effort (CPUE) for Statistical Zones 11 and 13 - 21 of the GOM (http://www.gsmfc.org/default.php?p=sm_ov.htm). These zones were selected because they are the zones where active brown and white shrimp fisheries are located.

River discharge data were obtained from the U.S. Geological Survey for the major rivers that empty into the Statistical Zones of interest in the GOM (http://waterdata.usgs.gov). Rivers were chosen only if data was available in units of volume discharge per unit time and the station was located reasonably close to the mouth of the river. The 7 rivers selected were; Pascagoula River, Mississippi River, Atchafalaya River, Sabine River, Trinity River, Brazos River and the Colorado River. The Colorado River was not included in correlation analysis because some data was missing from this variable.

Tide height data was collected from the National Oceanic and Atmospheric Administration (http://tidesandcurrents.noaa.gov/tides11/). Stations were chosen only if they were located within one of the SEAMAP statistical zones of interest and had tide data available from 1987 to

2010. The 6 selected station locations were; Port Isabel, Corpus Christi, Rockport, Galveston Pier 21, Sabine Pass North and Grand Isle. Verified hourly water surface height above reference datum was collected for each of these stations. The Sabine Pass North station was not used in correlation analysis because some data was missing from this variable.

Data Manipulation

The proportion of time tide height was 10cm above the marsh edge was the tide variable used in this analysis. Minello et al. (2011) found that water levels 5cm above marsh edge provide sufficient access to marsh edge habitat by penaeid shrimp to affect growth. For preliminary analysis, we used a slightly higher tide height threshold value than was determined in research by Minello et al. (2011). Further investigation showed that varying the threshold between 0 cm and 50 cm had little effect on analysis results. Because of the lack of accurate data on the exact height of marsh edge relative to tide data over the time span used in this analysis, I decided to keep the 10cm threshold. The tide variable was therefore converted into the proportion of time the data extended over the total hours spent 10cm above zero tide. Daily discharge data was converted into monthly mean discharge rates. The original data were in cubic feet per second, but was converted to cubic meters per second. Environmental data and shrimp data were temporally coordinated, where environmental data from February through May was associated with summer shrimp data and environmental data from July through October was associated with fall shrimp data.

Correlation Analysis between Shrimp CPUE and Environmental Variables

Brown and white shrimp data CPUE were transformed by taking the square root to stabilize the variance, and then standardized by taking the Z-score. Because the time series exhibited increasing trend, the data were stationarized. First, minimum/maximum autocorrelation factor analysis (MAFA, see Fujiwara and Mohr (2009)) was applied to each time series from the 10 statistical zones to find the common non-stationary factor among them. The first common factor was smoothed applying a five-point moving average. This smoothed factor (non-stationary trend) was removed by regressing the original time series for the 10 statistical zones against the smoothed factor and taking the residuals from the regression.

Tide data were transformed by taking square root to stabilize the variance, and then standardized by taking the Z-score. Because the time series exhibited increasing trend, they were stationarized. MAFA (Fujiwara and Mohr 2009) was applied to the time series from the 5 tidal data locations to find one common non-stationary factor among them. The common factor was smoothed applying a five-point moving average. This smoothed factor was removed by regressing the original time series from each location against the smoothed factor and taking the residuals from the regression.

Discharge data were transformed by taking square root to stabilize the variance and standardized by taking the Z-score. Square root transformation was performed to stabilize the variance. No trend was identified however the time series was stationarized to remove any possible trend. MAFA (see Fujiwara and Mohr (2009) was applied to the time series from the 6 rivers to find one common non-stationary factor among them. The common factor was smoothed applying a five-point moving average. This smoothed factor was removed by regressing the original time series from each location against the smoothed factor and taking the residuals from the regression.

Correlation analysis was performed with MATLAB using the residuals of shrimp CPUE time series and environmental variables. The significance of the correlation was determined using a significance level of 0.05.

Partial Least Square Regression Analysis

Partial Least Square Regression (PLSR) analysis was used to associate shrimp CPUE's and the environmental variables: tide and discharge. This technique is similar to multiple linear regression but is useful when using a large set of predictors, or independent variables with a small set of dependent variables, as is the case in this analysis (Abdi 2003).

Data was spatially and temporally coordinated for this analysis, where shrimp CPUE data (S) was associated only with the location of discharge (X) and tide data (Y) closest to the statistical zone where that shrimp data was collected (Table 1). Environmental data from spring and fall were associated with the corresponding Brown and White Shrimp CPUE.

Table 1: Spatial Associations used in PLSR Analysis

Shrimp CPUE Statistical Zone	Associated Tide Locations	Associated Discharge Locations
11	Grand Isle (GISL)	Pascagoula River (PASC)
13	Grand Isle (GISL)	Mississippi River (MISS) Atchafalaya River (ATCH)
14	Grand Isle (GISL)	Mississippi River (MISS) Atchafalaya River (ATCH)
15	Grand Isle (GISL)	Mississippi River (MISS) Atchafalaya River (ATCH)
16	Sabine Pass North (SABN)	Sabine River (SABI)
17	Sabine Pass North (SABN)	Sabine River (SABI)
18	Sabine Pass North (SABN) Galveston Pier 21 (GALV)	Sabine River (SABI) Trinity River (TRIN)
19	Galveston Pier 21 (GALV) Rockport (ROCK)	Brazos River (BRAZ) Colorado River (COLO)
20	Rockport (ROCK) Corpus Christi (CORP)	Colorado River (COLO)
21	Corpus Christi (CORP) Port Isabel (PISA)	Colorado River (COLO)

Function ‘plsregress.m’ in MATLAB was used to perform this analysis. Latent vectors, components from X that were also relevant to Y, were identified. X and Y were then decomposed, broken into constituent elements, so that they explained the greatest amount of covariance between X and Y as possible. The Z-score of both X and Y were taken in order to standardize the data. The Mean Square Prediction Error (MSE) was then determined by the leave-one-out cross-validation method. In the cross validation, a model was fitted to the data using partial least squares regressions without one data point, in this case data for 1 year. The removed data was then predicted with the fitted model, and prediction error was calculated. This was repeated over all data points, each time removing a different data point. The sum of squared prediction errors (MSE) was calculated. The model with the least prediction error was selected for each location.

This analysis identified how many components and how much of the variation in those components of the independent environmental variables (X and Y) could be used to explain how much of the dependent shrimp variable (S). Three models were possible, where shrimp (S) is a function of discharge (X) and tide (Y). In Model 1, the shrimp data is not explained by either environmental variable and is therefore explained by the error (Ei) only. In Models 2, 3 and 4, the shrimp data is explained by the error (Ei) and by 1, 2 or 3 uncorrelated linear combinations of the X and Y variables ($\alpha f(x, y)$), respectively. Of these, the model with the lowest MSE value was chosen because this represents the lowest error between observed and predicted values, and consequently is the best predictor of shrimp (S). Only those values that were statistically significant at a significance level of 0.05 were included in the results. Then, the same analysis was repeated with discharge data (X) alone and tide data (Y) alone to determine whether one type of variables is sufficient to explain the annual fluctuation in shrimp CPUE data.

- Model 1: $s_i = Ei$
- Model 2: $s_i = \alpha_1 f_1(x, y) + Ei$
- Model 3: $s_i = \alpha f(x, y) + \alpha_2 f_2(x, y) + Ei$
- Model 4: $s_i = \alpha f(x, y) + \alpha_2 f_2(x, y) + \alpha_3 f_3(x, y) + Ei$

CHAPTER III

RESULTS

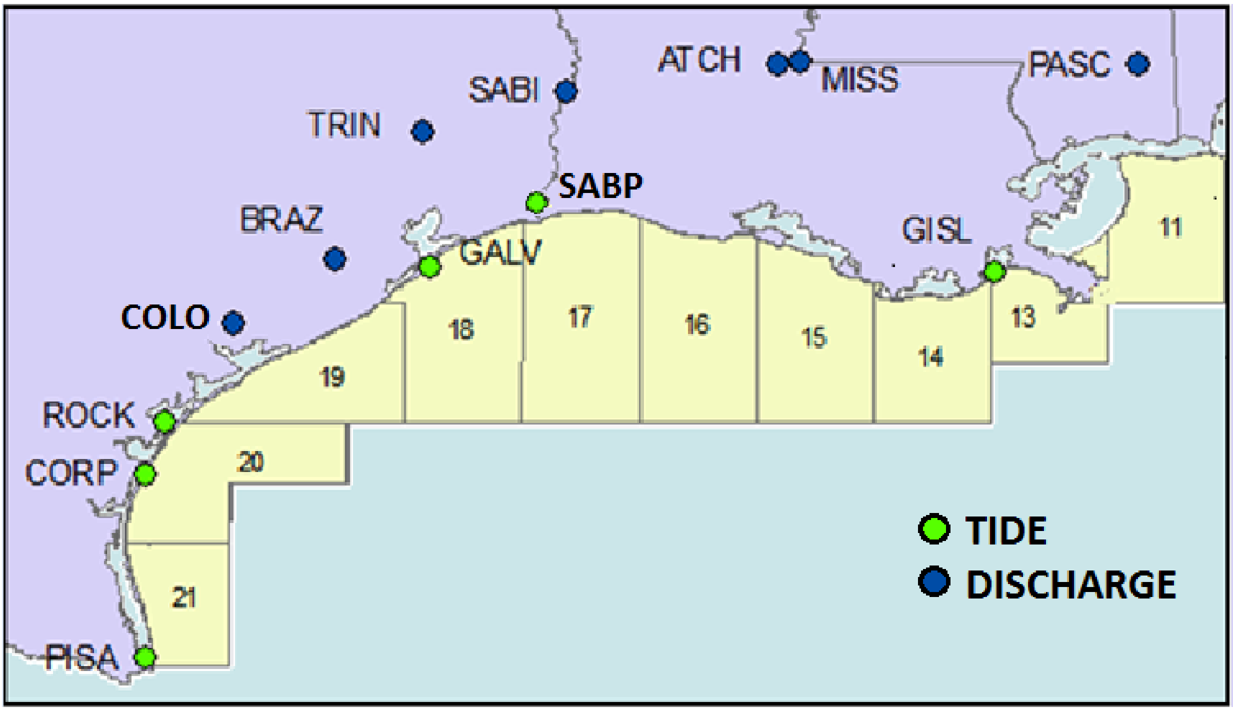

Figure 1: Tide and Discharge Datum Locations

Correlation Analysis between Shrimp CPUE and Environmental Variables

This analysis showed significant positive associations between shrimp CPUE data and river discharge as well as significant negative associations between shrimp CPUE and tide data. Overall, discharge data showed more associations with shrimp CPUE than tide data. The discharge data with the greatest number of significant associations with shrimp CPUE were Brazos River (BRAZ) and Mississippi River (MISS) while the Grand Isle (GISL).

Brown Shrimp

Figure 1 shows the locations where the tide and discharge data used in this analysis were collected. Table 2 and 3 show the results of simple correlation analysis which indicates associations between brown shrimp and environmental variables in the summer and fall at significance level 0.05, respectively.

Table 2: Significant Associations between Brown Shrimp, Summer CPUE and Environmental Factors

	21	20	19	18	17	16	15	14	13	11
PASC	X									
MISS									X	
ATCH									X	
SABI	X			X						
TRIN				X					X	
BRAZ	X		X	X			X	X	X	
GISL			X	X			X			
GALV			X	X						
ROCK			X							
CORP			X	X						
PISA			X							

Table 3: Significant Associations between Brown Shrimp, Fall CPUE and Environmental Factors

	21	20	19	18	17	16	15	14	13	11
PASC					X		X			
MISS				X			X	X		
ATCH				X			X	X		
SABI		X		X					X	
TRIN			X			X	X		X	
BRAZ			X			X	X		X	
GISL										
GALV										
ROCK										
CORP									X	
PISA										

White Shrimp

Tables 4 and 5 show the results of simple correlation analysis which indicates associations between white shrimp and environmental variables in the summer and fall at significance level 0.05, respectively.

Table 4: Significant Associations between White Shrimp, Summer CPUE and Environmental Factors

	21	20	19	18	17	16	15	14	13	11
PASC			X					X		
MISS			X	X				X		X
ATCH			X	X				X		
SABI	X	X	X	X				X		X
TRIN	X	X	X	X					X	
BRAZ	X		X						X	X
GISL		X								
GALV		X								
ROCK										
CORP										
PISA										

Table 5: Significant Associations between White Shrimp, Fall CPUE and Environmental Factors

	21	20	19	18	17	16	15	14	13	11
PASC				X						
MISS		X								
ATCH		X								
SABI								X		
TRIN										
BRAZ										
GISL										
GALV										
ROCK										
CORP										
PISA										

Partial Least Square Regression Analysis

Variation in brown shrimp summer data and white shrimp summer data were both explained by some percentage of environmental variables in 8 of the 10 statistical zones analyzed (Table 6, Table 7). Variation in brown shrimp fall data was explained by some percentage of environmental variables in 9 of the 10 statistical zones analyzed (Table 8). Variation in white shrimp fall data was explained by some percentage of environmental variables in only 2 of the 10 statistical zones analyzed (Table 9). No trends were immediately obvious in the data; however, white shrimp fall had very few associations compared to all other analysis.

Brown Shrimp, Summer

Table 6 shows how many components of which environmental variables were used to explain what percentage of variability in brown shrimp CPUE data in the best fit model. Figures 2 through 11 show the observed and fitted Z-score of brown shrimp CPUE in summer for statistical zones 11 and 13 through 21.

Table 6: Percent Variability of Environmental Factors used to Explain Brown Shrimp Summer CPUE Variability

Zone	Significant Environmental Variation that Explains Shrimp CPUE Variation			Number of Significant Environmental Components*	Shrimp CPUE Variance Explained by Environmental Variable*
	T+D	D	T		
11	*0.497	0.321	0.764	2	0.314
13	*0.375	0.563	0.760	1	0.328
14			*0.783	1	0.128
15	0.643		*0.783	1	0.346
16	0.462	*0.524		1	0.226
17				0	0
18	0.305	*0.532		1	0.212
19	0.387		*0.588	1	0.208
20			*0.561	1	0.140
21				0	0

* indicates the best model with least square prediction error represented in figure 2 through 11

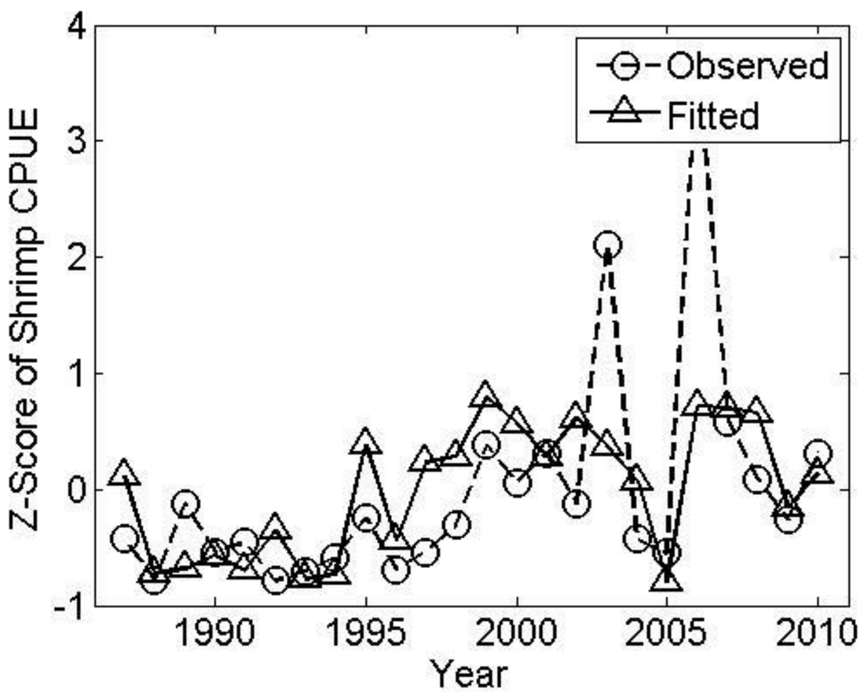

Figure 2: Zone 11 Observed and Fitted Summer Brown Shrimp CPUE

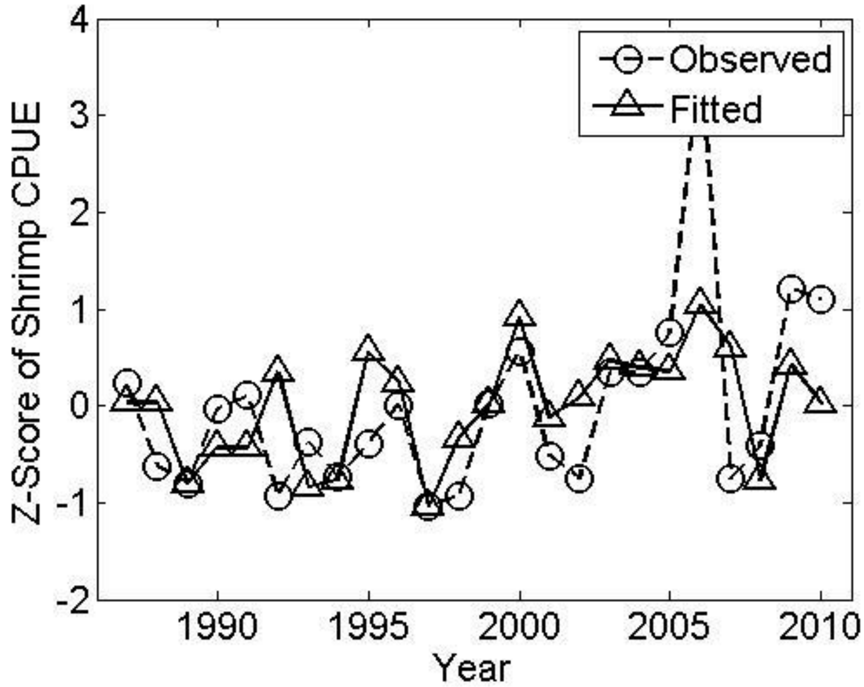

Figure 3: Zone 13 Observed and Fitted Summer Brown Shrimp CPUE

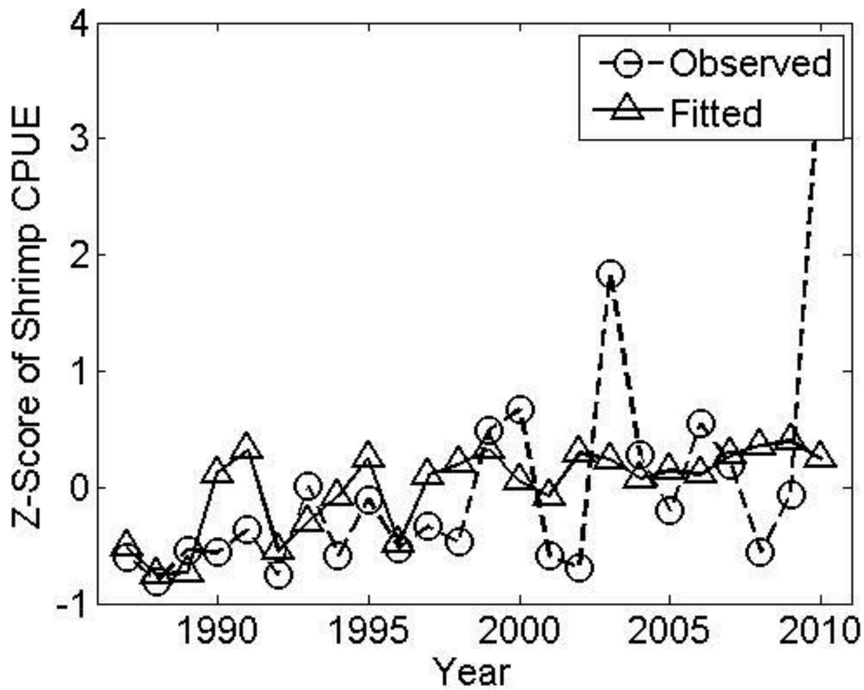

Figure 4: Zone 14 Observed and Fitted Summer Brown Shrimp CPUE

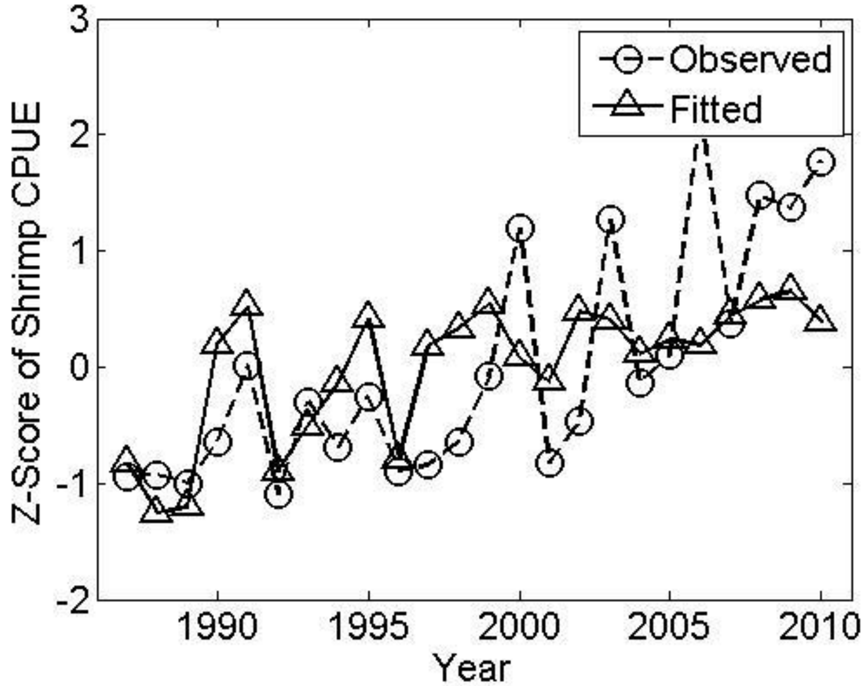

Figure 5: Zone 15 Observed and Fitted Summer Brown Shrimp CPUE

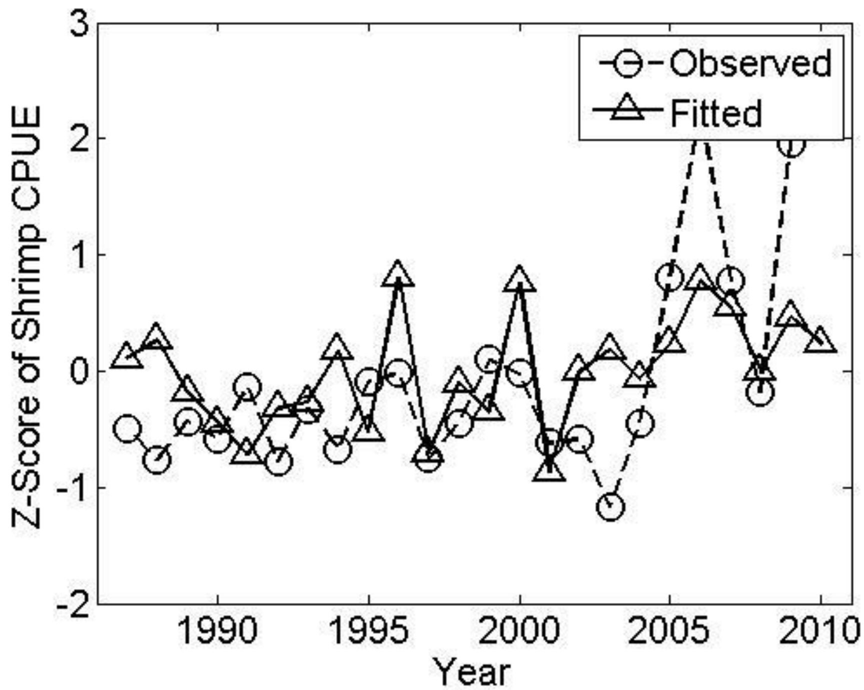

Figure 6: Zone 16 Observed and Fitted Summer Brown Shrimp CPUE

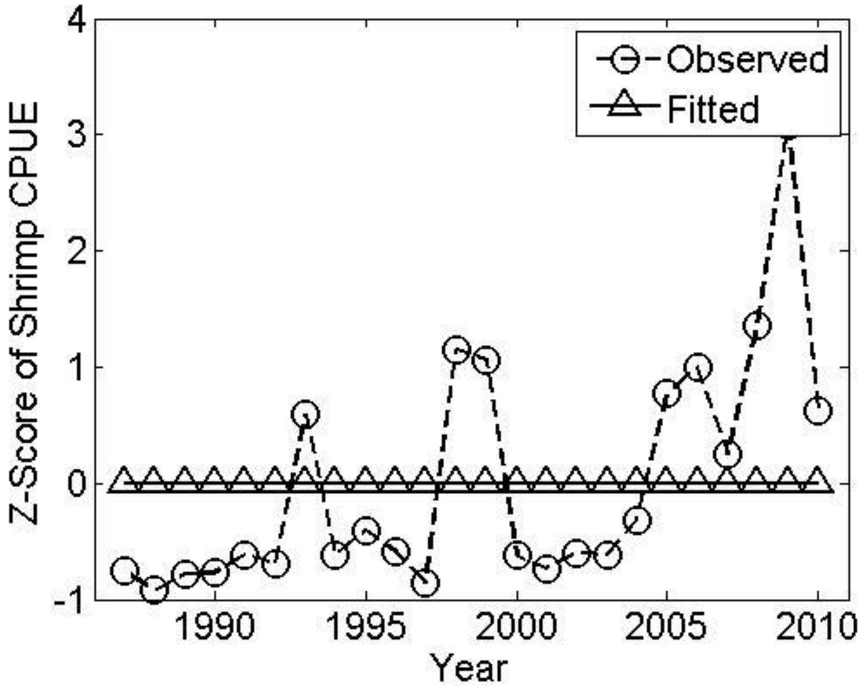

Figure 7: Zone 17 Observed and Fitted Summer Brown Shrimp CPUE

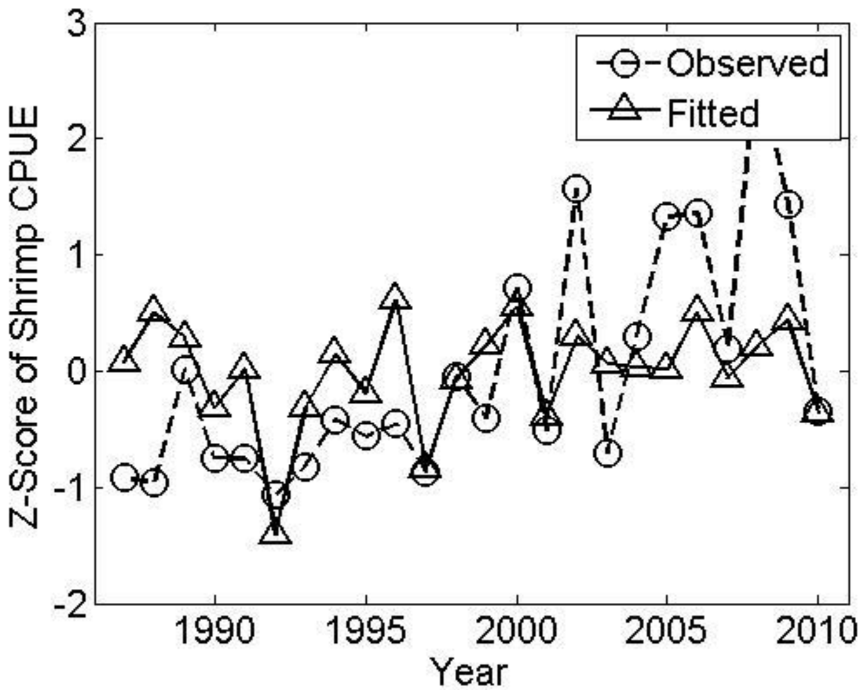

Figure 8: Zone 18 Observed and Fitted Summer Brown Shrimp CPUE

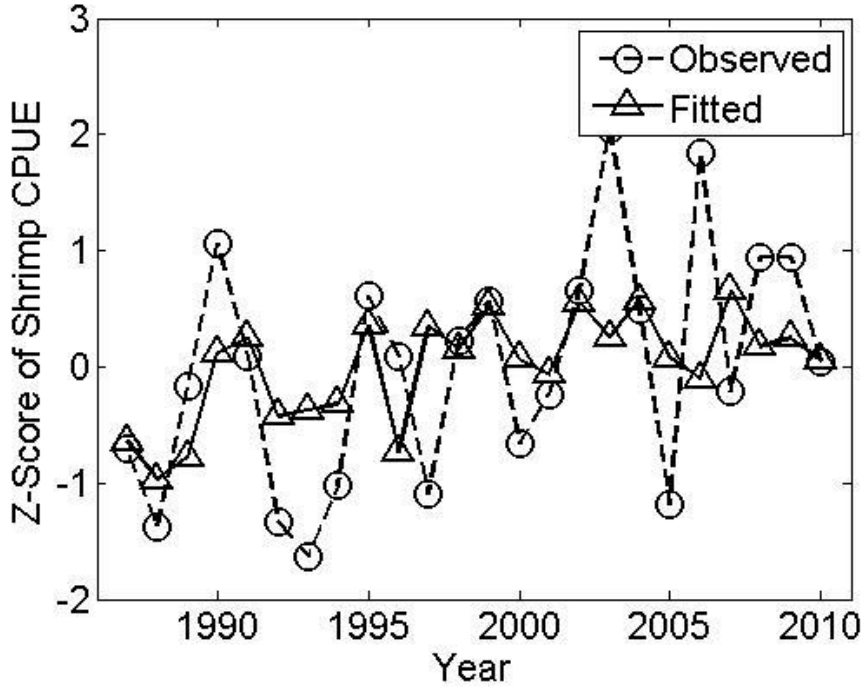

Figure 9: Zone 19 Observed and Fitted Summer Brown Shrimp CPUE

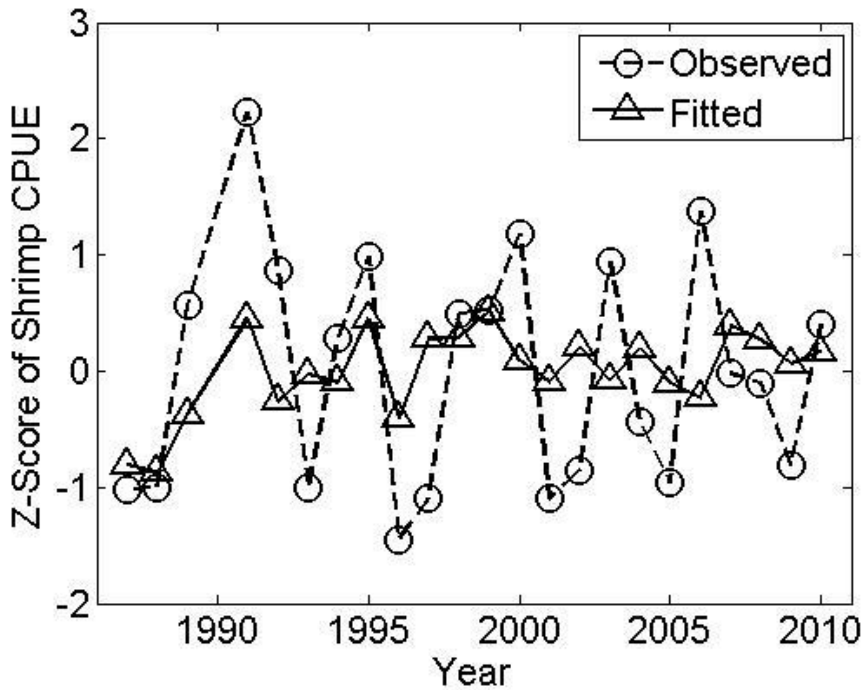

Figure 10: Zone 20 Observed and Fitted Summer Brown Shrimp CPUE

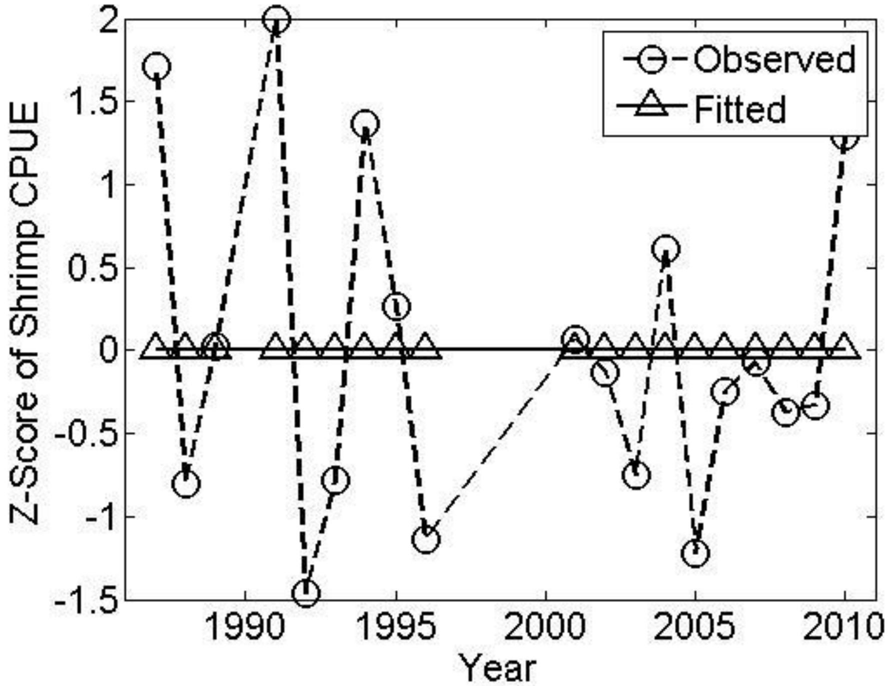

Figure 11: Zone 21 Observed and Fitted Summer Brown Shrimp CPUE

Brown Shrimp, Fall

Table 7 shows how many components of which environmental variables were used to explain what percentage of variability in brown shrimp CPUE data in the best fit model. Figures 12 through 21 show the observed and fitted Z-score of brown shrimp CPUE in fall for statistical zones 11 and 13 through 21.

Table 7: Percent Variability of Environmental Factors used to Explain Brown Shrimp, Fall CPUE Variability

Zone	Significant Environmental Variation that Explains Shrimp CPUE Variation			Number of Significant Environmental Components*	Total Shrimp CPUE Variance Explained by Environmental Variable*
	T+D	D	T		
11	0.384		*0.917	2	0.419
13				0	0
14			*0.965	3	0.434
15	*0.542	0.745	0.785	1	0.543
16	*0.514			3	0.776
17	0.419		*0.433	1	0.360
18	0.393	*0.251		1	0.445
19	*0.247	0.505	0.567	1	0.486
20	0.425		*0.561	1	0.231
21	0.731		*0.813	2	0.482

* indicates the best model with least square prediction error represented in figure 12 through 21

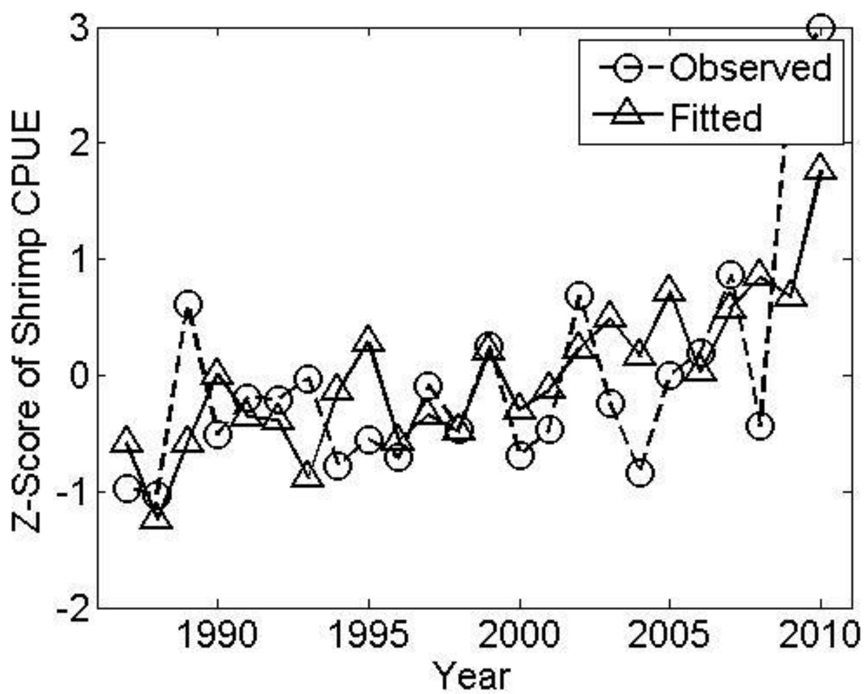

Figure 12: Zone 11 Observed and Fitted Fall Brown Shrimp CPUE

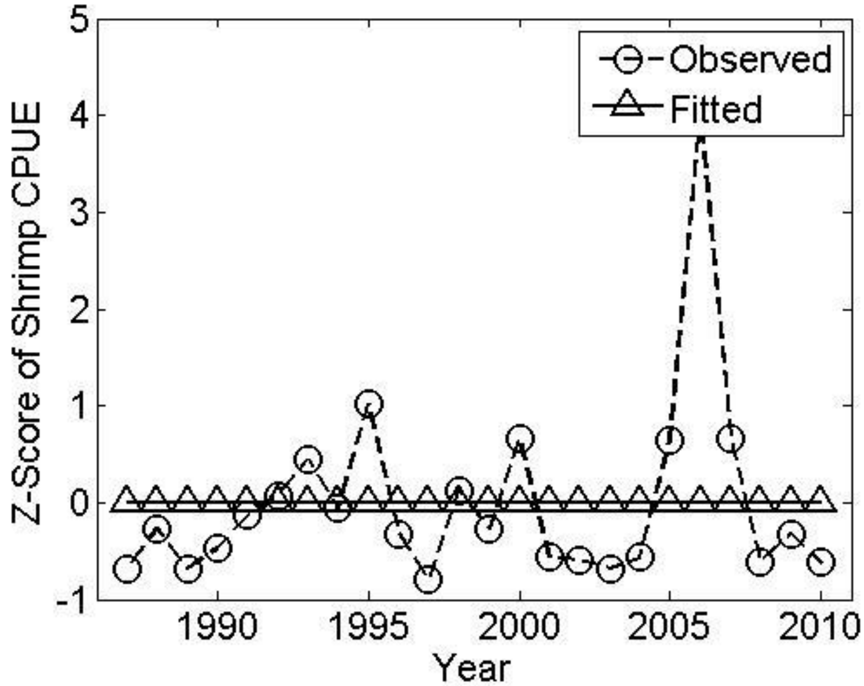

Figure 13: Zone 13 Observed and Fitted Fall Brown Shrimp CPUE

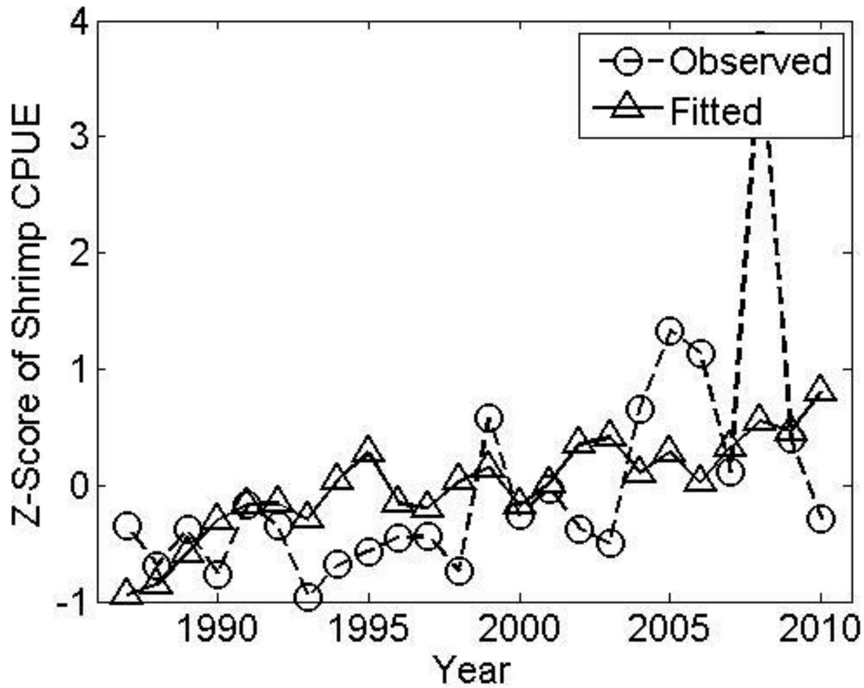

Figure 14: Zone 14 Observed and Fitted Fall Brown Shrimp CPUE

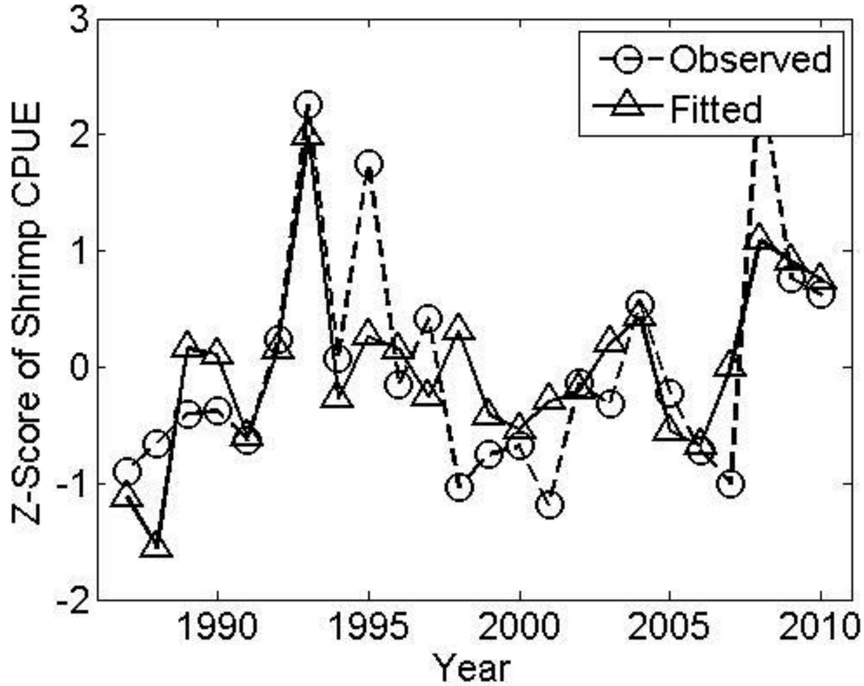

Figure 15: Zone 15 Observed and Fitted Fall Brown Shrimp CPUE

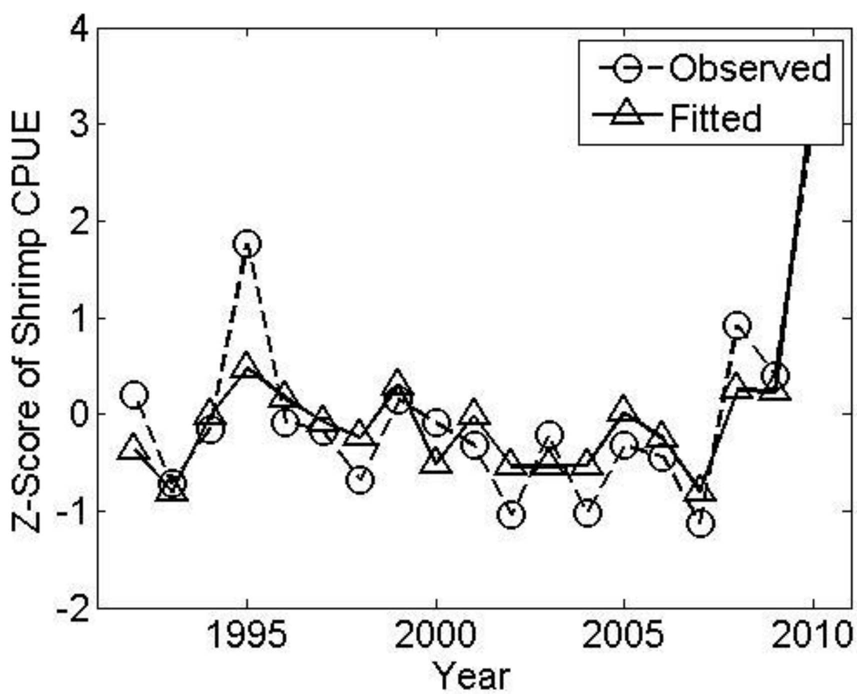

Figure 16: Zone 16 Observed and Fitted Fall Brown Shrimp CPUE

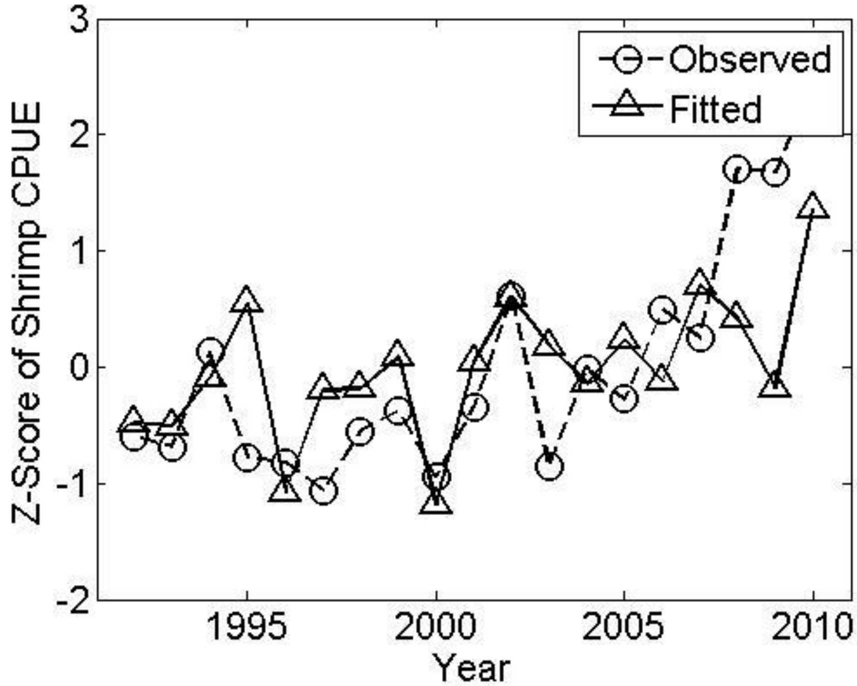

Figure 17: Zone 17 Observed and Fitted Fall Brown Shrimp CPUE

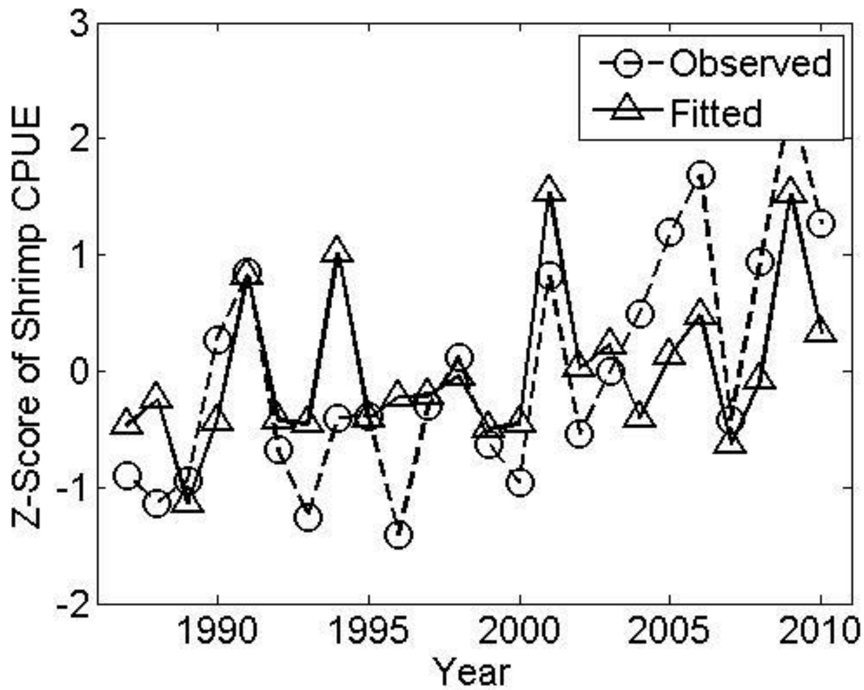

Figure 18: Zone 18 Observed and Fitted Fall Brown Shrimp CPUE

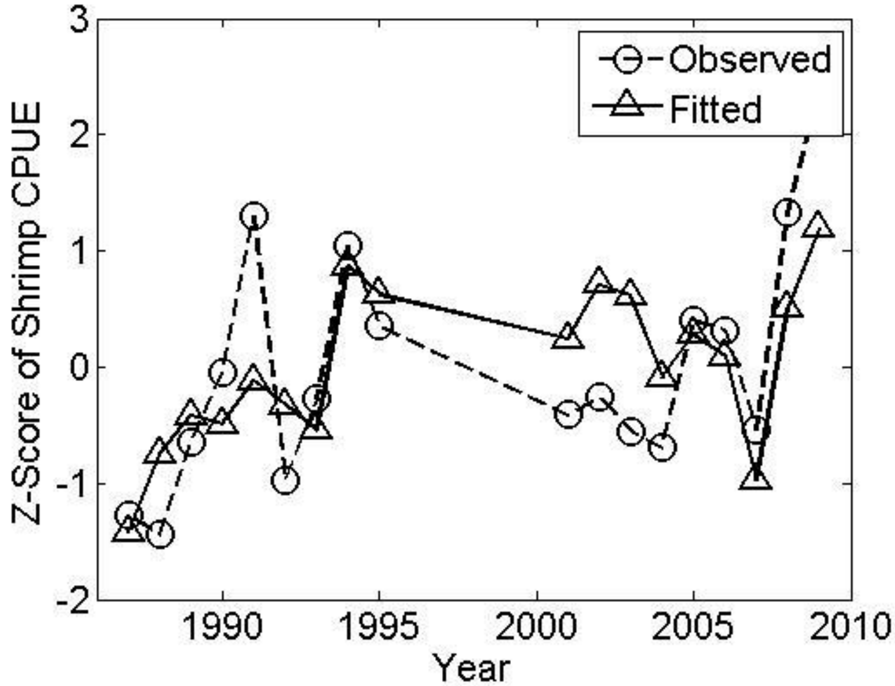

Figure 19: Zone 19 Observed and Fitted Fall Brown Shrimp CPUE

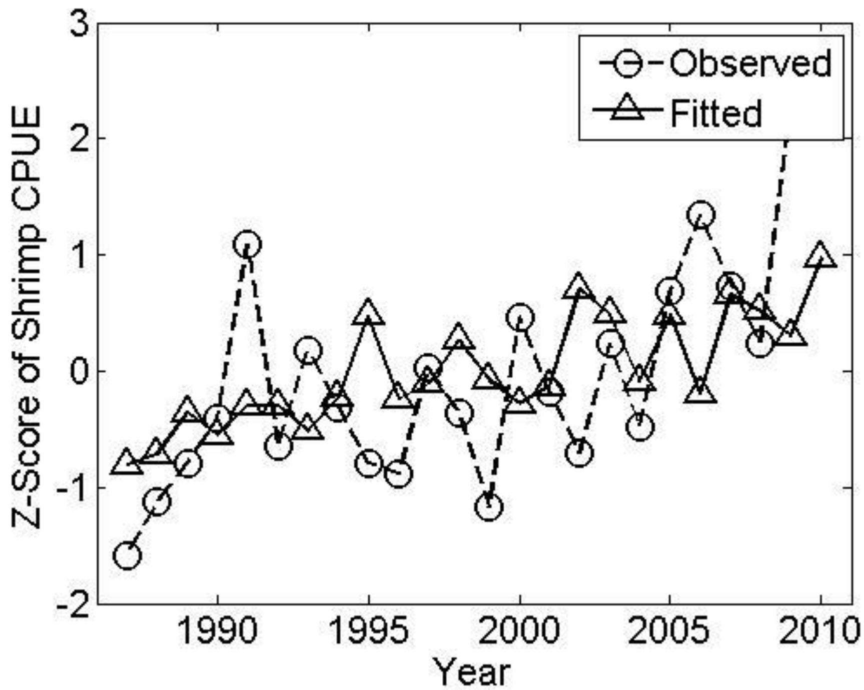

Figure 20: Zone 20 Observed and Fitted Fall Brown Shrimp CPUE

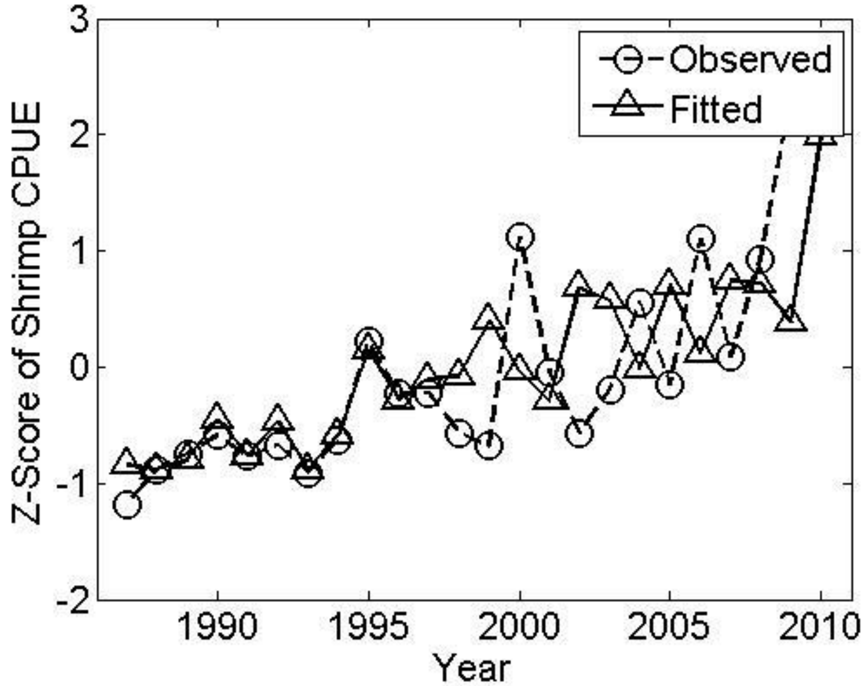

Figure 21: Zone 21 Observed and Fitted Fall Brown Shrimp CPUE

White Shrimp, Summer

Tables 8 shows how many components of which environmental variables were used to explain what percentage of variability in brown shrimp CPUE data in the best fit model. Figures 22 through 31 show the observed and fitted Z-score of white shrimp CPUE in summer for statistical zones 11 and 13 through 21.

Table 8: Percent Variability of Environmental Factors used to Explain White Shrimp, Summer Variability

	Significant Environmental Variation that Best Explains Shrimp CPUE Variation			Number of Significant Environmental Components*	Shrimp CPUE Variance Explained by Environmental Variable*
Zone	**T+D**	**D**	**T**		
11			*0.947	2	0.210
13				0	
14	0.317		*0.779	1	0.103
15	*0.578	0.737	0.763	2	0.327
16				0	
17	*0.729			3/0??	0.564
18	0.309	*0.522		1	0.136
19	0.390		*0.580	1	0.195
20	*0.382	0.968	0.590	1	0.250
21		*0.922		1	0.776

* indicates the best model with least square prediction error represented in figure 22 through 31

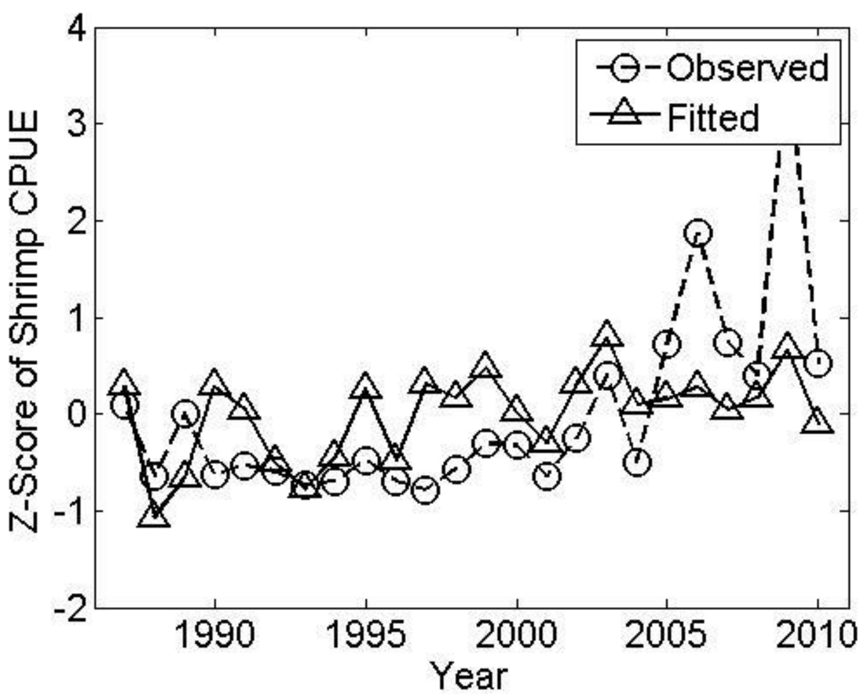

Figure 22: Zone 11 Observed and Fitted Summer White Shrimp CPUE

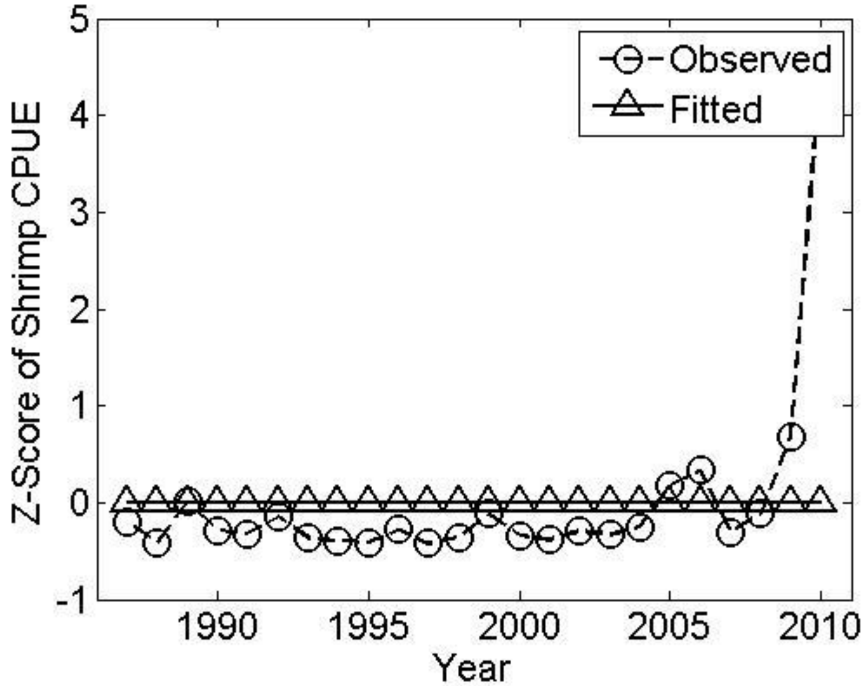

Figure 23: Zone 13 Observed and Fitted Summer White Shrimp CPUE

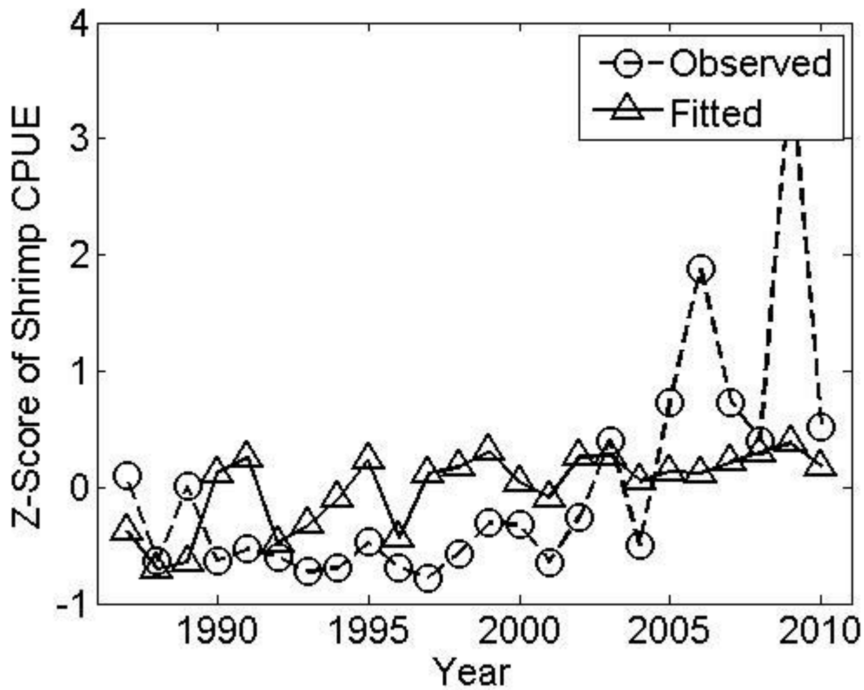

Figure 24: Zone 14 Observed and Fitted Summer White Shrimp CPUE

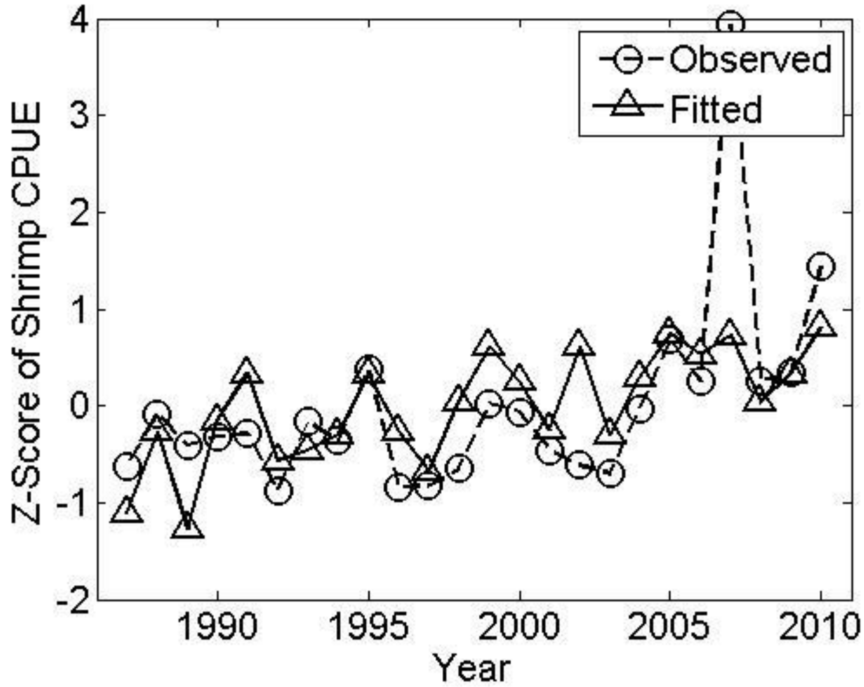

Figure 25: Zone 15 Observed and Fitted Summer White Shrimp CPUE

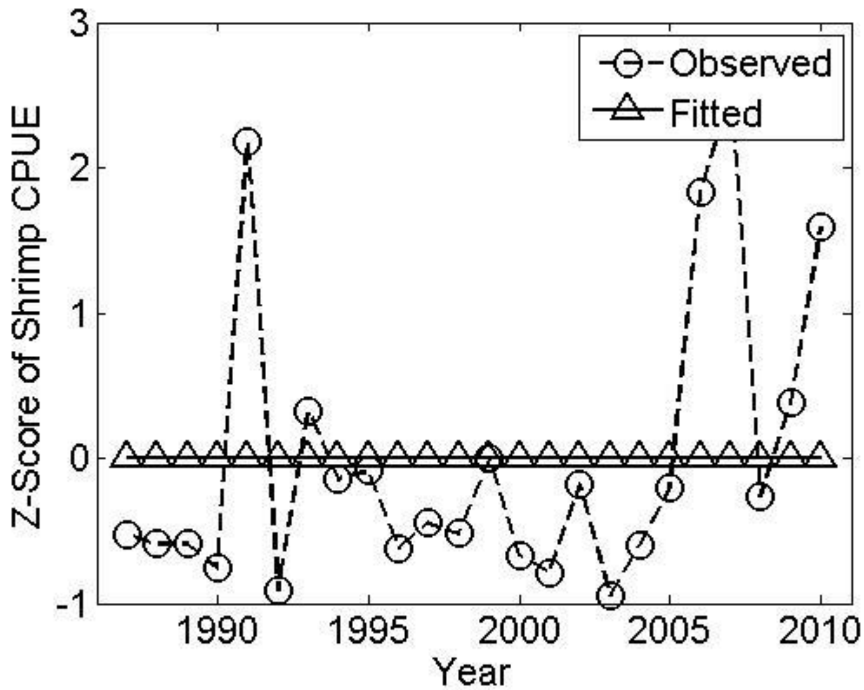

Figure 26: Zone 16 Observed and Fitted Summer White Shrimp CPUE

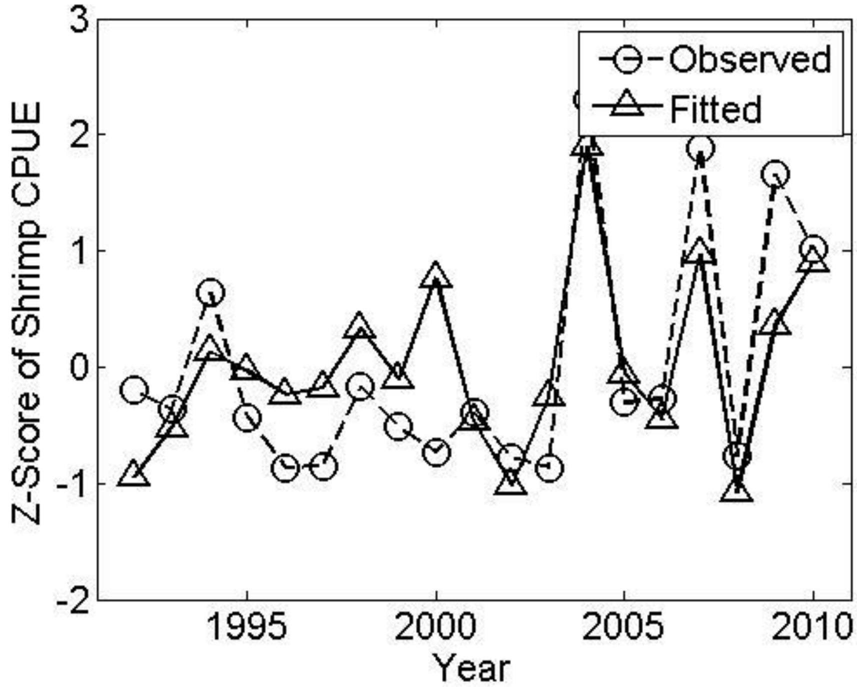

Figure 27: Zone 17 Observed and Fitted Summer White Shrimp CPUE

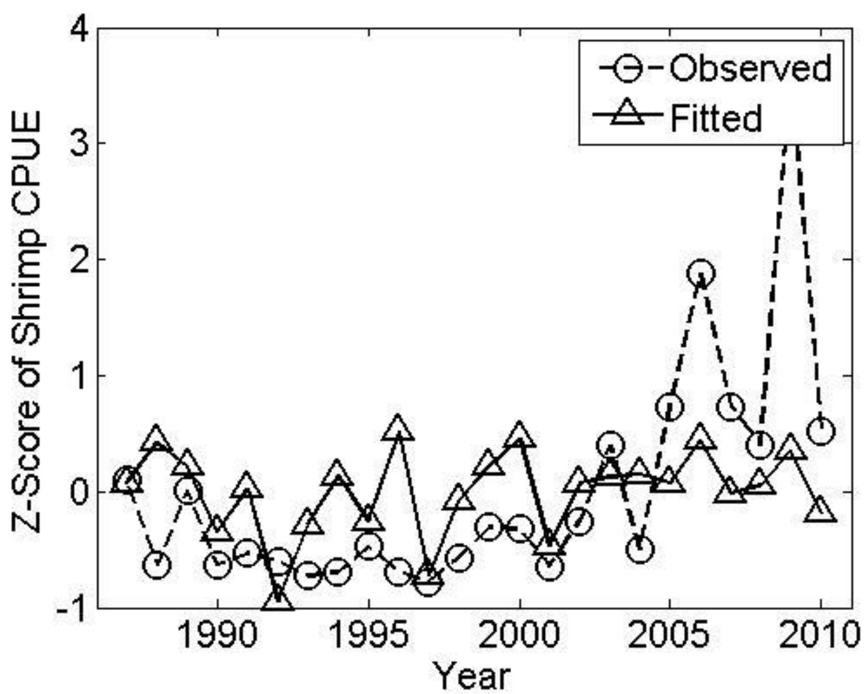

Figure 28: Zone 18 Observed and Fitted Summer White Shrimp CPUE

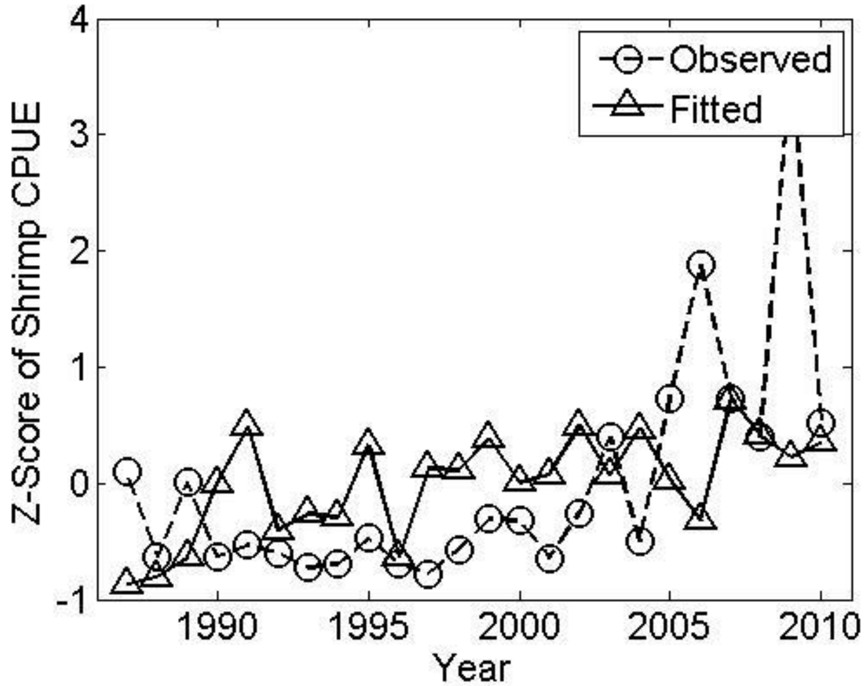

Figure 29: Zone 19 Observed and Fitted Summer White Shrimp CPUE

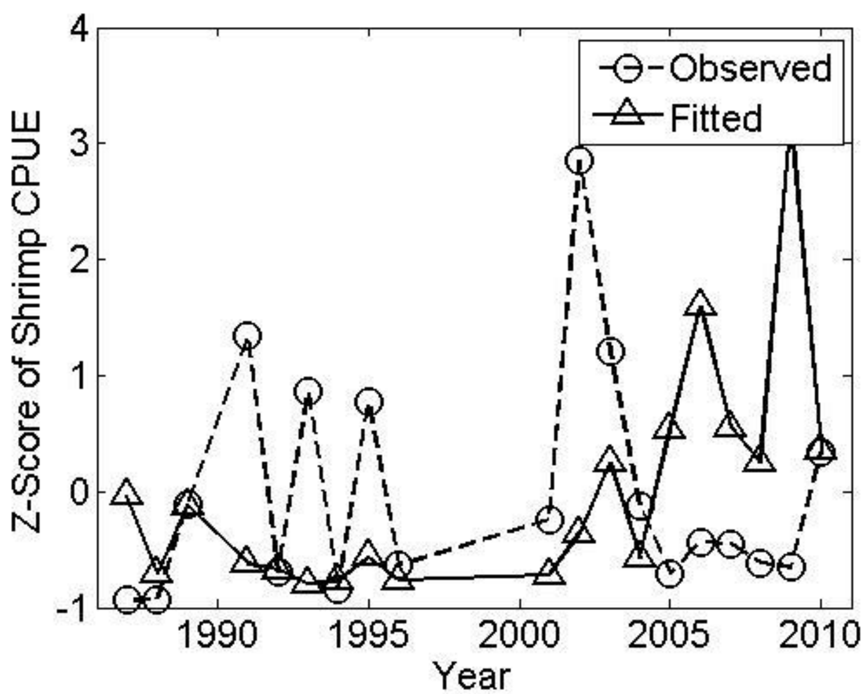

Figure 30: Zone 20 Observed and Fitted Summer White Shrimp CPUE

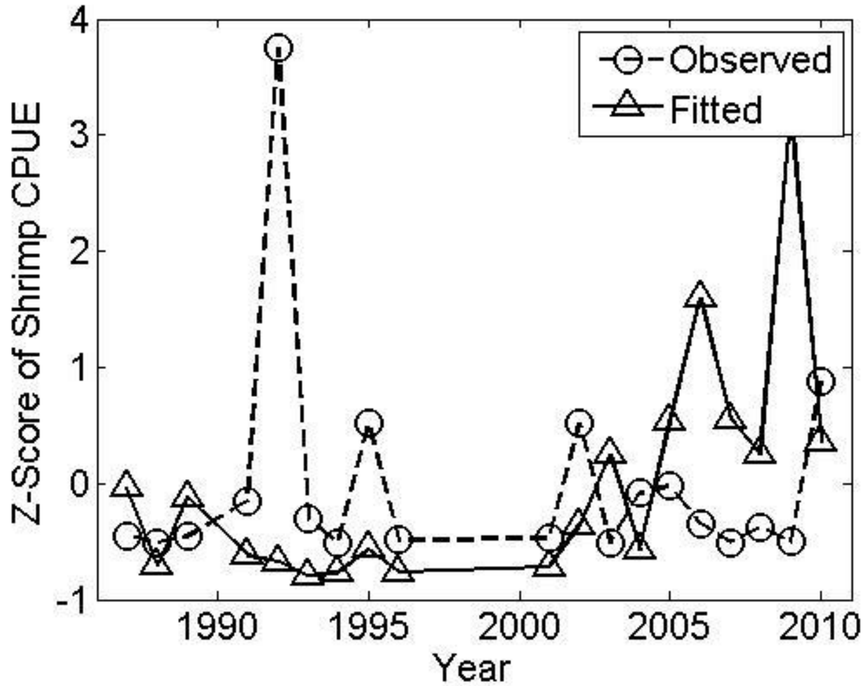

Figure 31: Zone 21 Observed and Fitted Summer White Shrimp CPUE

White Shrimp, Fall

Tables 9 shows how many components of which environmental variables were used to explain what percentage of variability in brown shrimp CPUE data in the best fit model. Figures 32 through 41 show the observed and fitted Z-score of white shrimp CPUE in fall for statistical zones 11 and 13 through 21.

Table 9: Percent Variability of Environmental Factors used to Explain White Shrimp, Fall Variability

Zone	Significant Environmental Variation that Best Explains Shrimp CPUE Variation			Number of Significant Environmental Components*	Total Shrimp CPUE Variance Explained by Environmental Variable*
	T+D	D	T		
11				0	0
13				0	0
14				0	0
15				0	0
16	*0.395	0.354	0.242	1	0.203
17				0	0
18				0	0
19	0.390		*0.580	1	0.195
20				0	0
21				0	0

* indicates the best model with least square prediction error represented in figure 32 through 41

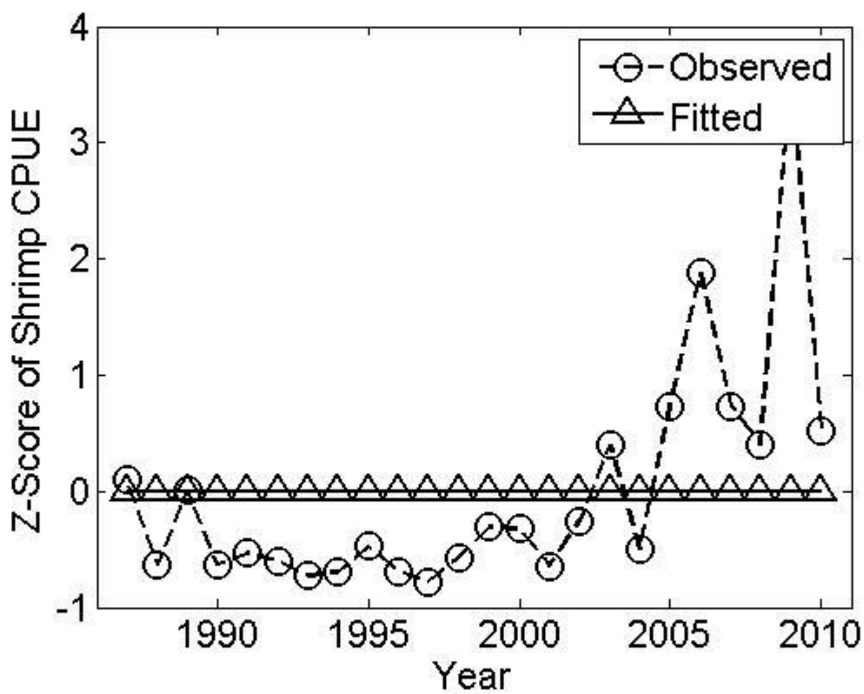

Figure 32: Zone 11 Observed and Fitted Fall White Shrimp CPUE

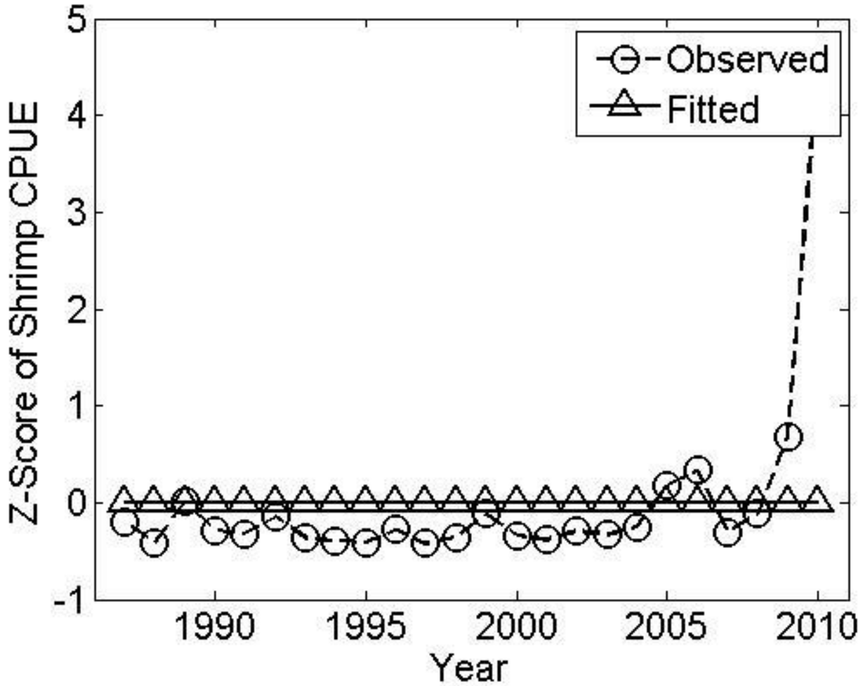

Figure 33: Zone 13 Observed and Fitted Fall White Shrimp CPUE

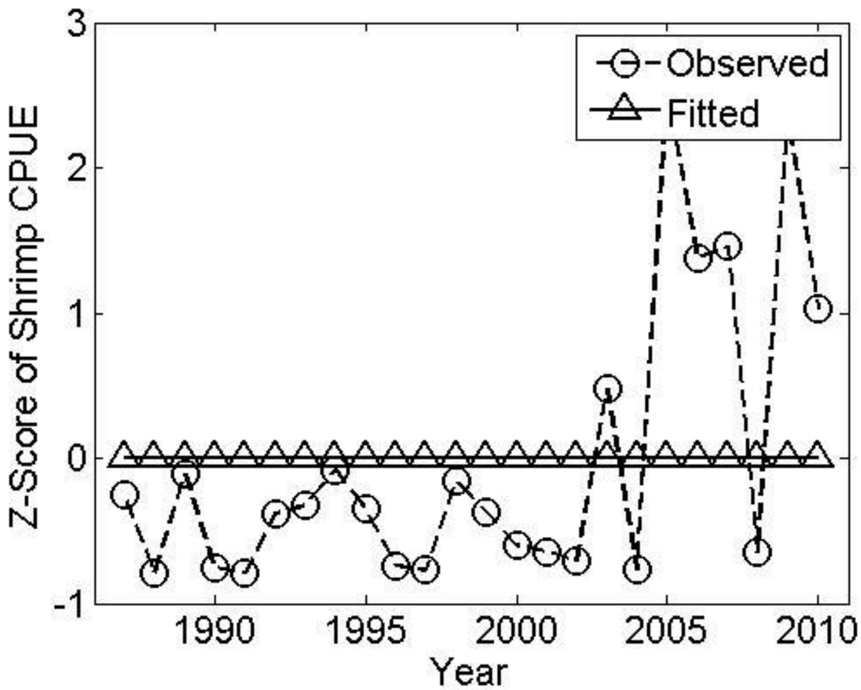

Figure 34: Zone 14 Observed and Fitted Fall White Shrimp CPUE

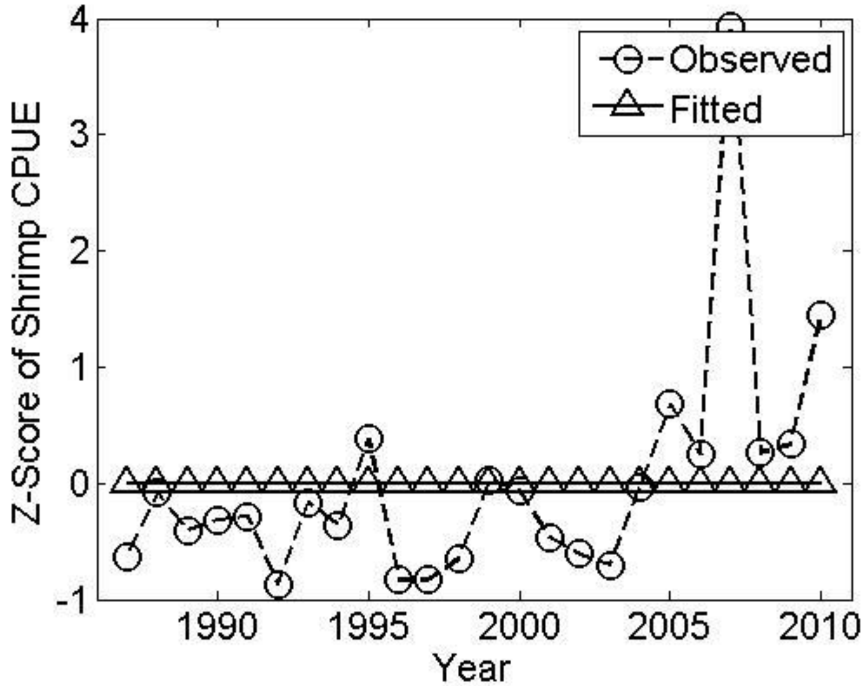

Figure 35: Zone 15 Observed and Fitted Fall White Shrimp CPUE

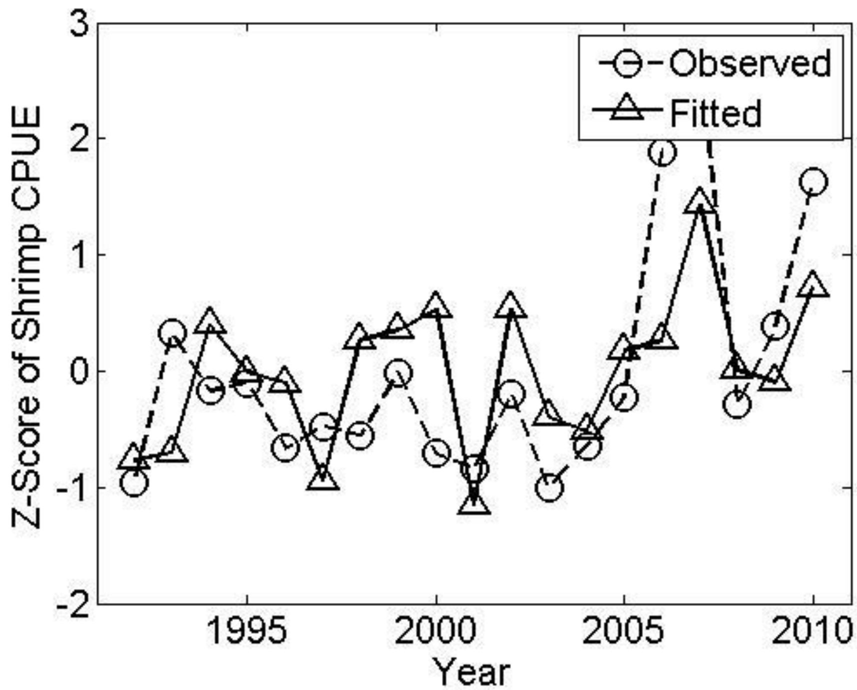

Figure 36: Zone 16 Observed and Fitted Fall White Shrimp CPUE

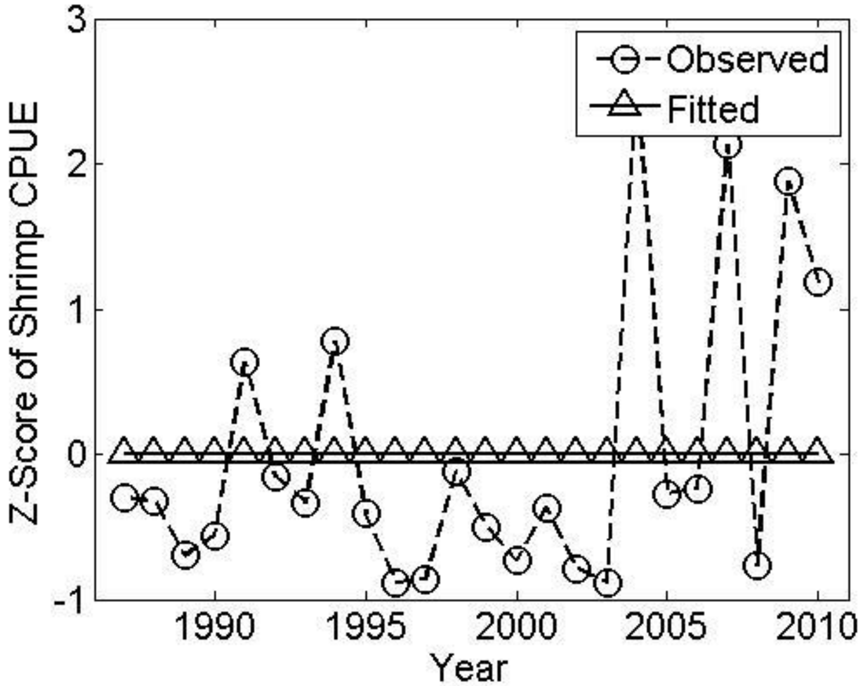

Figure 37: Zone 17 Observed and Fitted Fall White Shrimp CPUE

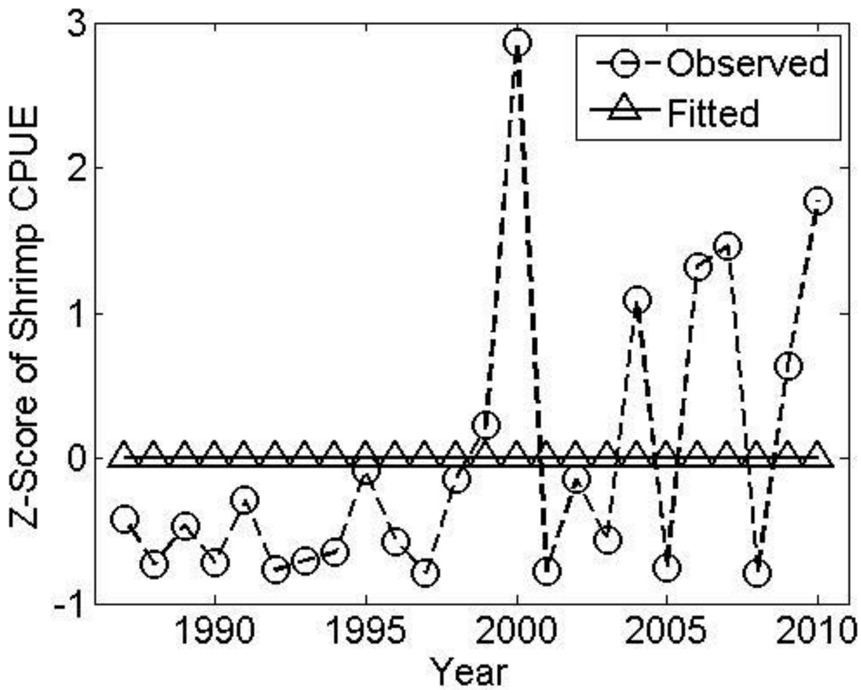

Figure 38: Zone 18 Observed and Fitted Fall White Shrimp CPUE

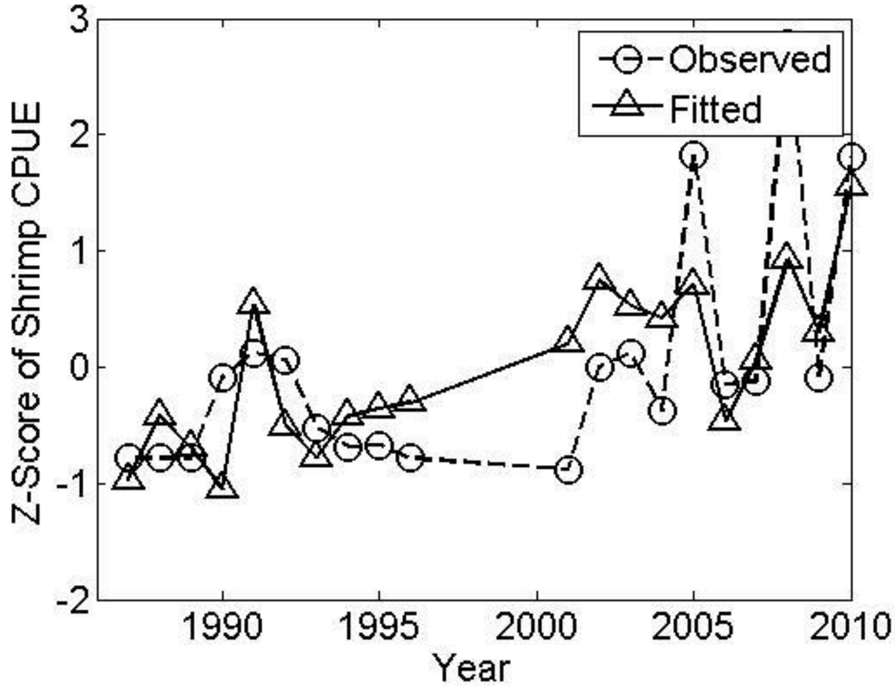

Figure 39: Zone 19 Observed and Fitted Fall White Shrimp CPUE

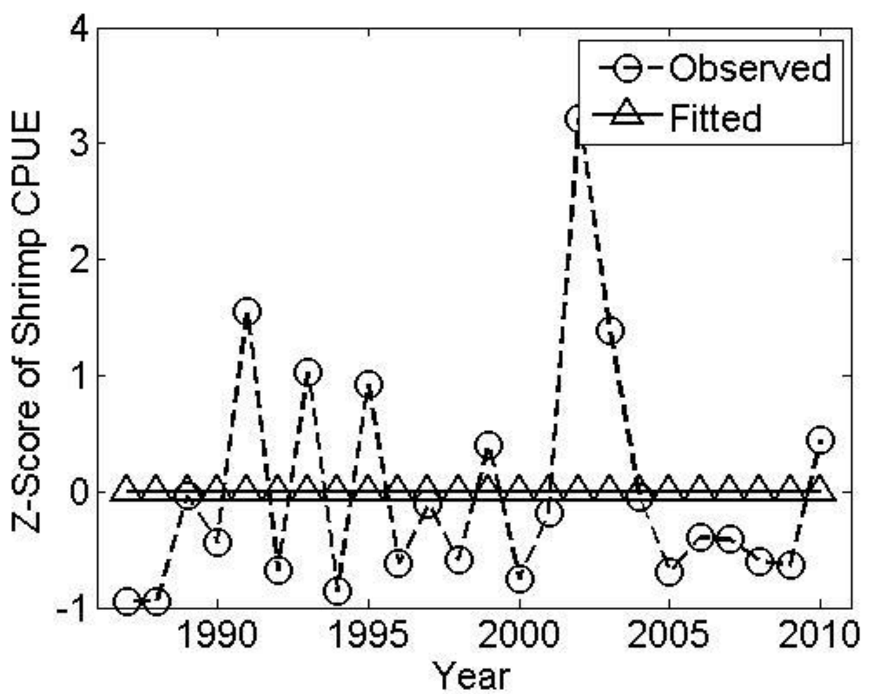

Figure 40: Zone 20 Observed and Fitted Fall White Shrimp CPUE

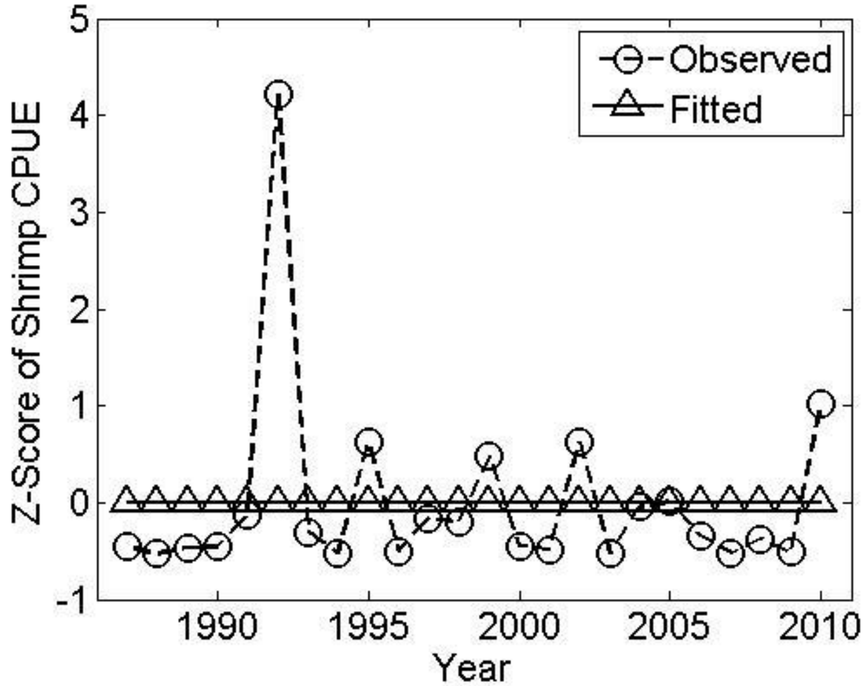

Figure 41: Zone 21 Observed and Fitted Fall White Shrimp CPUE

CHAPTER IV

DISCUSSION

Correlation analysis between tide and both species of shrimp gave consistently positive associations when the results were statistically significant. This agrees with past research which has shown that increased access to marsh edge increases survival (Minello et al. 2011). Correlation analysis between discharge and both species of shrimp gave consistently negative associations when the results were statistically significant. These results also agree with past research which shows that increased river diversions reduce shrimp growth (Adamack et al. 2012). PLSR analysis demonstrated that environmental variability can explain some of the variation in white and brown shrimp CPUE. Results from both analytical methods indicate that the association between environmental variables and shrimp CPUE are small, but present and statistically significant, which is consistent with past research. Because tide and discharge were intended to serve as proxies for estimating those factors that directly affect shrimp survival and growth and because shrimp are also affected by many other factors not included in this analysis, small associations were expected. Our PLSR analysis combined effect size estimation and confidence intervals. Consequently, even though the associations identified are small, they can still be interpreted as biologically important and used as a tool for managing shrimp populations (Nakagawa and Cuthill 2007).

There are no clearly discernible patterns in the results. Brown shrimp summer CPUE, brown shrimp fall CPUE, and white shrimp summer CPUE all show a similar number of significant associations with environmental variables, while white shrimp fall has very little association in both correlation and PLSR analysis. This difference between brown and white shrimp CPUE in fall may be a result of behavior, specifically differences in distribution and activity between the species (Muncy 1984). The lack of clear overall patterns suggests the importance of further investigation with the inclusion of more variables that affect shrimp survival. These variables might include locations of high density post-larval shrimp in estuaries, salinity gradients present in estuaries and species specific behavior and growth rates.

Further investigation is necessary to fully understand the mechanisms behind the associations observed in this study. Past research has identified temperature as a major contributor to shrimp metabolic rates; however, the effects of salinity are less well understood (Adamack et al. 2012). Adamack et al. (2012) found that longer diversions and slower prey responses caused the effects of diversions on shrimp production to be magnified and that diversion had greater impacts during certain months. In order to predict when shrimp populations will be most affected by diversion, future analysis should also identify which months are most influential on shrimp production. The conditions created by higher tide and increased discharge may also impact many aspects of the ecosystem not accounted for, including impacts on prey species and crucial habitat such as sea grasses, which impact shrimp productivity. Further investigation would be necessary to determine topography of GOM estuaries and then incorporate that information with ideal habitat conditions in terms of water depth, sea grass abundance, access distances and flooding frequency.

The results of this analysis were also limited by our limited understanding of shrimp movement once they leave estuaries. PLSR analysis assumed that the environmental variables closest to each statistical zone influenced the shrimp caught in that statistical zone, but without conclusive evidence, we cannot be sure this assumption is correct. Additionally, some research indicates that white shrimp may emigrate from estuaries to deeper waters when temperatures drop below the species tolerance (Muncy 1984). This may have contributed to the extremely low number of associations observed in the white shrimp fall CPUE analysis.

In this analysis, tide and discharge served as a proxy for estimating temperature, salinity and access to marsh edge, factors which affect shrimp growth and survival by influencing habitat availability, metabolic rates and prey availability among others (Minello et al. 2011, Adamack et al. 2012). The specific effects tide and discharge have on shrimp and the mechanisms by which these mechanisms act are not fully understood. Consequently, the noise in our data may have led to Type II errors, causing us to miss relationships that do actually exist because we do not understand the underlying processes causing the effect. Conversely, our results could also be a result of Type I errors, where we have concluded that significant associations do exist when they actually do not. This error could be a product of overfitting, which our data is particularly susceptible to because we have many environmental predictor variables and few dependent shrimp variables. This type of error would result in a model with significant associations but poor predictive power. We addressed this issue with our data set in both analysis methods to minimize the chance of overfitting. In our correlation analysis, we performed cross-validation while PLSR analysis was used specifically because it is a statistical technique designed for this type of data; however, the possibility of Type I errors is still present. Also, because we performed a large number of associations, statistically some of the associations found may be simply a result of chance.

As environmental conditions continue to change and possibly become more extreme (e.g. the effects of global climate change), what are weak associations now could become more influential on shrimp populations over time. Minello et al. (2011) found that greater flooding duration and frequency gave shrimp greater access to marsh edge, which increased shrimp growth however. As sea levels rise, access to marsh edge may actually diminish, depending on the topography of the marsh. Sea level rise may also cause fragmentation of estuarine habitat causing higher predation and increase shrimp stranding, resulting in lower survival (Roth et al. 2008). Changing conditions may also affect seagrass survival and distribution, which would affect shrimp habitat selection as seagrasses provide foraging opportunities and protection from predation (Roth et al. 2008) Changes in plant life may contribute further to habitat loss by increasing susceptibility to erosion (Roth et al. 2008). These changing environmental conditions have the potential to lead to changes in shrimp survival and ultimately may have economic impacts.

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