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Technical Report Number 13
May, 1994

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1 May, 1994

Abstract

Loggerhead turtle populations have been on the decline in recent years throughout much of their range, partially as a result of mortality in shrimp trawling nets. To curtail this decline, regulations have been enacted that require the use of devices that allow turtles to escape unharmed from the trawl nets. These devices are known as turtle excluder devices or TEDs. Little data have been published that demonstrate the effectiveness of TEDs in enhancing turtle populations. In this report, loggerhead turtle strandings (i.e. dead turtles that wash ashore) from South Carolina are examined for possible relationships to the use of these devices. A linear statistical model is proposed that includes components representing aspects of the observed South Carolina strandings record, and allows the inclusion of a TED parameter. We fit this model by ordinary least squares, but the residuals from this model were found to be both autocorrelated and heteroscedastic. Fitting a regression model with a time-series error structure using the natural log transformed (strandings + 1) provided a very good statistical fit to the data. But interpretation of the parameters is not straight forward on the log scale. We used several methods to enable interpretation on the original scale. First, we interpreted the parameter estimates based on the log transformation approximately as percentage changes. Second, we used an approximation based on a Taylor series expansion to back-transform the parameters of the log transformed model to the original scale. Finally, the model was fit using ordinary least squares and the standard errors adjusted for serial correlation and heteroscedastic variance. These various methods each have their drawbacks which are discussed. The TED effect is estimated to be -16 *turtles/bi-weekly period* based on the log-strandings analysis, indicating that TEDs

*Supported through the National Institute of Statistical Sciences by the U.S. Environmental Protection Agency under Cooperative Agreement #CR819638-01-0.

reduce strandings. This is roughly a 44 *percent* decline in strandings as a result of TED use, and was highly significant. The estimated trend in strandings is found to closely mimic what is believed to be occurring in the SC loggerhead population based on aerial surveys. Finally, we are able to detect spring and fall peaks in strandings in addition to that occurring in the summer months. Future analyses pertaining to these data are suggested.

Keywords: Loggerhead turtles, turtle-excluder devices, TEDs, shrimp fishery.

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1 Introduction

Most populations of sea turtles have been declining in recent years, particularly those of loggerheads in the southeastern United States (National Research Council (1990, Chapter 2)). Because of this, in 1978 loggerheads were listed as a threatened species under the Endangered Species Act. Death of turtles in shrimper's nets is the most important human associated cause of adult and sub-adult turtle mortality (National Research Council (1990, Chapter 6)). This would seem to imply that reducing the mortality associated with the shrimp fishery would have a large effect on the recovery of loggerhead populations. Because of the mortality associated with shrimping, and the listing of the loggerhead as threatened, regulations requiring the use of turtle excluder devices (TEDs) in shrimp nets have been enacted. Throughout the 1980s the National Marine Fisheries Service (NMFS) tested various TED designs, and South Carolina became the first state to require TED use in shrimp trawls in 1988. Crowder, Crouse, Heppell and Martin (1994) have modified the stage-based population model for loggerhead sea turtles of Crouse, Crowder and Caswell (1987) and use it to project potential population level effects from the use of turtle excluder devices (TEDs) in the shrimp fisheries of the southeastern U.S.. Based on their model, a 20 *percent* decline in mortality associated with TED use will maintain the loggerhead population at it's current levels.

The purpose of these analyses is to attempt to construct a statistical model of turtle strandings (i.e. dead turtles that wash ashore mostly associated with trawling activity) based on characteristics evident in the data. This model will incorporate a parameter to account for a possible effect on turtle strandings of turtle excluder device use in shrimp nets. We can then estimate this parameter, the TED effect adjusted for other effects such as trend and seasonality. And by accounting for the variability in strandings, we can test the relevant statistical hypothesis of the true parameter being such that the effect of TED use reduces turtle strandings. We assume strandings to be indicative primarily of turtle mortality associated with shrimping activity National Research Council (1990). Therefore a decrease in strandings would suggest a decrease in shrimp fishery-related turtle mortality.

As George Box once said "All models are wrong, but some are useful." We hope that we can provide a model that is useful in that it will provide some insight into the effects of shrimping and TED use on turtle strandings. This insight can then be used to predict the impact of TED use on loggerhead population levels as in Crowder et al. (1994).

2 Description of Data

2.1 Strandings data

The strandings data consist of bi-weekly counts of loggerhead turtle carcasses washed ashore (i.e. turtle strandings) on South Carolina beaches between April 1 and November 30 each year from 1980 through 1993. The bi-weekly counts are given in Table 1, for periods beginning on the 1*st* and 16*th* of each month. These data were provided to us by Sally Hopkins-Murphy of the SC Wildlife and Marine Resources Department. To achieve these counts, South Carolina beaches were monitored on the ground or by aerial survey as part of the Sea Turtle Stranding and Salvage Network (STSSN) which was established to collect data on stranded turtles. Reports of dead turtles from the public were referred to a network member assigned that particular beach. Standardized data forms were developed and used by all members of the network. Data on strandings were sent by those surveying the beaches to a state coordinator where the forms were checked for errors or omissions. Each state coordinator then sent copies of the data forms to the Southeast Fisheries Center of NMFS in Miami, Florida to be archived and summarized for quarterly, semiannual and yearly reports of the STSSN. Measurements were standardized, and steps were taken to assure that carcasses were not counted twice. Approximately 50 percent of the 35 beaches and islands in South Carolina were surveyed in 1980, as the network was being established, and approximately 90 percent were surveyed in subsequent years.

Table 1: Bi-weekly loggerhead strandings. Dates are those of the beginning of the period.

Year	4-1	4-16	5-1	5-16	6-1	6-16	7-1	7-16	8-1	8-16	9-1	9-16	10-1	10-16	11-1	11-16	Total
1980	0	20	28	6	22	64	145	141	67	37	22	18	15	2	0	0	587
1981	10	22	4	7	4	12	62	90	55	10	24	12	5	2	0	0	319
1982	3	35	7	23	26	30	58	27	20	14	2	9	8	1	0	0	263
1983	0	6	9	17	22	18	43	23	14	8	7	2	1	0	1	0	171
1984	4	13	12	2	0	31	43	13	7	4	0	3	0	0	0	0	132
1985	2	14	2	1	2	17	29	13	9	5	5	1	2	0	0	0	102
1986	0	2	5	0	11	40	34	41	15	11	4	5	5	4	3	4	184
1987	0	0	7	22	115	28	33	19	8	7	12	12	3	2	0	0	268
1988	0	2	10	5	0	2	22	21	17	9	5	5	4	0	1	2	105
1989	0	0	1	4	22	8	5	14	11	4	7	4	0	2	1	0	83
1990	3	3	4	1	5	12	14	3	7	1	8	16	12	7	2	2	100
1991	5	5	5	9	5	8	5	5	2	5	2	5	1	2	2	3	69
1992	2	3	4	9	7	5	9	11	4	3	4	3	1	8	1	0	74
1993	2	1	6	1	14	10	6	7	4	8	9	11	1	3	1	0	84

It is not known what proportion of turtles killed wash up on the shore, but it seems reasonable to assume that this number is proportional to the total number killed. The observed strandings are plotted in Figure 1. We are treating this record as an unbroken record across years, although data are missing from December through the end of March every year. The number of strandings during these times is zero in almost all periods and including these periods would serve no obvious purpose. As a result of this, the models constructed in following sections apply to only those periods from which data are included.

2.2 Shrimping Season and the TED Regulation

Table 2 shows the yearly dates that the shrimp season started. Although the shrimp season runs through December and sometimes into January, we took the last day of the season to be October 30*th* in all years. After this date there is generally very little shrimping done (< 15 *percent of annual effort per month*) (see Table 3), and most turtles have migrated further south (see Section 3.2), thus are not present to be affected by shrimping activity in any great numbers. It makes some sense to categorize periods of low shrimping effort as off-season since turtle mortality in these periods would be most like that of the off-season. Ideally, we would define a *turtle mortality-influencing shrimp season* as being that part of the legal shrimp season where shrimping is having a significant mortality effect on turtles, *and* there are turtles present in large enough numbers to show up as strandings. But the seasonality of turtle abundance (Section 3.2) is not well-known, so we could only come up with a subjective definition of this with respect to turtle abundance.

Table 2 also gives the dates that the TED regulation was in effect each year. In years where the TED regulation ran over the boundaries of the bi-weekly periods that the strandings data exist, we counted the TED regulation to be in effect only during those periods in which a minimum of 5 days were covered by the regulation. If a TED effect exists, we feel this to be a reasonably long period of TED use in which to have an effect on turtle strandings in that period. Because the strandings data only exist as bi-weekly counts and the TED regulation was implemented in periods that don't necessarily coincide with these survey periods, there will be some periods that had TEDs in effect only part of the time. Thus the period may be designated as a TED period when really TEDs were in affect only part of the time and *vice versa*. This will cause the number of strandings associated with TED use to be smaller than it actually is, or cause the number of strandings associated with shrimping during non-TED periods to be smaller than it actually is. This may cause some bias in the estimate of the TED effect and of other model parameters. Because this only occurred two years (1988 and 1989), this bias should not be large.

The shrimp season too, generally does not coincide with the boundaries of the two week periods in which strandings counts were made. Again, if shrimping occurred in at least 5 days of a given period, we included that period as a shrimping period. The same problem discussed above exists here, except that this is liable to increase the number of strandings associated with non-shrimping activity, or reduce the number of strandings associated with shrimping activity.

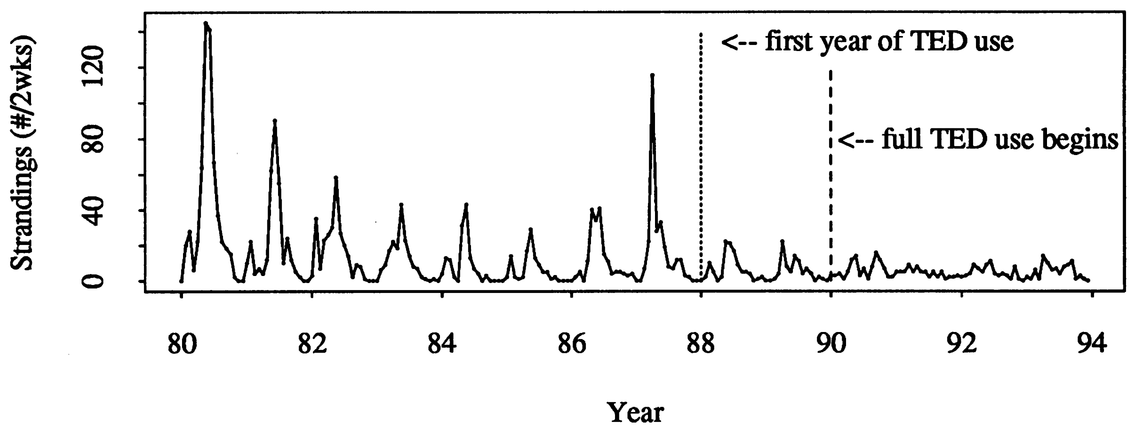

Figure 1: Bi-weekly loggerhead strandings.

Table 2: Beginning of shrimp season and effective dates of TED regulation.

Year	Shrimp season begins	TED regulation dates
1980	June 10	none
1981	May 15	none
1982	May 17	none
1983	May 16	none
1984	June 15	none
1985	June 25	none
1986	June 18	none
1987	June 4	none
1988	June 28	June 28 - July 10, July 25 - Aug 11
1989	June 1	July 1 - Aug 31
1990	June 1	June 1 - Aug 31
1991	May 15	May 15 - Oct 31
1992	May 20	May 20 - Oct 31
1993	June 1	June 1 - Oct 31

The bias caused by these two problems, that of the TED regulation not coinciding with bi-weekly period boundaries and the shrimp season not coinciding with bi-weekly period boundaries, is against a TED effect, thus we may be getting a conservative estimate of the TED effect based on these issues.

2.3 Shrimping Effort Data

Since the shrimp fishery is a significant mortality factor for sea turtles, one would expect strandings to be related in some way to the shrimp season. It seems reasonable that this relationship would be proportional to shrimping effort, although this is not a standard catch/effort relationship as turtle mortality is affected by other sources, both human induced and natural. Among these may be other seasonal fisheries, of which no effort data are readily available.

We have available the monthly total days spent shrimping for the region between 32 *degrees* N and 34 *degrees* N latitude, which covers the entire coast of South Carolina. These data are broken down by coastal zone, defined as distance from the shore. These zones are *inshore*, which includes sounds, bays and estuaries, $0 - 3$ miles from shore, $3 - 12$ miles from shore, and > 12 miles from shore. The great majority of shrimping effort was conducted in the $0 - 3$ mile zone. The monthly distribution of total days of shrimping effort in the $0 - 3$ mile offshore zone is given in Table 3. Generally, June through October are heavy shrimping months. Except for 1986-1989, little effort occurred in November and December and in 1984 and 1990 little effort occurred after August.

The effort data cover the period 1980-1990, whereas the strandings data are through 1993. Since the effort data covering 1991 to 1993 is unavailable to us at this time, relationships between strandings and effort will be the focus of future work. Preliminary work was done (but not discussed here) by including effort into a regression model using strandings from 1980 to 1990. This indicated that effort is not an important variable given that shrimp season was in progress.

3 Changes in Turtle Abundance

If strandings are proportional to turtle abundance, then it is reasonable to expect that the abundance of turtles would show up in the strandings record in the form of more strandings corresponding to high populations and *vice versa*. Changes in turtle abundance can be both seasonal, reflecting inter-year migrational activity and mortality of turtles, or long-term representing intra-year changes in regional turtle abundance. We will refer to the later type of fluctuation as *long-term trend* or simply *trend*. The former will be referred to as *seasonal abundance*. This section briefly mentions what is known concerning both types of population changes.

Table 3: Monthly distribution of days of shrimping effort in the 0-3 mile offshore zone.

Year	Jan	Feb	Mar	Air	May	Bun	Jug	Aug	Pep	Oct	Nov	Dec
1980	1.2	0.1	0	0.0	0.5	10.5	20.0	20.6	15.3	18.4	8.6	4.7
1981	0.3	0.0	0	0.0	0.1	3.6	29.1	24.7	17.9	14.9	6.1	3.1
1982	0.3	0.0	0	0.0	1.6	10.3	21.6	14.9	19.7	16.8	8.3	6.6
1983	2.2	0.3	0	0.0	3.6	8.2	20.5	18.2	21.2	12.7	7.6	5.5
1984	0.3	0.0	0	0.0	0.0	24.1	31.1	21.5	7.0	8.3	6.3	1.4
1985	0.2	0.0	0	0.0	0.0	5.5	30.5	29.8	14.1	10.3	5.9	3.6
1986	0.7	0.0	0	0.1	0.2	8.1	18.7	13.8	18.4	19.2	13.7	7.2
1987	2.8	0.0	0	0.0	0.5	9.9	15.5	11.0	21.4	19.3	11.6	8.0
1988	2.4	0.0	0	0.0	0.0	1.5	17.3	17.5	20.0	17.1	11.8	12.3
1989	0.8	0.0	0	0.1	1.0	14.0	16.3	13.9	15.9	14.1	13.3	10.6
1990	0.0	0.0	0	0.5	0.5	36.2	35.2	13.7	3.9	4.9	2.9	2.0
Average	1.0	0.0	0	0.1	0.7	12.0	23.3	18.1	15.9	14.2	8.7	5.9

3.1 Long-term Trend of Turtle Populations

As stated above, loggerhead populations have been on the decline in recent years. Over a 5 year monitoring period in the 1980s, Hopkins-Murphy and Murphy (1988) observed a decline of more than 26 *percent* in aerial surveys of nesting loggerheads in South Carolina. It was this information that first led to the implementation of the TED regulation in South Carolina. This decline is typically stated as a *percent per year* implying that the trend is thought to be, or is at least treated as a linear trend. Hopkins-Murphy (1994), in an update of the aerial survey data, has observed a leveling off in nesting turtle numbers in recent years, and even a slight increase. This is also evidenced in the data of Table 1; thus it seems that the trend in strandings and nesting loggerheads at least superficially resemble one another.

3.2 The Seasonal Abundance of Turtles

Sea turtles are not present in the waters off South Carolina in constant numbers year round. Their migrational patterns are likely to be water temperature dependent since VanDolah and Maier (1993) found no turtles present in waters below 16 *degrees* C. Data on the seasonal distribution of turtles along the Eastern United States is scarce, but aerial surveys show that turtles migrate into the waters of the study area every year in the early summer, and reach a peak abundance in May or June, declining in the summer as turtles move northward with warming water temperatures. This reduces the local populations in the summer, but the population increases significantly in the fall again as turtles begin to move south as northern waters cool.

They reach their lowest local seasonal density in the winter as they've migrated even further south. Table 4 shows the estimated density of turtles/10,000 km^2, based on aerial surveys for the latitudes between 32 *degrees* N and 34 *degrees* N. These data were taken from appendix D of National Research Council (1990). Thus, turtles off of South Carolina reach a peak abundance in the spring and the fall of every year, which should be reflected in the strandings record as high strandings in both of these periods, assuming that there is some relationship between background populations of turtles and strandings. Perhaps what is important in characterizing the seasonal relationship between turtle abundance and strandings is the population of *resident* turtles. That is, the population of turtles that spend their summer months in the waters off the South Carolina coast and do not migrate further north. This population may be quite large as a percentage of the overall population of turtles that come north in the spring, since few turtles are found to nest further north than North Carolina.

4 Preliminary Analyses and Observations

Figure 2 shows a plot of shrimping effort with strandings. Effort has been scaled to allow easy comparison with strandings. Several features are evident from studying Figure 1, and Figure 2. These will be discussed here.

4.1 The Shrimping Season, Shrimping Effort and Turtle Strandings.

In all years, the largest numbers of strandings occurs in the few periods immediately following the beginning of shrimp season.

Figure 2 shows a very large increase in turtle strandings associated with a very large increase in shrimping effort, signaling the beginning of the shrimp season. The effort remains high for as long as 5 or 6 months each year, while strandings decrease substantially. This combined with the fact that in the spring and fall periods of some years, strandings are high but effort is

Table 4: The seasonal abundance of turtles off South Carolina, estimated density/10,000 square km.

Season	32-33 degrees N	33-34 degrees N	Total
Winter	1244	390	1634
Spring	891	2502	3393
Summer	475	1491	1966
Fall	545	2426	2971

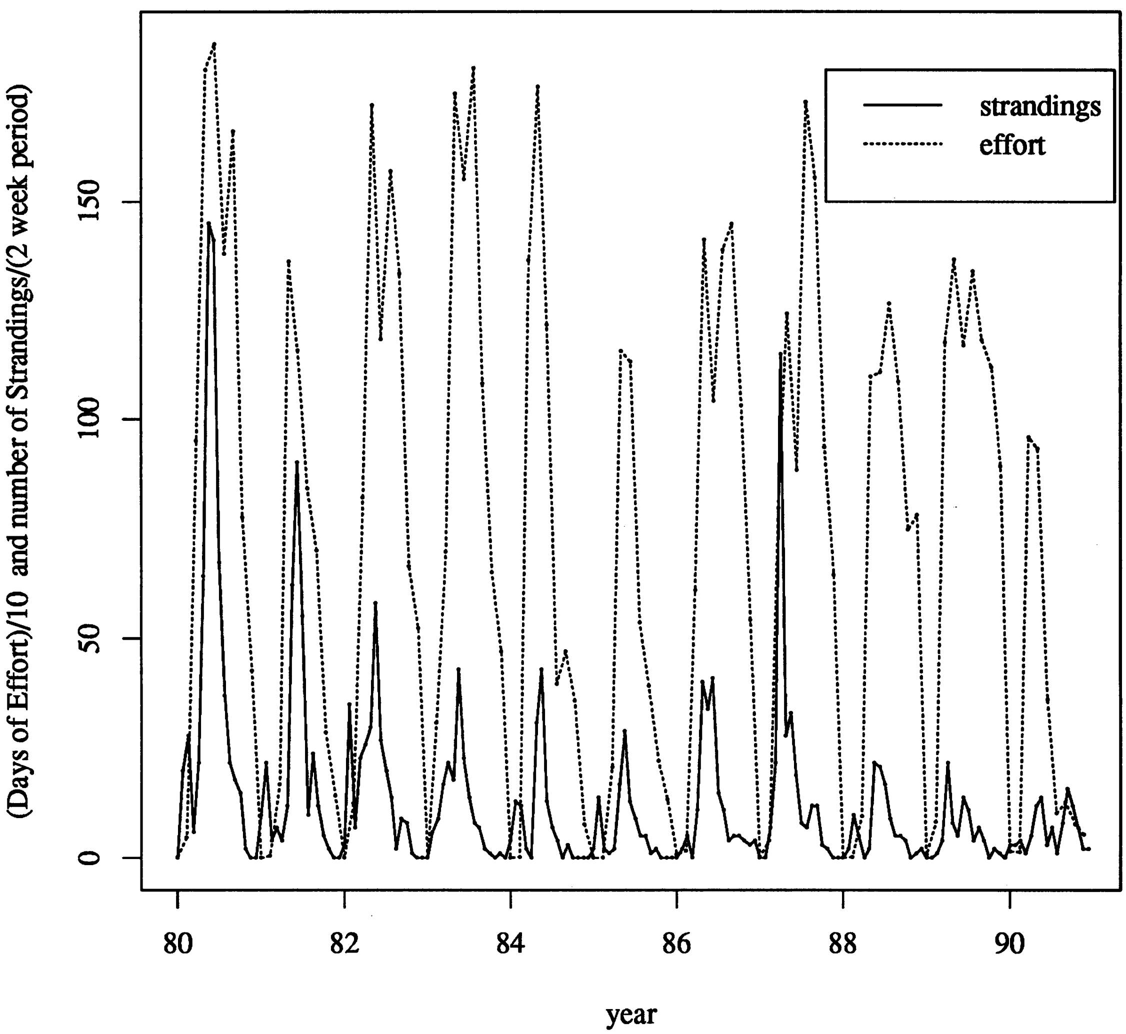

Figure 2: Monthly shrimping effort and bi-weekly turtle strandings

not, would seem to indicate that effort will not help predict strandings. The onset of shrimping is the most important aspect of shrimping activity. Further, the decline in strandings through the season may be due to a quick depletion of turtles on the quality shrimping grounds. At the onset of shrimping, turtles in these areas are killed in large numbers, leaving few to be killed later in the season. Strandings later in the season may be due to other turtles moving into the quality shrimping grounds, or shrimpers moving to shrimp in other areas.

4.2 Periodicity in the Strandings Record

Figure 1 shows a dramatic increase in strandings in the early summer of every year, followed by a decline through the summer months to almost nothing in the fall. Can this be modeled as a smooth function such as a cosine wave, as might occur if this were related to seasonal turtle abundance? Or is this simply a step-function increase related to the onset of the shrimp season? From Section 3.2, based on turtle abundance alone, we would expect to see two peaks in strandings each year. However, this is not the case. Rather, we see the initial peak in the late spring or early summer corresponding to the onset of shrimping, but nothing of a comparable magnitude in the fall, even though in most years shrimping is largely continuing on the same scale as in the beginning of the season. This suggests that the early summer increase in strandings is largely due to shrimping effort, rather than the seasonality of turtle abundance. The subsequent decline in strandings is consistent with both seasonal abundance patterns and mortality. Thus it is likely that a seasonal effect exists, on top of the shrimping effect. The occasional fall increases in strandings may be due to the influx of northern turtles migrating south, coupled with continuing heavy shrimping pressure.

Spring and fall increases in strandings appear in some years as shown in Figure 1. Aside from migrational activity of turtles, the fall increase may be due to other seasonal fisheries. A flounder fishery operates in the late fall of every year, although this fishery tends to occur further north and may not affect turtle populations off the South Carolina coast significantly. The spring component prominent in 1980-1986 coincides with a sturgeon gill net fishery that existed at this time, although generally this was earlier in the season, before turtles are present in large numbers.

4.3 Observed Trend

An important question to biologists is, does a trend exist in the turtle population? If so, then we might expect to see this trend in the strandings record. Figure 1 shows a definite decline in the numbers of strandings from the early eighties to the end of the record. As a rough estimate of the trend in strandings, Figure 3 shows the yearly means of loggerhead strandings per period. It appears that the decline from 1980 through 1993 is not a linear trend, and perhaps quadratic. Given that the means from the early years will be highly influenced by the few very large numbers of strandings that occurred then, this plot will possibly reveal a larger trend than actually exists. We can make a similar plot, using a more robust method known as median

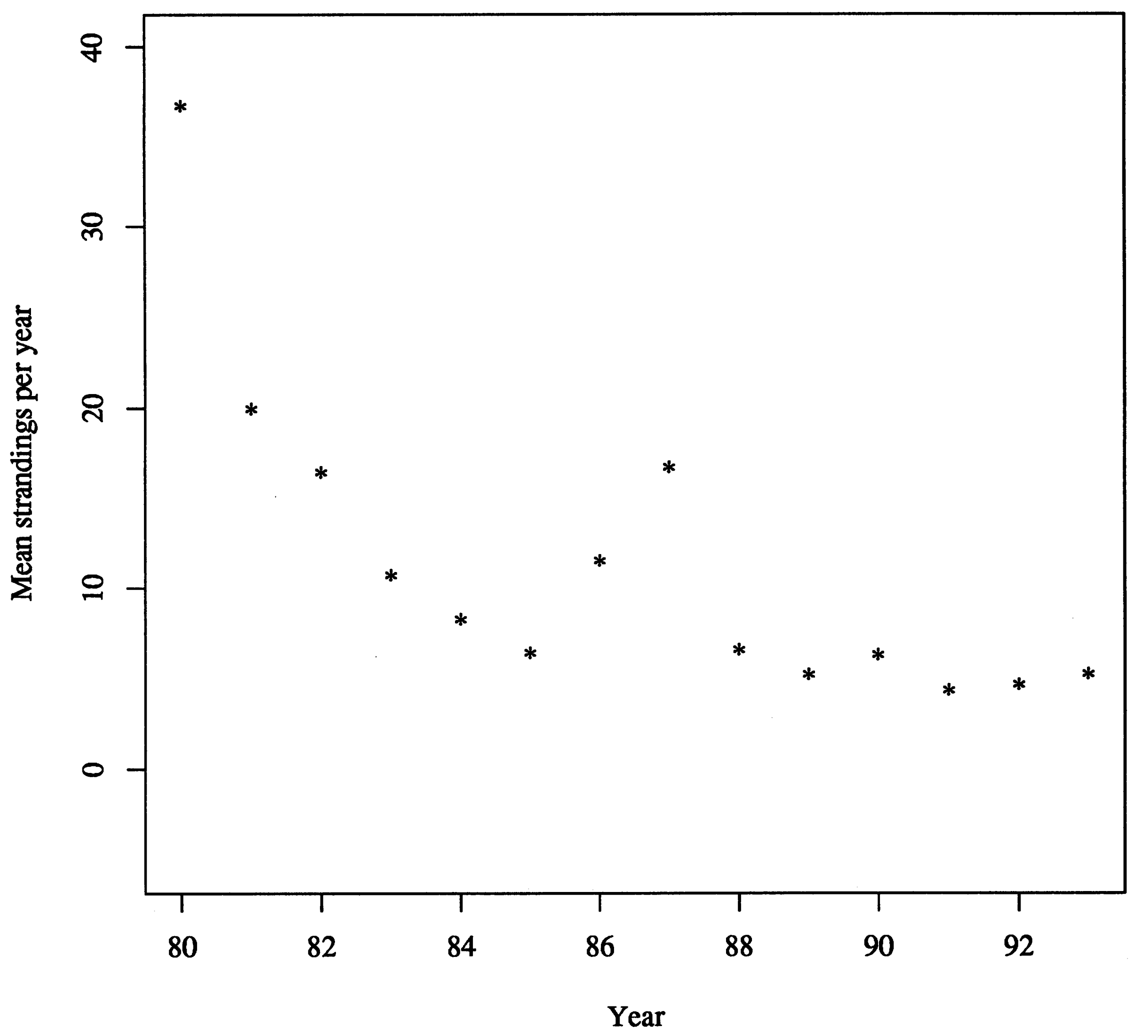

Figure 3: Yearly mean number of strandings per bi-weekly period.

polish, to get estimates of the yearly average strandings per period. We used a median polish (Tukey (1977)) on the year *by* period matrix of strandings to estimate the *yearly effects* and the *period effects*. This allows us to get estimates of the yearly effects free of period effects which include seasonality and shrimping effects. Thus we hopefully get a more reasonable estimate of the trend across years. The yearly effects are robust estimates of the yearly means and similar to the yearly median strandings per period. Either interpretation will suffice. A similar interpretation can be made for the period effects. Figure 4 shows a plot of the yearly effects. Notice that the general form of the trend is similar, although the yearly effects of the years with unusually large number of strandings (1980 and 1987), are relatively much smaller than the means. The overall level of the yearly effects is smaller than that of the yearly means, due to the fact that the period effects are removed and the larger values do not weigh as heavily in these calculations. It appears that a quadratic trend term may adequately describe the long-term trend of turtle strandings. This is consistent with the observation of Hopkins-Murphy (1994).

This observed decline in strandings may be due to two factors. As mentioned, a decline in turtle populations is one factor. A decline in shrimping activity may also affect strandings. Figure 5 shows the yearly total number of days spent shrimping in the study area between the beginning of the shrimp season and the end of December. The horizontal line is the mean yearly effort over the 13 year period. There is no significant trend observed here comparable to that of Figure 3 or Figure 4. We can likely conclude from this that the observed trend in strandings is primarily due to a declining turtle population.

4.4 A Naive Estimate of the TED Effect

The most important issue and the main focus of this analysis is whether TEDs have an impact on strandings. More specifically, do they decrease turtle mortality as they are meant to? And if so, what is the magnitude of this decrease? If TEDs reduce mortality then we would expect to see a decrease in turtle strandings during the periods when TEDs are in use. Figure 1 clearly shows that strandings decline after the implementation of TEDs. In fact, every year before TED implementation *except* 1985 has more strandings than in *any* of the TED years. The four years with full TED use required have lower strandings than any other years. Of course, the TED effect is confounded in some way with the suspected downward trend in turtle numbers. Thus we need to model both effects, which is done in Section 6.1.

An obvious initial estimate of the effect of TEDs on turtle strandings is simply the mean or median number of strandings in periods when TEDs were in effect minus the mean or median number of strandings in periods when TEDs were not in effect. A negative value of this quantity would indicate that TEDs reduce strandings by that amount each period, on average. Since there were many more strandings early in the study which may be due to larger populations or other factors, we could make this more reasonable by restricting our estimate to later years, say 1984-1993.

For the years 1980 to 1993, the mean number of strandings per bi-weekly period when TEDs were not in effect was 19.78. The mean when TEDs were in effect was 6.84. Thus

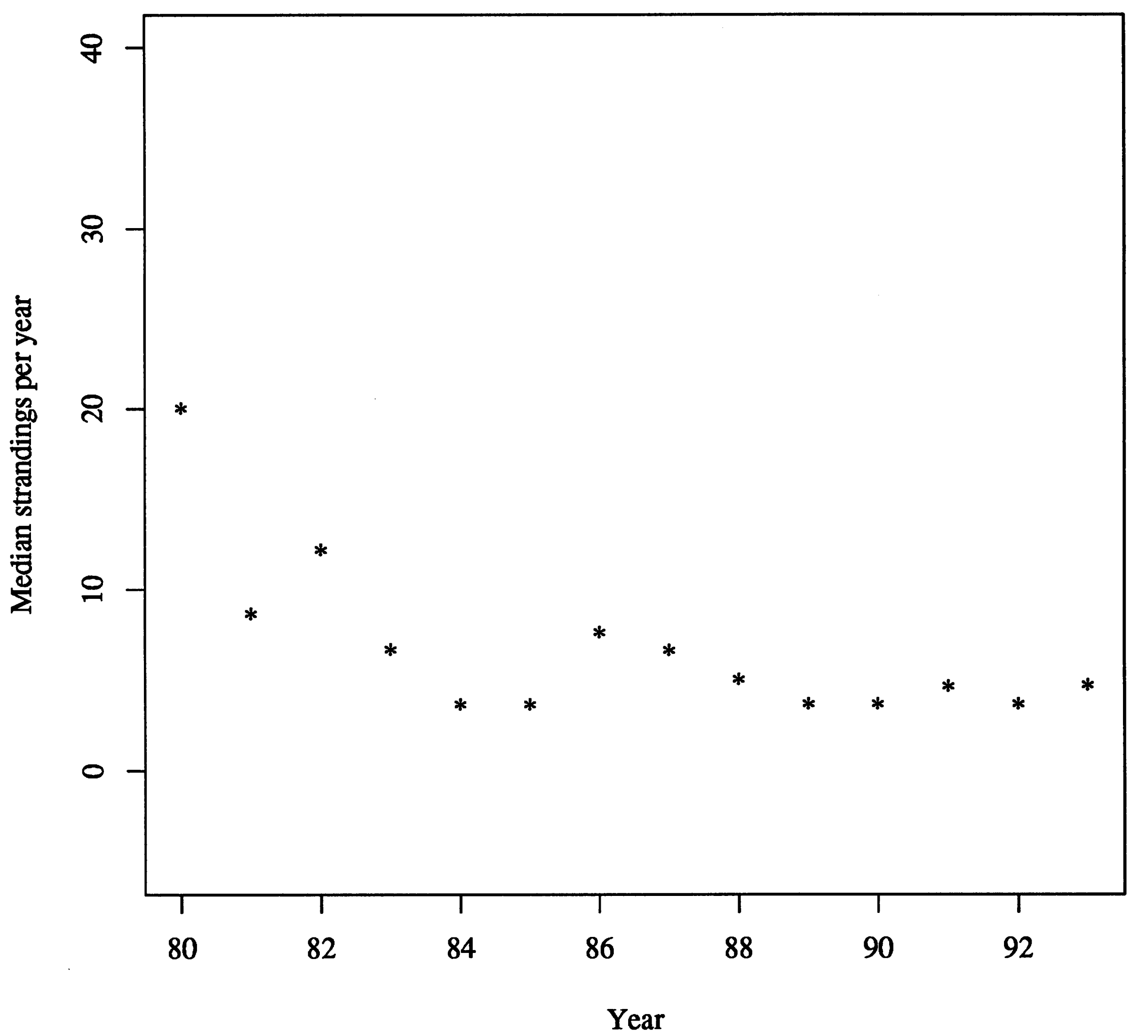

Figure 4: Yearly effect (strandings) from median polish.

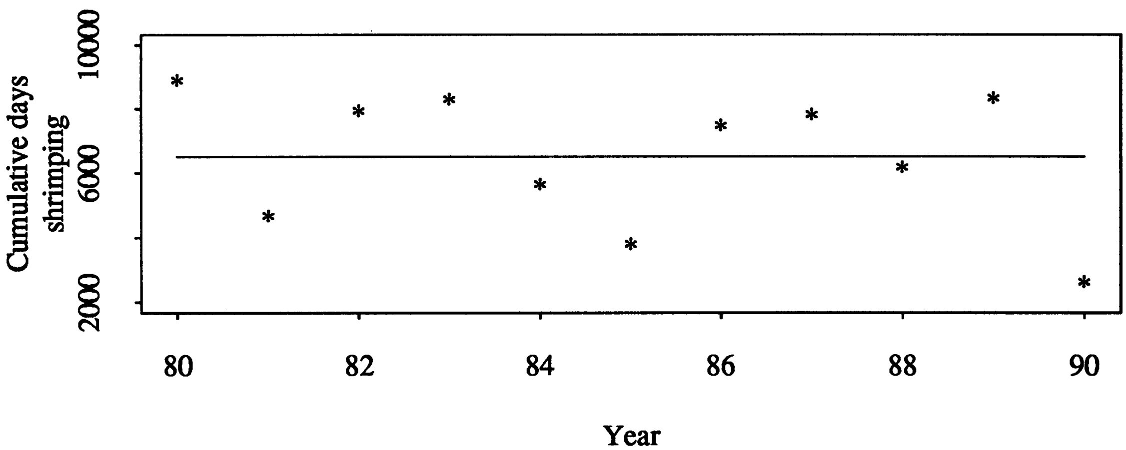

Figure 5: Total days spent shrimping through December of each year.

our naive estimate of the TED effect is ≈ -13 turtles per period, or a decline of 65 percent. Restricting ourselves to the years 1984 to 1993 so that we have 4 no TED years, 4 full TED years, and 2 partial TED years, we get a mean of 13.40 with no TEDs and 6.84 with TEDs. This is approximately a 49 percent decline in strandings per period.

Performing these same calculations using the *median* strandings per period we get, for 1980 to 1993, a median of 11.5 with no TEDs and a median of 5 with TEDs, which is a decline of ≈ 57 percent. Again, restricting our estimate to the years 1984 to 1993 we get a median of 7 with no TEDs and a median of 5 with TEDs, which is a 29 percent decline. The use of medians gives us an estimate that is more robust to (that is, not as affected by) extreme values, which in particular are the high strandings of 1980, 1981 and 1987.

Although these estimates of the TED effect are confounded with the negative trend in strandings, these do provide some indication that there is a TED effect. We shall compare these naive estimates of the TED effect to those calculated when we adjust strandings for seasonality and trend in Section 6.1.

5 A General Model

Given the observations of Sections 3 and 4 we might propose a model that has the general form

$$\begin{aligned} \text{strandings} &= (\text{background mean}) + (\text{periodic components}) \\ &+ (\text{long-term trend}) + (\text{TED effect}) \end{aligned} \tag{1}$$

In this equation the *background mean* reflects the number of strandings that might occur as a result of mortality on a constant turtle population. That is, one with no seasonality, trend or TED effect. *Periodic components* may be one or more cyclical components to account for the observed annual or semi-annual cycles of some years. This may include both the seasonal abundance of turtles, or other seasonal effects including seasonal fisheries. The *long-term trend* will be some function that captures the observed trend in strandings, likely related to the underlying trend in the turtle population. And the *TED effect* will be an indicator of when the TED regulation was in effect, thus serving as an adjustment to the *background mean* during these periods. This section discusses how we may build a parametric model to the strandings data.

5.1 Background Mean

The mortality of turtles is plainly different during the shrimping season than otherwise. At issue here then is, how does one parameterize the effect of shrimping on turtle strandings? A logical parameterization is to simply allow the mean strandings to be different in these two periods. In its simplest form, this model contains only a constant and a parameter to represent the effect of the shrimping season, and is of the form: $Strandings_t = \mu + \beta X_t$ where X_t is an indicator of shrimp season. That is, it takes on a value of 1 when shrimping season is in progress, and a value of 0 otherwise. This is saying that strandings are just a constant, *plus* some effect due to shrimping activity. When shrimping season is not in effect, the mean strandings is expected to be μ, and when shrimping season is in progress, the mean strandings is expected to be $\mu+\beta$. The parameter β will have the interpretation as an addition or subtraction from the mean, depending on whether it is negative (shrimping season reduces strandings) or positive (shrimping season increases strandings). An equivalent model would allow for an off-season mean and a separate on-season mean. This model can be represented as $Strandings_t = \beta_1 X_{1t} + \beta_2 X_{2t}$. Here X_{1t} is an indicator of off-season, X_{2t} is an indicator of shrimp season, β_1 is the expected off-season mean strandings and β_2 is the expected mean strandings during the shrimp season. The formal definition of X_{1t} is as follows

$$X_{1t} = \begin{cases} 1 & \text{if period t was on-season} \\ 0 & \text{if period t was off-season} \end{cases}$$

The variable X_{2t} is defined similarly as

$$X_{2t} = \begin{cases} 0 & \text{if period t was on-season} \\ 1 & \text{if period t was off-season} \end{cases}$$

In the presence of other effects discussed in the following sections, these will have the interpretation as the mean strandings *adjusted* for these other effects. This parameterization is straight forward and easy to interpret. Thus we will use it in our basic model (Section 6.1). It may be possible that the effect of a given amount of effort is not the same later in the shrimp season. This difference may exist as a result of the seasonal abundance of turtles, and also mortality of resident turtles.

5.2 Long-term Trend in Turtle Abundance

From the discussion of Section 4.3 it seems that a low order polynomial will reasonably approximate the observed long-term trend in strandings evident in Figure 1 and Figure 4. That is, we can add a term of the form ($\theta \times \textit{time}$) to the model in the previous section in the case of a linear trend, and ($\theta_1 \times \textit{time} + \theta_2 \times \textit{time}^2$) in the case of a quadratic trend. Higher order trends can be considered.

5.3 Modeling the TED Effect

The simplest way to parameterize the effect of TEDs is as an adjustment to the number of strandings during the shrimp season. That is, set up an indicator variable that takes on the value 1, when TEDs are in effect and the value 0 otherwise.

If the overall mean is parameterized as simply a mean during the shrimp season and a mean off-season as discussed in Section 5.1, then the parameter for the TED effect will have the interpretation as either decreasing strandings from the shrimp season mean if it is negative, or increasing strandings from the shrimp season mean if it is positive. More formally, we have the model $Strandings_t = \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t}$ where X_{1t} and X_{2t} are as defined in Section 5.1 and X_{3t} is defined as

$$X_{3t} = \begin{cases} 1 & \text{if TEDs were on for period t} \\ 0 & \text{if TEDs were off for period t} \end{cases}$$

Now, the expected number of strandings off-season is β_1, the expected number of strandings on-season with no TEDs is β_2 and the expected number of strandings on-season with TEDs is β_2 + β_3. Here, β_3 is the TED effect, and if TEDs have the effect of reducing strandings, we would expect to see a negative estimate of this quantity.

The estimate based on the mean given in Section 4.4 is essentially this estimate, *unadjusted* for the other effects of Equation 1. Incorporating the TED parameter with other model components will give us an *adjusted* TED effect.

5.4 Modeling the Seasonality

As stated in Section 5.1, a *shrimping effect* might be parameterized as a step-function. A seasonal component due to the relatively slow migration of turtles would likely be fit well by a sine or cosine wave. Thus, to account for the one or more periodic components observed in the strandings record, we may add terms like $R_i \cos(2\pi\omega_i t + \phi_i)$ to the model. Here R_i and ϕ_i are the amplitude and phase of the ith sinusoid. The amplitude is simply the 'height' of the sinusoid, and the phase is the shift from zero. These must be estimated. The frequency, ω_i is assumed known; logical choices include frequencies of 1 cycle per year in the case of a possible annual frequency associated with the spring northward migration of turtles, 2 cycles per year to include the possibility of additional fall increases in strandings due to the southward migration, and even 3 cycles per year to account for the possibility of an early spring increase due to other seasonal fisheries. Since we appear to have both a shrimp season effect and seasonal components due to turtle movements and other factors, adding these sinusoidal components to the model containing the step-function shrimping effect term is reasonable.

One difficulty with this parameterization of the seasonality is that that amplitude and phase parameters enter this model nonlinearly. To allow estimation using least-squares, we can linearize the sinusoidal components using the trigonometric identity:

$$R_i \cos(\frac{2\pi it}{17} + \phi_i) = A_i \cos(\frac{2\pi it}{17}) + B_1 \sin(\frac{2\pi it}{17}) \tag{2}$$

Here the parameters to be estimated are the A_i and B_i rather than the R_i and ϕ_i. And this can be done using least-squares rather than non-linear least-squares thus making computation a bit simpler. All model fitting in this report was done using this identity, and least-squares. One can recover the R_i and ϕ_i by simply inverting this identity to get $R_i = (A_i^2 + B_i^2)^{.5}$ and $\phi_i = \arctan(-B_i/A_i)$. In this way the estimates can be reported in either form.

5.5 Separating Seasonal Turtle Abundance and the Shrimping Effect

The seasonal abundance of turtles reaches its peak in May or June, which corresponds with the onset of shrimping every year. This makes the separation of these two effects quite difficult. But, as stated in Section 3.2, turtles are nearly as abundant in the fall as in the spring. Thus we would expect to see a large increase in strandings in the fall of every year as in the late spring due to the abundance of turtles alone. Although perhaps not as large due to mortality over the course of the year and the fact that these migrating turtles are not caught in significant numbers. Generally, we do not see an increase in strandings comparable to that early in the year. From this, we could conclude that the predominant effect on strandings is shrimping activity, and not the seasonal abundance of turtles. But, we would like to include terms in a statistical model to account for the seasonal abundance of turtles and other seasonal effects.

The fact that strandings drop off after the beginning of the shrimp season may be due to several things. First, this is consistent with the northward migration of some of these turtles, and also mortality within local populations of 'resident' turtles, possibly associated with shrimping grounds that are heavily favored by shrimpers. If one makes the assumption that migrating turtles have a lower probability of being caught due to the fact that they are simply 'passing through', (i.e. the probability of capture is proportional to the time spent in the shrimping grounds of the study area) than it seems reasonable that we would not see a large increase in strandings in the fall.

Figure 6 shows a plot of the average number of strandings in each period over all years. If strandings were only proportional to population, this plot would have two distinct, large peaks based on the discussion of Section 3.2. What we see is nearly 0 strandings for the first week of April, followed by a large jump mostly due to the years in which the shrimp season started in early May. Even larger increases occur in July and August, corresponding to the months of intense shrimping pressure. This is followed by a sudden decrease through September, and a gradual fall from there through December. This plot suggests that the majority of strandings are due to shrimping effort. But the fact that the shrimp season starts on different dates every year makes this plot less meaningful.

We can make a similar plot, but define our periods as deviations from the starting date of the shrimping season. Doing this will allow us to gain a great deal of insight into separating the seasonality of strandings from the shrimping effect. This is because in some years we have 6 full periods of pre-shrimp season strandings data available. We will call these periods *relative periods*. More precisely, for all years we will number the bi-weekly periods according to their distance from the start of the shrimp season. In this way the strandings of a given period are all representative of the same shrimping pressure relative to the start of the shrimping season. We make no attempt to account for the varying amount of absolute shrimping effort (in days) discussed in Section 2.3. The plot of the mean strandings per bi-weekly *relative* period is given in Figure 7. This plot distinctly shows a gradual increase for the first 3 months leading up to the beginning of the shrimp season, followed by a dramatic increase. We can assume that turtle movements are relatively slow, so the difference between any 2 bi-weekly counts should not be large based on turtle migration alone. Thus the very large increase at the start of the season, and the following large values can be attributed to shrimping activity. There is a strong hint of seasonality in this plot which shows up as a gradual increase in the spring and a gradual decrease in strandings later in the year. Since effort is relatively constant over the whole year, we can assume that the decrease in strandings after the beginning of the shrimp season seen in Figure 7 is due to a depletion of resident turtles. Given the obviously large magnitude of this shrimping effect, a better idea of the seasonality might be exhibited by making a plot similar to Figure 7, but using only those years after the TED regulation went into effect (1988 to 1993). Figure 8 shows this plot. For comparison, Figure 9 shows the same plot using only those years with no TED use, 1980 to 1987. The difference in the shrimp season effect is obvious. This suggests an alternate parameterization to those given in Section 5.1 and 5.3. We could model the shrimp season effect as being different in the years 1980-1987 than in 1988-1993, and possibly different in 1988 and 1989 than in 1990-1993. This will provide an estimate of the shrimping season effect in the years of TED (full or partial) use that will be that reduction in strandings due to TED use. This alternative parameterization will not be considered here. This parameterization would be slightly more general in that it would allow the difference between the mean strandings on season with *no* TED use and the mean strandings on season *with* TED use to take on 2 values, rather than just 1 as is the case with the parameterization of Section 5.3

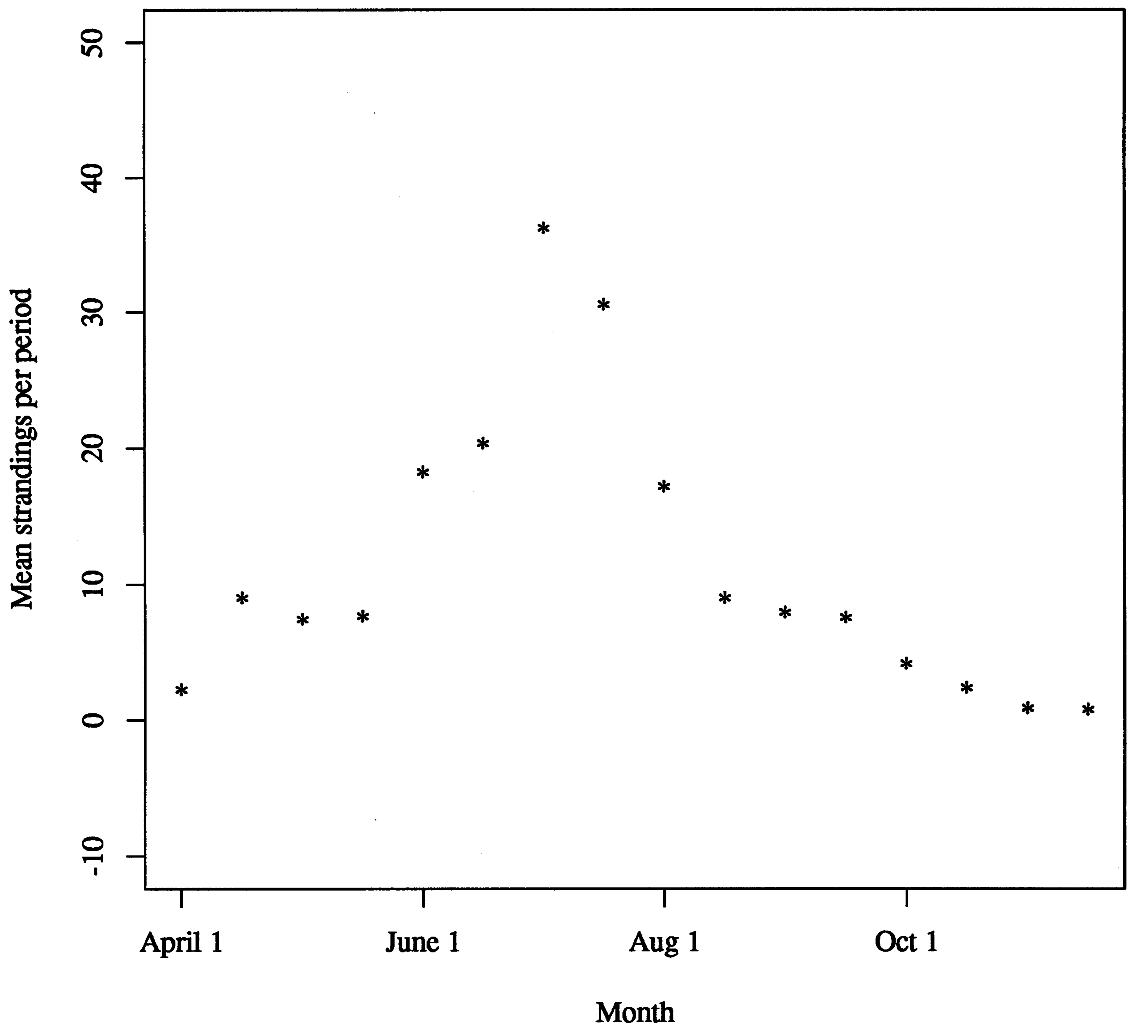

Figure 6: Mean strandings per bi-weekly period for 1980-1992.

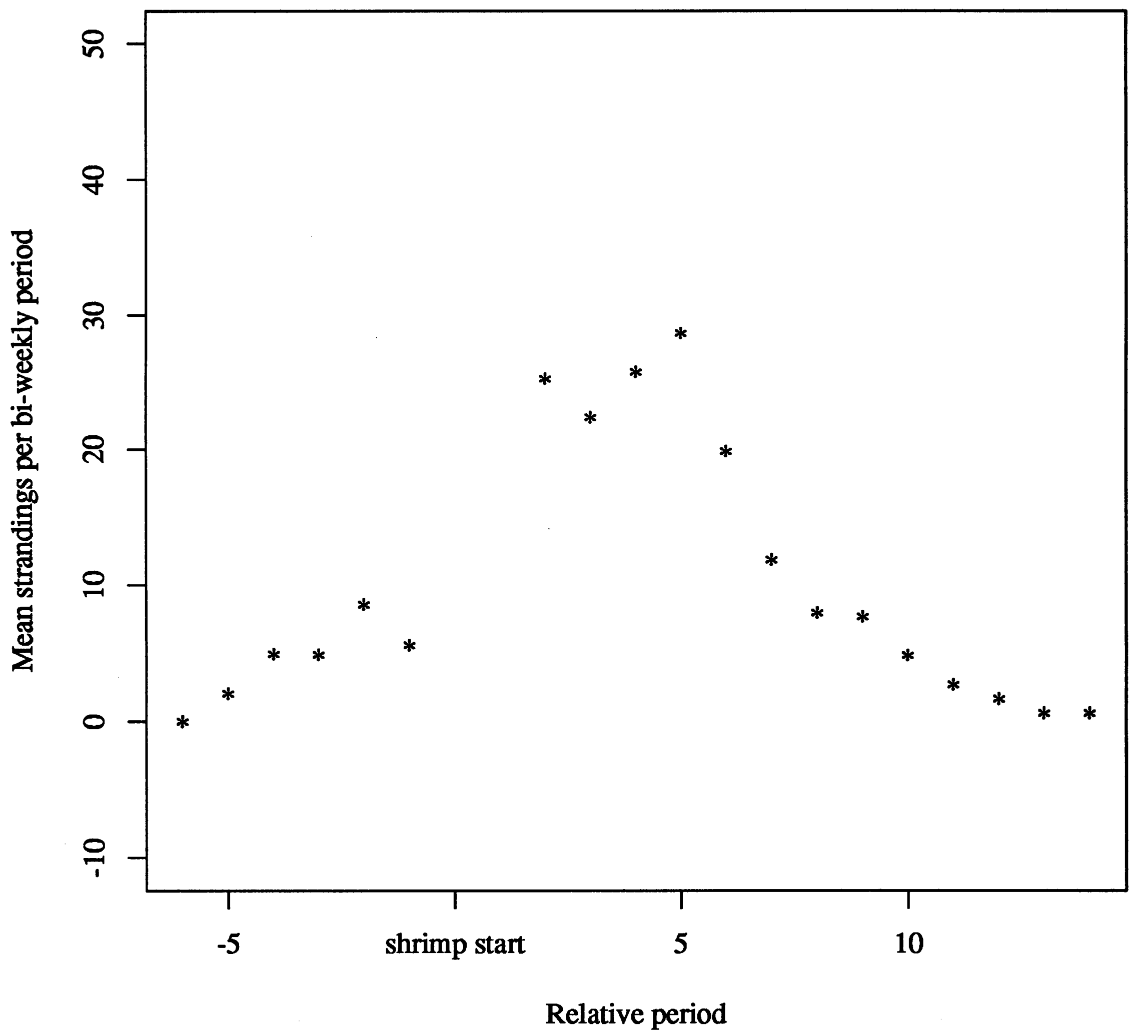

Figure 7: Mean number of strandings per period relative to the start of the shrimping season.

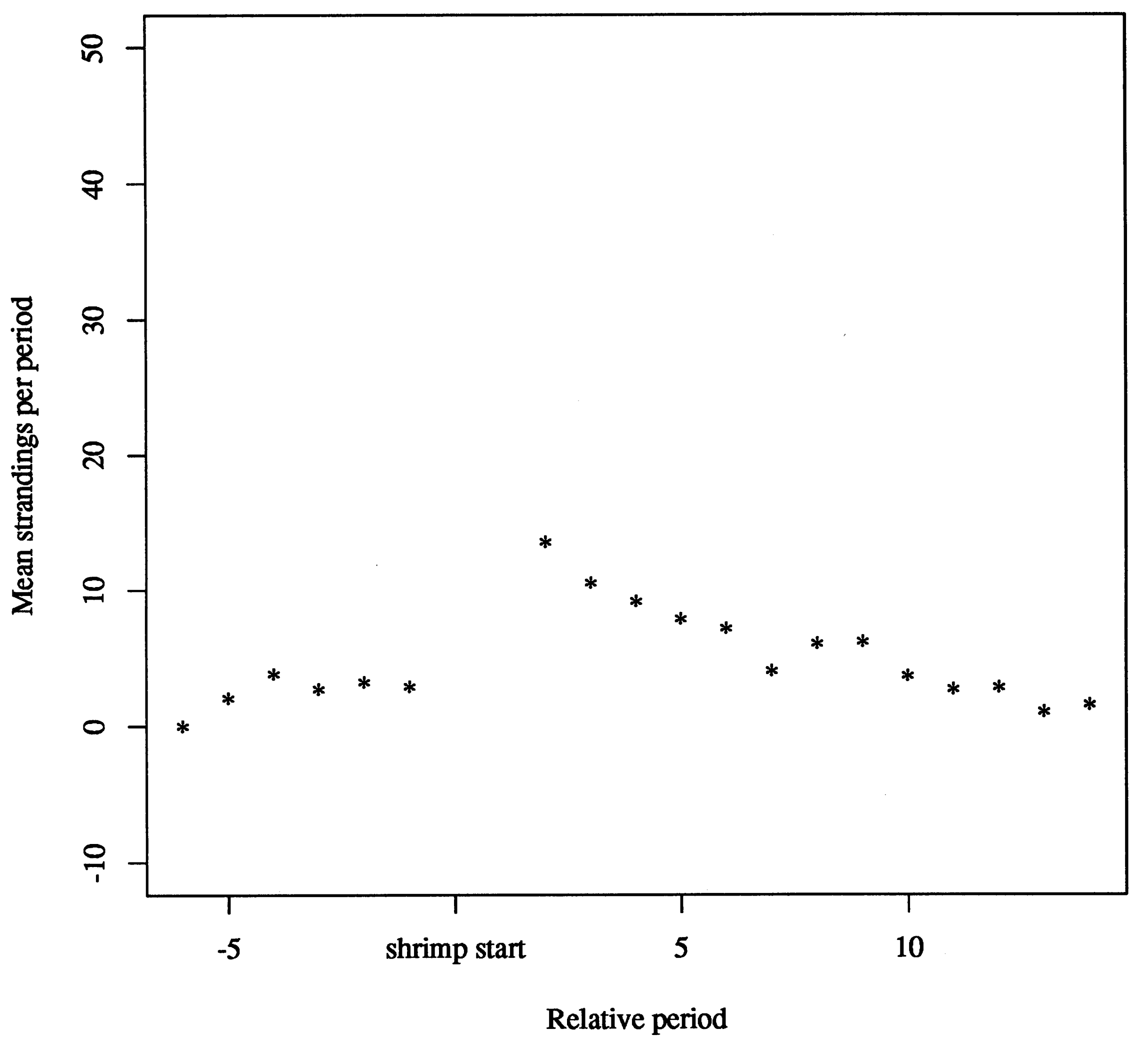

Figure 8: Mean strandings per relative period, 1988-1993.

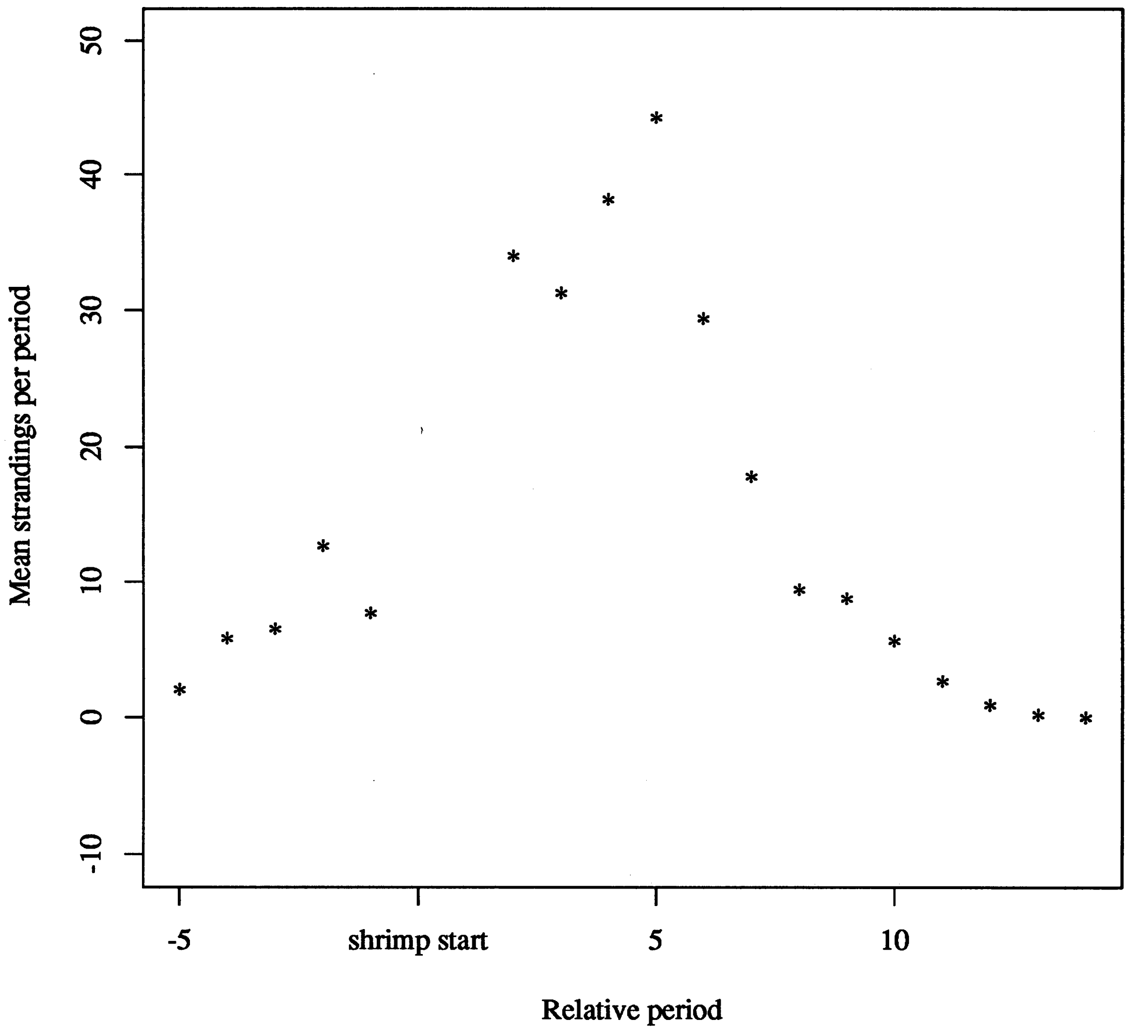

Figure 9: Mean strandings per relative period, 1980-1987.

and Section 5.1. In effect, we would be allowing for a different TED effect in full TED years than in partial TED years.

Figure 8 gives a much clearer representation of the seasonality of strandings, free of shrimping effects for the most part. It appears that we do see a slight increase in strandings in the fall, toward the end of the shrimping season. We also see the peak strandings at the beginning of the season, as we would expect, followed by the gradual decrease through the seventh period of the season. Additionally, there is a small increase early in the season, two months prior to the onset of shrimping.

6 Building a Statistical Model for Turtle Strandings

6.1 The Basic Model

As an initial model that incorporates the components of the model given in Equation 1, let us consider a model that contains multiple periodicities in the form of 3 cosine waves with frequencies of 1, 2, and 3 cycles/year (Section 5.4), a linear trend (Section 5.2), a step function to model the effect of the shrimping season (Section 5.1), and an indicator that models the effect of TEDs as an adjustment to the shrimp season mean (Section 5.3). This includes terms for all of the major effects discussed in the previous sections. More specifically, the model can be written as:

$$\begin{aligned} Y_t &= \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + R_1 \cos(\frac{2\pi t}{16} + \phi_1) \qquad (3) \\ &+ R_2 \cos(\frac{4\pi t}{16} + \phi_2) + R_3 \cos(\frac{6\pi t}{16} + \phi_3) + \theta_1 t + \theta_2 t^2 + \epsilon_t \end{aligned}$$

Where $\{\epsilon_t\}$ are independent and distributed normally with mean zero and constant variance, the standard regression assumptions. Here the parameters that must be estimated are the amplitude and phase parameters R_i and ϕ_i, the trend parameters θ_1, θ_2 the off-season and on-season mean strandings β_1 and β_2 and the TED effect, β_3. Note that this model is parameterized without a constant mean. Here the two variables X_{1t} and X_{2t} added together take the place of an overall constant. The variables X_{1t}, X_{2t}, and X_{3t} are defined as discussed in Section 5.1 and Section 5.3. We will use the identity given in Section 5.4 to linearize the sinusoids of Model 3, and use least-squares to obtain parameter estimates.

Given this parameterization the least-squares estimate of β_1 will be the mean number of strandings during the shrimp season in periods of no TED use, adjusted for the periodicity and trend in strandings. Similarly, the estimate of β_2 will be the adjusted mean number of strandings off-season. And β_3, the TED effect, will be the estimated difference between the on-season, no-TED use mean and the on-season, with-TED use mean. If TEDs are effective in reducing turtle deaths, hence there are less turtle strandings, β_3 will be negative. Therefore an estimate of this will be negative on average. An estimate of 0 for β_3 will indicate no TED effect, and we can test the hypothesis that $\beta_3 = 0$ using a t-test. Since TEDs should not *cause* strandings, it is appropriate to use a 1-tailed t-test in this case, and test $H_o : \beta_3 = 0$ *versus* $H_a : \beta_3 < 0$.

6.2 Fitting a Model to the Raw Strandings

Model 3 was fit using ordinary least squares. The sinusoid corresponding to 3 cycles per year was found to be only marginally significant, however we will retain it in the model since we believe a mechanism exists to account for this. Additionally, adding a cubic trend term to the model increased the R^2 significantly, and the estimate was statistically significant. Thus Model 3 was modified adding the cubic trend term $\theta_3 t^3$. Fitting this modified model by least squares produces the estimates given in Table 5. The R^2 of this fit was 0.61. A standard assumption in all regression models is that the variance of the errors is constant. Violation of this assumption renders the standard errors of parameter estimates invalid. A plot of the residuals over time is shown in Figure 10. It is plain to see from this plot that the error variance is heteroscedastic (i.e. not constant) over time, rather it appears to be proportional to the number of strandings. That is, in years of high strandings the variance appears to be much higher than in other years. Figure 11 demonstrates this point nicely by showing the yearly standard deviation of the residuals from Model 3 plotted against the yearly mean strandings per period. This occurrence is common when analyzing count data, and typically can be rectified by *log* transforming the dependent variable. The Box-Cox procedure also indicated that the *log* transformation was the best one for this particular model. The Box-Cox procedure determines the transformation in the class of power transformations that minimizes the mean-square error. In this sense then, the log transformation (which is defined to be the 0*th* power) is the best transformation for this particular problem. Here, the *log* transformation is that of the *natural log* or log_e. Because of this error heteroscedasticity, we will not bother to interpret the estimates from the fit to the raw strandings.

6.3 Fitting a Model to the Log-strandings

Log transformation will have an effect on which variables are significant in the model since if the appropriate model for $\log(Y)$ is a linear model, then the appropriate model for Y must be multiplicative in some way. Therefore, one generally cannot expect to get the same significant variables in both the linear model fit to Y and the linear model fit to $\log(Y)$.

In the case of the strandings record, a multiplicative model may make a good deal of sense. As an example that illustrates this point, suppose we have the model *Strandings* = $(S(t) * k(shrimp))^{\theta}$, where S(t) reflects the seasonal abundance of turtles, and k(shrimp) takes on two distinct values, one when shrimp season is in effect, and one when it is not. This says that strandings are proportional to the seasonal abundance of turtles, and the proportionality constant is different during shrimp season than off shrimp season. Raising this to the power $\theta > 1$ then allows the strandings to be relatively much higher when turtle abundance is high, than when it is low. Taking the *log* of this gives us a linear model with a seasonal component,

Table 5: Parameter estimates and standard errors by ordinary least squares.

Parameter	Estimate	Standard error	t-Value	P-Value
β_1	42.48256	4.23399	10.034	0.0001
β_2	32.13626	5.17819	6.206	0.0001
β_3	-16.22992	3.79739	-4.274	0.0001
A_1	-10.03695	2.57701	-3.895	0.0001
B_1	6.12757	2.04491	2.997	0.0031
A_2	5.09764	1.47037	3.467	0.0006
B_2	-1.88836	1.60676	-1.175	0.2412
A_3	-2.41310	1.40010	-1.724	0.0863
B_3	2.49537	1.39513	1.789	0.0751
θ_1	-0.75746	0.15410	-4.915	0.0001
θ_2	0.00586	0.00159	3.693	0.0003
θ_3	-0.00001	0.00000	-2.871	0.0045

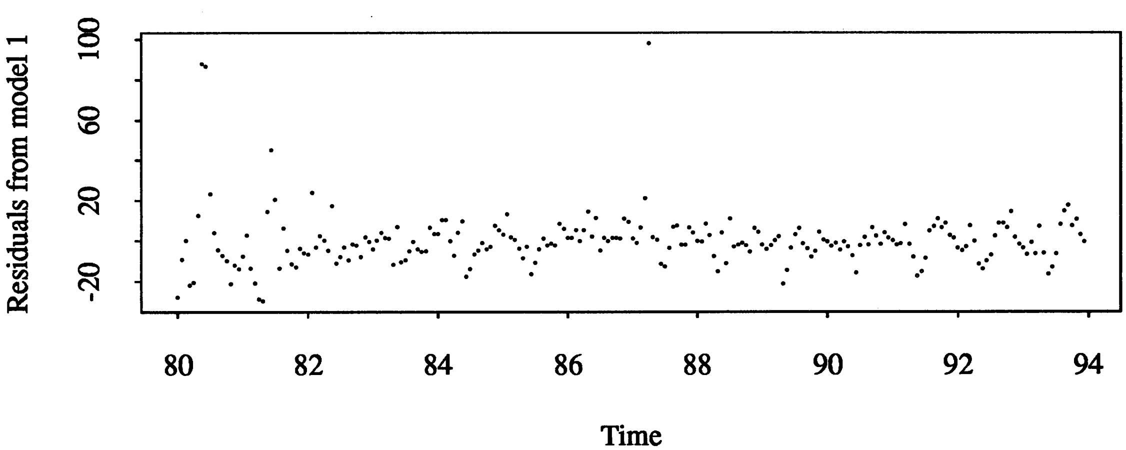

Figure 10: Residual plot from raw strandings model.

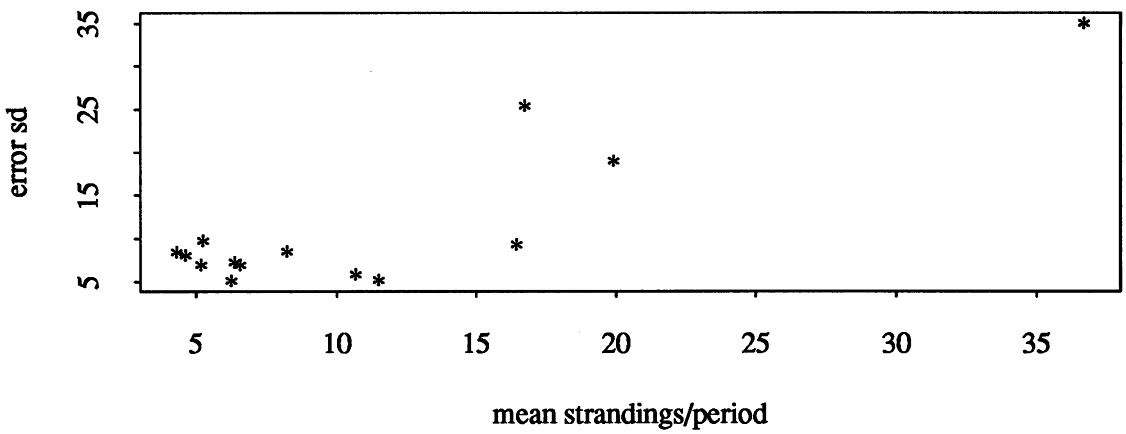

Figure 11: Yearly std deviation vs. mean strandings per period.

and two constants, one to reflect the shrimp season effect, and one to reflect the off-season effect.

We fit Model 3 with a linear, quadratic and cubic trend to the *log* strandings using least-squares. We added 1 to the strandings before taking the *log* to allow periods of zero strandings to have some meaning. The cubic trend term was statistically significant but added less than 0.005 ($\frac{1}{2}$ of 1 *percent*) to the R^2 of the model and was only non-zero in the 9th decimal place. So, this term was deleted from the model, giving the revised model

$$\begin{aligned}\log(Y_t) &= \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + R_1 \cos(\frac{2\pi t}{16} + \phi_1) \\ &+ R_2 \cos(\frac{4\pi t}{16} + \phi_2) + R_3 \cos(\frac{6\pi t}{16} + \phi_3) + \theta_1 t + \theta_2 t^2 + \epsilon_t\end{aligned} \tag{4}$$

This was fit using ordinary least-squares and the resulting parameter estimates are given in Table 6. The R^2 of this fit was a very respectable 0.877. The residual plot indicated a small degree of non-constant variance, but not to the same degree as prior to the log transformation. This residual plot is shown in Figure 12. To examine whether the assumption of normality seems reasonable, we can examine the normal probability plot of the residuals from this model. This plot simply plots the observed residuals against the expected quantiles from a normal distribution. Figure 13 shows this plot. Under normality, the points should lie along a 45 *degree* line. In this case they do, and we can conclude that the residuals from this model are normally distributed. Interestingly, the third sinusoid becomes significant in this fit and the second sinusoid becomes less so.

Table 6: Ordinary least squares estimates from log strandings model.

Parameter	Estimate	Standard error	t-Value	P-Value
β_1	3.09070	0.16821	18.3737	0.0001
β_2	1.97048	0.22448	8.7779	0.0001
β_3	-0.80878	0.19366	-4.1763	0.0001
A_1	-0.68898	0.13150	-5.2393	0.0001
B_1	0.58251	0.10410	5.5957	0.0001
A_2	0.06529	0.07504	0.8702	0.3852
B_2	0.16988	0.08191	2.0738	0.0393
A_3	-0.18918	0.07145	-2.6477	0.0087
B_3	0.17009	0.07118	2.3894	0.0177
θ_1	-0.01616	0.00316	-5.1074	0.0001
θ_2	0.00007	0.00001	4.5731	0.0001

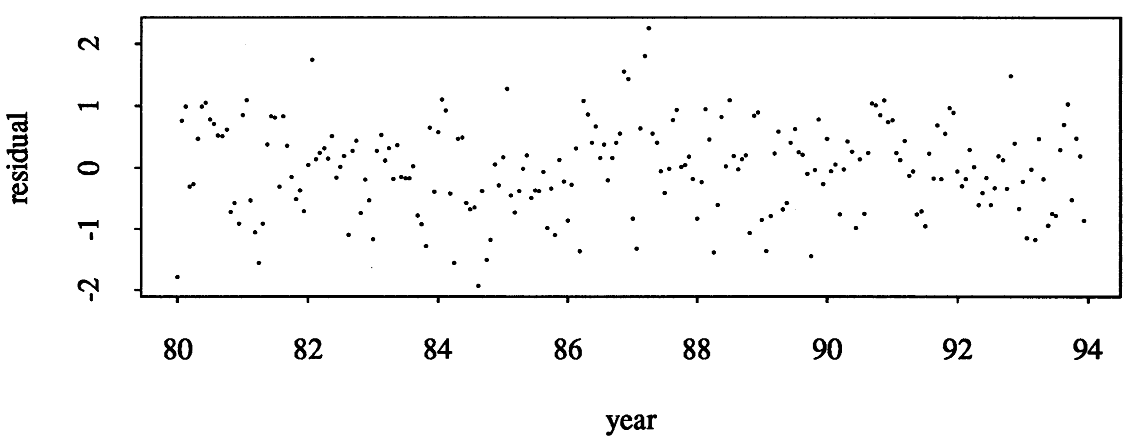

Figure 12: Residual plot from log-strandings model.

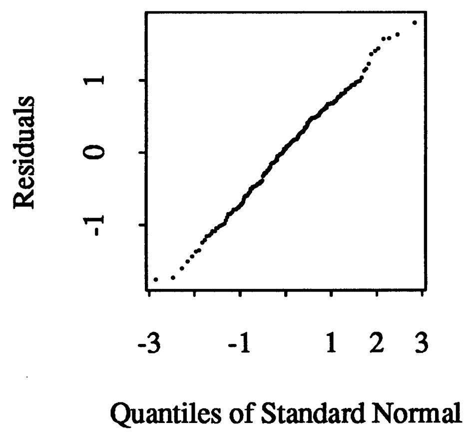

Figure 13: Normal probability plot of log-strandings model residuals

6.4 The Error Correlation Structure

Another assumption when fitting a regression model using ordinary least-squares is that the errors are uncorrelated. Violation of this assumption can be assessed by examining the auto-correlation function (ACF) and the partial auto-correlation function (PACF) of the residuals. Figure 14 shows the ACF and PACF of the residuals from Model 4. In these figures, the horizontal lines correspond roughly to two standard deviations. It is evident from these two plots that there is significant correlation among these residuals.

A class of models that is useful for correlated data are the ARIMA models. These are discussed fully in Box and Jenkins (1976). Two particular models of this class that might explain the ACF and PACF of these residuals are the AR(1) and MA(1) models. These stand for auto-regressive and moving average of order 1, respectively. An MA(1) model will have a significant lag 1 autocorrelation and an AR(1) model will have a significant lag 1 partial autocorrelation. These plots show both a significant lag 1 autocorrelation *and* a significant lag 1 partial autocorrelation. This suggests that either an AR(1) or an MA(1) model may be appropriate and perhaps even a combination of the two, an ARMA(1,1) model, may fit these residuals.

An AR(1) model in it's most basic form says that the current value of U_t depends on the previous value only,

$$U_t = \rho U_{t-1} + \nu_t$$

where ν_t is random error. The basic form of an MA(1) model is,

$$U_t = \nu_t + \alpha \nu_{t-1}$$

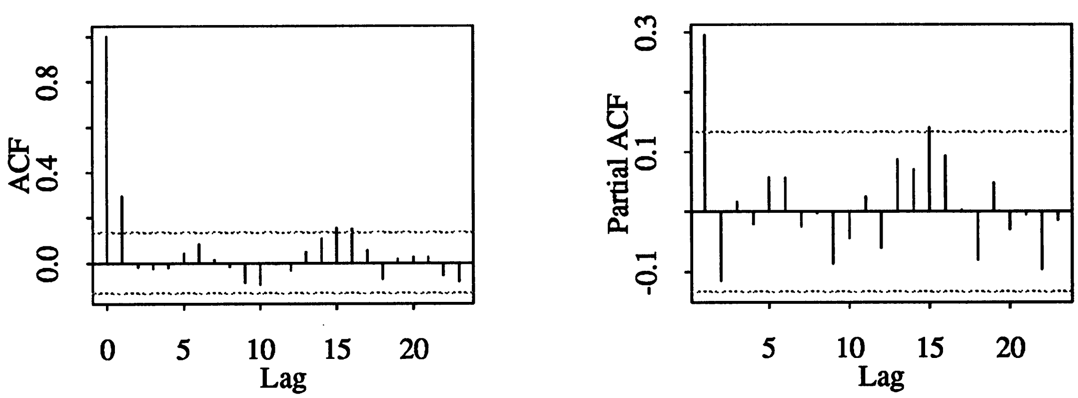

Figure 14: ACF of the residuals from log-strandings model.

here U_t depends on the previous error, ν_{t-1}.

Here, we are using these two models as models for the residuals of Model 4. That is, the ϵ_t from Model 4 take the place of the U_t above.

Using SAS PROC ARIMA, we fit an AR(1), MA(1), and an ARMA(1,1) model to the residuals. All gave significant fits, but the MA(1) fit gave the minimum Akaike Information Criteria (AIC), which is a measure of the quality of the fit of the particular model. The model with the minimum AIC is optimal in some sense. The residuals of this fit showed no significant correlation so we may conclude that fitting Model 4 with an MA(1) correlation structure is a reasonable model. Under this model, using PROC ARIMA produces the best (minimum variance) linear unbiased estimates. The standard errors associated with these parameter estimates are valid and can be used to conduct statistical hypothesis tests. The estimates and standard errors from Model 4 using PROC ARIMA are given in Table 7. As in Section 6.3, the model fit is extremely good. The R^2 from this fit was 88 *percent*. Figure 15 shows a plot of the log-strandings and the predicted values from Model 4 with MA(1) errors. The predictions are generally good over the whole study period, with the exception that they tend to fall significantly below the peaks of the very high strandings years, and in some cases we get slightly negative predictions, in the periods of zero strandings. Figure 16 shows the inability of this model to predict the periods of 0 strandings, and the very high strandings periods. This is evident from the fact that the residuals are largest at these two extremes. This is generally the case, as models predict mean behavior rather than the behavior of the extreme observations.

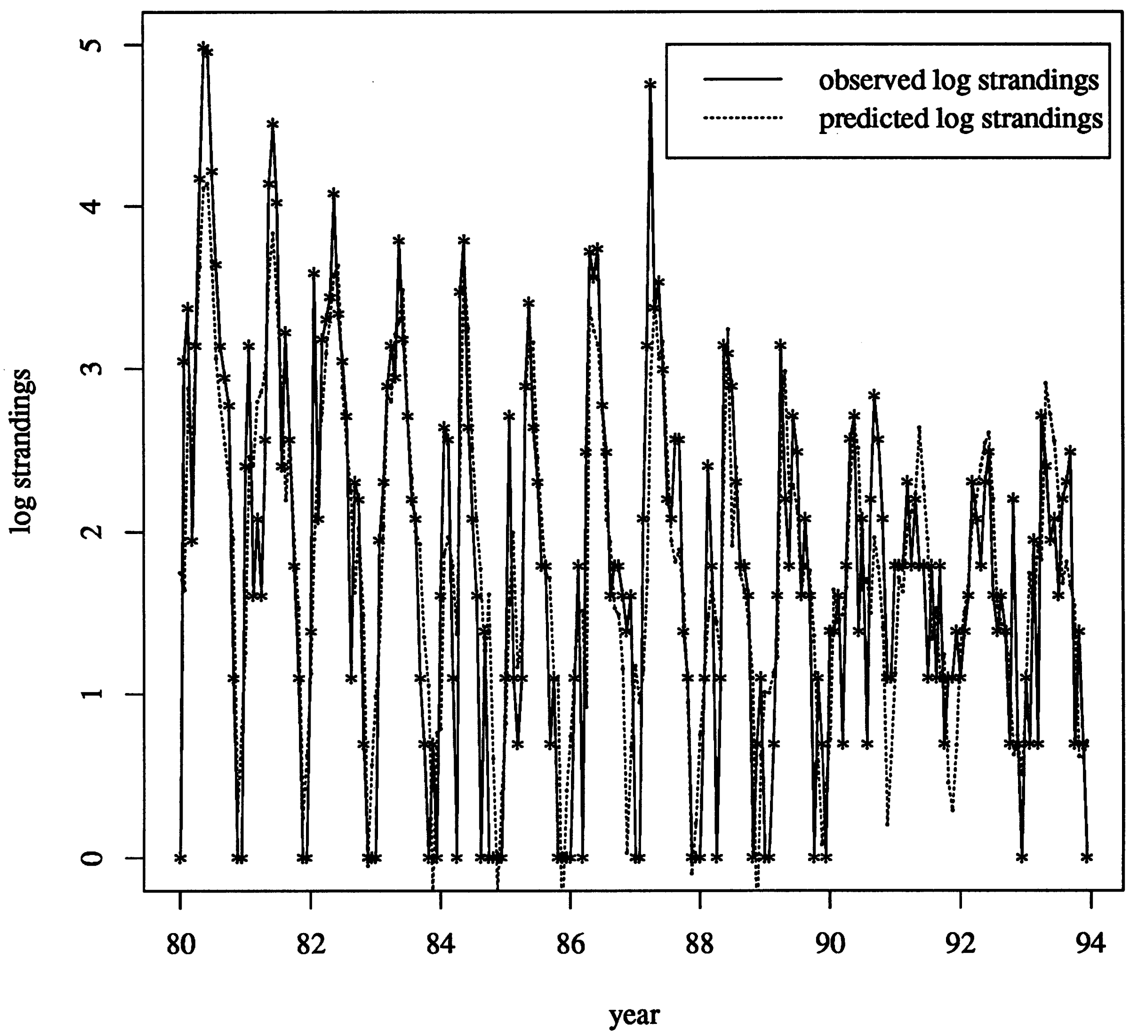

Figure 15: Predicted log-strandings and actual log-strandings.

Table 7: Estimates of MA(1) model parameters from log-transformed strandings.

Parameter	Estimate	Standard error	t-Value	P-Value
β_1	3.0071	0.20456	14.70	.0001
β_2	1.9706	0.24680	7.98	.0001
β_3	-0.5764	0.21436	-2.69	.0040
A_1	-0.6961	0.13537	-5.14	.0001
B_1	0.5586	0.11436	4.88	.0001
A_2	0.0431	0.08822	0.49	.3130
B_2	0.1599	0.09356	1.71	.0900
A_3	-0.2000	0.07955	-2.51	.0070
B_3	0.1696	0.07942	2.14	.0200
θ_1	-0.0147	0.00401	-3.66	.0001
θ_2	5.64e-5	1.81e-5	3.12	.0010
ρ	-0.3556	0.06542	-5.44	.0001

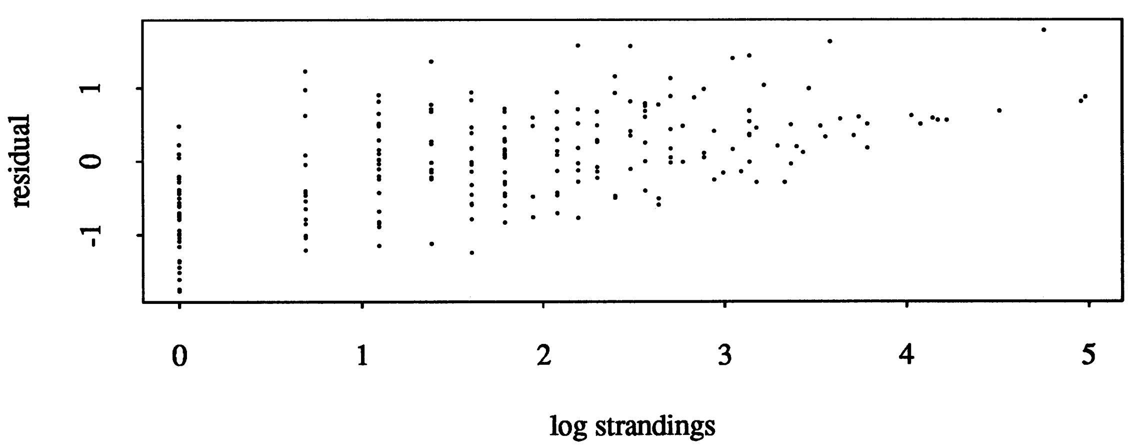

Figure 16: Residuals plotted against log strandings.

6.5 Interpretation of Parameters Using a Log Transformation

One problem with fitting a model to the log_e strandings is that the parameter estimates have no obvious interpretation. For example, on the original scale, a TED effect estimate of -10 can be interpreted as TEDs having the effect of reducing strandings by 10 turtles per period. On the log scale, this statement cannot be made. On the natural log scale, an approximation can be made that is reasonable for small relative changes on the original scale. By noting that (from the definition of the derivative)

$$\frac{\log(Y + \Delta Y) - \log(Y)}{\Delta Y} \approx \frac{1}{Y}$$

if ΔY is small. Here, $\log(Y + \Delta Y) - \log(Y)$ is that change in $\log(Y)$ measured by β for a unit increase in X in a linear model. Thus we can say that $\beta \approx \frac{\Delta Y}{Y}$. Rearranging this a bit, and if ΔY is *negative*, we get $\log(1 - \frac{\Delta Y}{Y}) = \beta$, or $\frac{\Delta Y}{Y} = 1 - e^{\beta}$. Note that $\frac{\Delta Y}{Y}$ is the *relative* change in Y. Hence if β measures changes in $\log(Y)$, $1 - e^{\beta}$ measures relative changes in Y.

From Table 7, we get an estimate of the TED effect of -0.576 on the log scale, which is to say that TED use reduces the log of the strandings by 0.576. Using the above approximation, this translates into a 44 *percent* decline in strandings as a result of TED use.

6.6 Back-transforming the Parameter Estimates

Aside from this approximate relative interpretation, we can get approximate estimates of the parameters on the original scale. Thus, they will have a more direct interpretation. Sakia (1990) discusses this approximation, which is based on a Taylor series expansion. If Y is our untransformed response variable and Y' is our log-transformed variable, and we assume the linear model $Y' = X\beta' + \epsilon'$ then we can make the approximation $\hat{Y} \approx exp(X\hat{\beta}' + \hat{\epsilon}')$. Then we can solve $\hat{Y} = X\hat{\beta}$ for $\hat{\beta}$, our parameter estimates on the original scale. By noting that the $Var(\hat{Y}) \approx Var(X\hat{\beta})$, we can get approximate variances for these estimates. These estimates and standard errors are given in Table 8. Since both the estimates and standard errors are biased (see Sakia (1990)), thus the distribution of the t-statistic is unknown, we should judge the significance of the parameters based on the estimates and standard errors on the log strandings. We can use the approximations for the purpose of interpretation. For example, the TED effect (β_3) is highly significant based on Table 6, and this parameter has the interpretation that the mean strandings in periods of TED use is approximately 16 *less* than when TEDs were not used. These estimates are biased, but the order of the bias is not large.

6.7 Adjusting the Standard Errors for Correlation and Non-constant Variance

If we work on the assumption that the residuals from the model exhibit the correlation structure of an AR(1) process we have yet another alternative to getting parameter estimates on the

Table 8: Approximate back-transformed parameter estimates and standard errors.

Parameter	Estimate	Standard Error	t-value
β_1	35.8516	4.42060	8.11
β_2	25.2905	5.89936	4.29
β_3	-15.8104	5.08928	-3.10
A_1	-9.9180	3.45583	-2.87
B_1	6.5437	2.73573	2.39
A_2	5.0505	1.97194	2.59
B_2	-1.6746	2.15266	-0.79
A_3	-2.4600	1.87768	-1.29
B_3	2.5870	1.87066	1.39
θ_1	-0.3524	0.08317	-4.24
θ_2	0.001378	0.00038	3.63

original scale. Assuming an AR(1) model for the residuals, a method discussed in Gallant (1987) allows for the estimation of parameters using the untransformed data, but provides standard errors that are corrected for *both* autocorrelation and non-constant variance. This may be worth while in our case because, as stated above, even the residuals from the log-transformed model fitting exhibit a certain degree of non-constant variance. Therefore, while we may compromise the model in that we are assuming AR error structure, we are at least acknowledging the non-constant variance which we assume to not exist in the log transformed data.

Generally, if we have the model $Y = X\beta + \epsilon$, where $Var(\epsilon) = V$ and we estimate β as $\hat{\beta} = (X'X)^{-1}X'y$ (i.e. the OLS estimate as opposed to the GLS estimate), then the variance of the OLS estimate is $(X'X)^{-1}X'VX(X'X)^{-1}$, and not $\hat{\sigma^2}(X'X)^{-1}$ as is the case under the assumption that V is the identity matrix. If we assume that V has the structure of an AR(1) model and the errors are heteroscedastic than we can estimate V. Gallant (1987) gives the details of this for nonlinear models, and this has a direct linear model analogy which we have implemented here..

Applying this method to get adjusted standard errors for the OLS estimates of Table 5 gives the standard errors shown in Table 9. Assuming the error correlation structure to be misspecified as an AR(1), these standard errors will be biased, but the order of the bias should not be large.

Table 9: Parameter estimates with standard errors computed conventionally and adjusted for non-constant variance and serial correlation.

Parameter	Estimate	Conventional		Adjusted	
		Standard error	t Value	Standard error	t Value
β_1	42.48256	4.23399	10.034	10.62588	3.998
β_2	32.13626	5.17819	6.206	12.06651	2.663
β_3	-16.22992	3.79739	-4.274	3.98981	-4.068
A_1	-10.03695	2.57701	-3.895	3.33828	-3.007
B_1	6.12757	2.04491	2.997	2.67012	2.295
A_2	5.09764	1.47037	3.467	1.65126	3.087
B_2	-1.88836	1.60676	-1.175	1.41421	-1.335
A_3	-2.41310	1.40010	-1.724	1.79221	-1.346
B_3	2.49537	1.39513	1.789	1.36702	1.825
θ_1	-0.49061	0.07851	-6.249	0.19673	-2.494
θ_2	0.00190	0.00034	5.631	0.00077	2.471
θ_3	-0.00001	0.00000	-2.871	0.00001	-1.820

7 Discussion

We have presented several methodologies for estimating a TED effect and assessing it's significance. Additionally, we have estimated other components of the strandings record that are of interest. These include the effect of shrimping, periodicity in strandings and long term trend.

7.1 Estimate of the TED Effect

A naive estimate based on the mean strandings per bi-weekly period (Section 4.4) is the simplest of these, and suggests a TED effect on the order of -13 *turtles per period* or a 65 *percent* decline in strandings as a result of TED use based on an average of 20 strandings per period when TEDs were not in use and 7 when TEDs were in use. This does not include effects due to other factors such as trend, or periodicity and so is biased in that it includes parts of these effects.

Fitting Model 3 by least squares provides an estimate of the TED effect of -16.2 (Section 6.2). That is, the effect of TED use reduces the number of strandings by 16.2 from the mean number of strandings during the shrimp season, a 38% decline based on an average of 42 strandings per period during the shrimping season. Additionally, this accounts for trend and the periodic behavior of strandings. Although this was significantly less than 0, the standard errors used to make this test are invalid due to the obvious non-constant variance. However, provided that the model specification is correct, this is an unbiased estimate. This is unlikely to be the case though, since a variance stabilizing *logarithmic* transformation of strandings produces a much better fit. This suggests a multiplicative model, rather than additive.

The fit of Model 4 (using the log transformed strandings) is extremely good, giving an R^2 of 88 *percent* (Section 6.3). However, we find that the errors are not independent, so again the standard errors are not valid. Fitting this model, but allowing the errors to exhibit dependence in the form of an MA(1) model (Section 6.4), gives valid standard errors with which to assess the significance of the parameters. The residuals from this model indicate a very slight departure from the assumption of constant variance. We can expect the effect of this to be marginal. From Section 6.4, the estimate of the TED effect from this model was -0.576 with a standard error of 0.214 giving a t-value of -2.69. The appropriate 1-tailed critical value with which to compare this with is 1.65, indicating that the TED effect is significantly negative with a P-value less than 0.005. Since this model was fit to the log-strandings, a direct interpretation of this estimate in numbers of turtles cannot be made. However we can say that TEDs reduce strandings by approximately 44 *percent* from the shrimp season mean (Section 6.5). Alternatively, we can use an approximation to back-transform the parameter estimates to the original scale (Section 6.6). Doing this gives us a TED effect estimate of -16 and a shrimp season mean strandings of 36 indicating a reduction in strandings of 44 *percent* as a result of TED use. This provides us with an estimate of the TED effect in units of turtles/period which may be useful.

Finally, by accepting some misspecification in the error correlation, structure we can use the least-squares estimates based on the untransformed strandings and adjust the standard errors for non-constant variance and *autocorrelated* errors (Section 6.7). This is as opposed to *moving-average* errors which is the structure indicated by our analysis in Section 6.4. Furthermore, as some effects may enter the model multiplicatively, there likely exists model bias which effects our parameter estimates. The TED effect is estimated to be -16.2 using ordinary least squares, and the adjusted standard error is 3.99, producing a t-value of -4.1 which again is highly significant. Again, this is a 38 % decline in strandings as a result of TED use.

The results based on the log strandings lack interpretation on the original scale and the results based on the raw strandings of Section 6.7 are most likely biased since the true model may be multiplicative in some fashion. Here also, the standard errors will be biased if we have indeed misspecified the autocorrelation structure. Due to the very good fit to the log-strandings, we recommend that inference be based on the results from the log strandings. Where necessary, interpretation should be done using either the approximate relative interpretation of Section 6.5 or the results of Section 6.6. So we believe an estimate of 44 % or -16 turtles/period is a sound estimate of the TED effect.

This estimate can be considered as being adjusted for trend, seasonality, and the shrimping season. The naive estimate (or unadjusted) is *smaller* than the adjusted estimate (-13 *vs*. -16 for the adjusted) however the percentage decline is considerably *larger* (65 % for the unadjusted vs 44 % for the adjusted).

7.2 The Estimated Trend in Strandings

The estimated form of the trend, based on the log transformed strandings estimates is shown in Figure 17. This shows the sharp decline in strandings through 1988, a relatively stable number of strandings for two years, and then a slight increase beginning in 1990. Based on this trend, we would expect strandings to reach the average level seen in 1980 again in 1997. Note too, that this trend is not nearly as extreme as is first suggested by Figure 1. This is because the 2 very high strandings that occurred in 1980 (141 and 145 in consecutive periods) create a strong visual effect on the plot of strandings over time. This effect is partially diminished by the log transformation, and the fact that the model fits the mean behavior as opposed to individual large values. The overall shape of this trend is consistent with the results of Section 4.3. That is, strandings have not continued to decrease in recent years and have even increased slightly. The horizontal line is the average of the off-season and on-season mean strandings.

As an estimate of the average decline in strandings per year over the study period we can fit Model 4 with only the linear trend term. Doing this provides an estimate of -0.00245 which is approximately a 4 % linear decline in strandings per year. This trend was highly significant. Fitting only the linear trend model to the untransformed strandings gives us a linear trend estimate of approximately -5.6 %/year.

7.3 Estimated Periodicity of Strandings

The estimated periodic components of strandings is shown in Figure 18. The spring and summer components are obvious, and the fall component is slightly obscured, however it is seen as

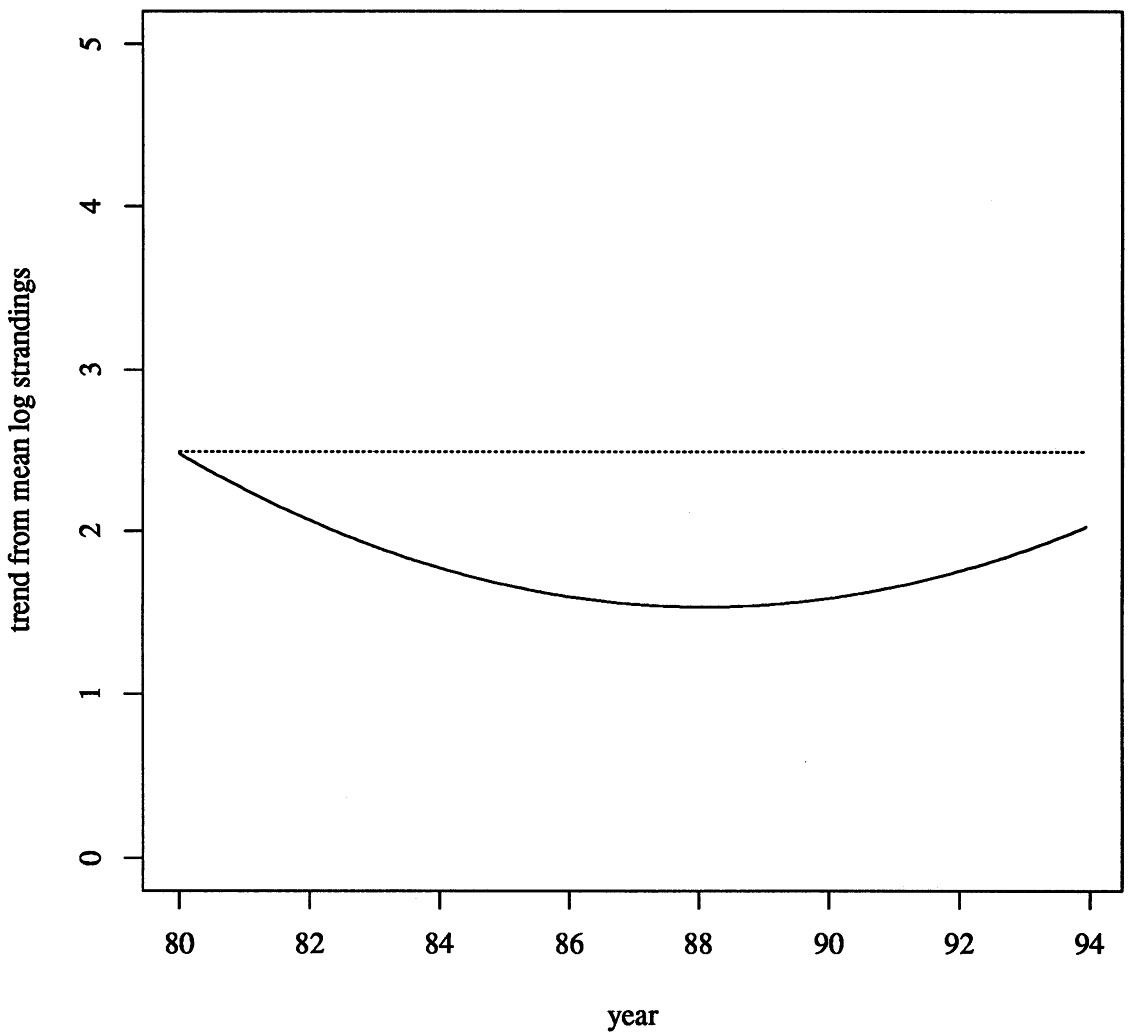

Figure 17: Estimated long-term trend in turtle abundance

a slight rise late in the summer (approximately the 12th bi-weekly period which corresponds to September). The horizontal line is the average of the off-season and on-season mean log strandings. Since this fitted curve is the sum of the three periodic components representing frequencies of 1, 2 and 3 cycles/year it may be useful to examine each of the components separately. Figure 19 shows each of these components. The annual frequency is the largest of these and is attributed to the abundance of turtles in the summer during shrimping season. The bi-annual frequency is not obvious to interpret since one peak occurs very late in the summer, and the second peak occurs at the end of the year, running over to the beginning of the year. It is worth noting that this component was not significant. The third sinusoid produces peaks where we would expect to see them. This sinusoid was highly significant based on the model fit to the log strandings. This is consistent with both the historical sturgeon gill net fishery in the spring and the southward migration of turtles in the fall.

8 Conclusions and Future Work

We proposed a linear statistical model for loggerhead turtle strandings that included terms for the effect of shrimping activity, long-term trend, and seasonal variations in turtle strandings. This model also included a parameter to represent the TED effect, in which we were primarily interested. We log transformed strandings to account for heteroscedastic error variance and used an MA(1) model to account for the observed error correlation. Several different attempts were made to provide estimates of the parameters from this model on the original scale.

Our model fit to the log strandings produced a good fit with an R^2 of 88 %. The estimate of the TED effect on the log scale is -0.58, which is approximately a 44 *percent* decline in strandings as a result of TED use, or 16 turtle strandings per period less in periods of TED use than in periods of no TED use. Several attempts to estimate the TED effect on the original scale are examined, all resulting in estimates comparable in magnitude to this. A naive estimate based on the mean strandings per period results in an estimate of -13, which is a 65 % decline. The former estimate is adjusted for a negative trend in strandings, seasonality, and the shrimping season and the later is unadjusted for these effects.

The estimate based on the log-strandings is *adjusted* for the annual periodicity in strandings, a downward trend in strandings, and also the effect of shrimp season. Attempts to fit a model to the raw strandings produces larger estimates of the TED effect than the estimate based on the log-strandings but, given that the data exhibit strong heteroscedasticity, the log transformation gives acceptable standard errors with which to assess significance. All attempts to assess significance of the TED effect using the log strandings or otherwise indicated a highly significant TED effect. Our estimate of a 44% reduction in strandings as a result of TED use is considerably different than that based only on the mean strandings per period. The later 'unadjusted' estimate was a 65% decline in strandings as a result of TED use.

The estimated trend in strandings is quadratic and indicates that strandings are on the increase. This is evident on viewing the raw strandings, and closely mimics what is believed to

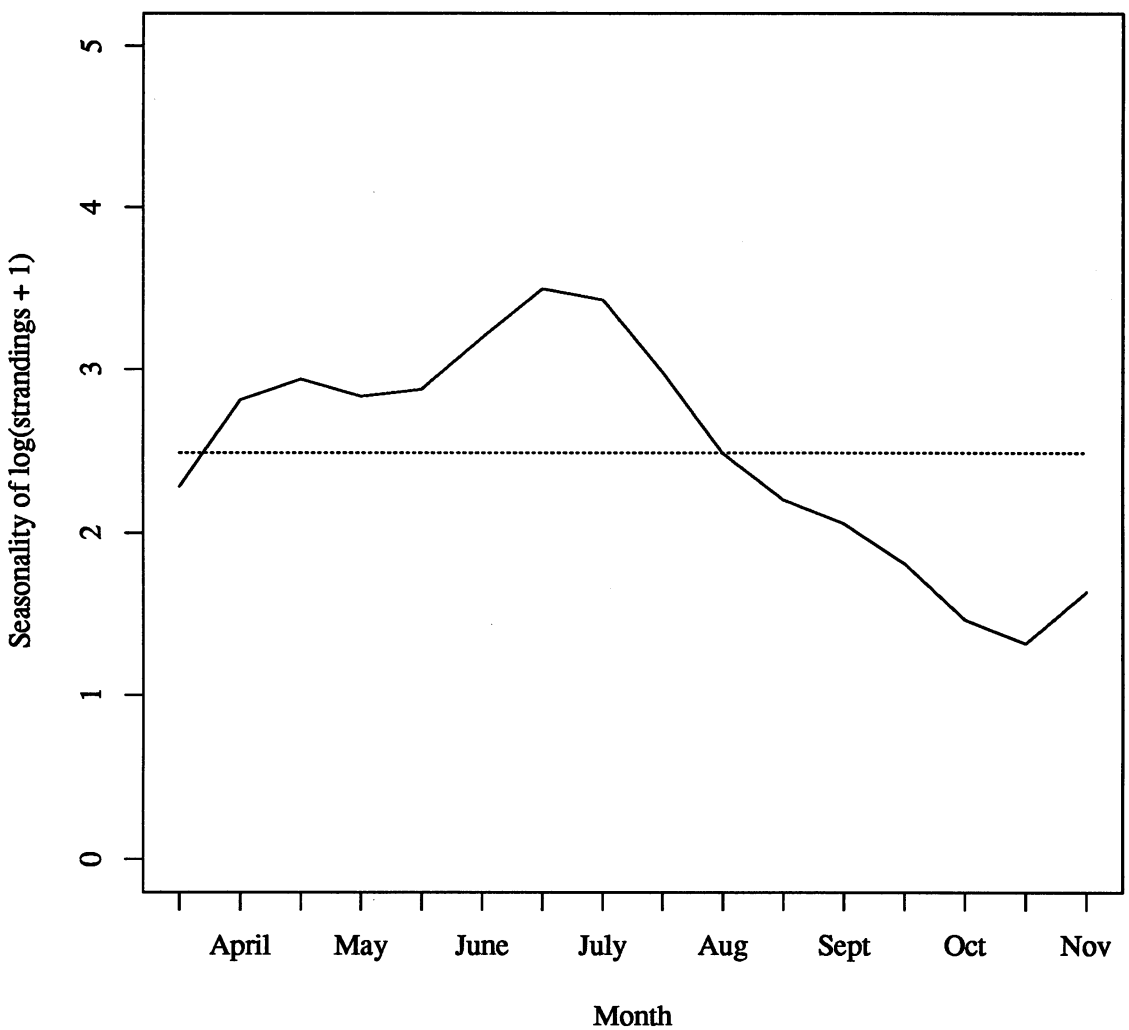

Figure 18: Estimated periodicity of turtle strandings

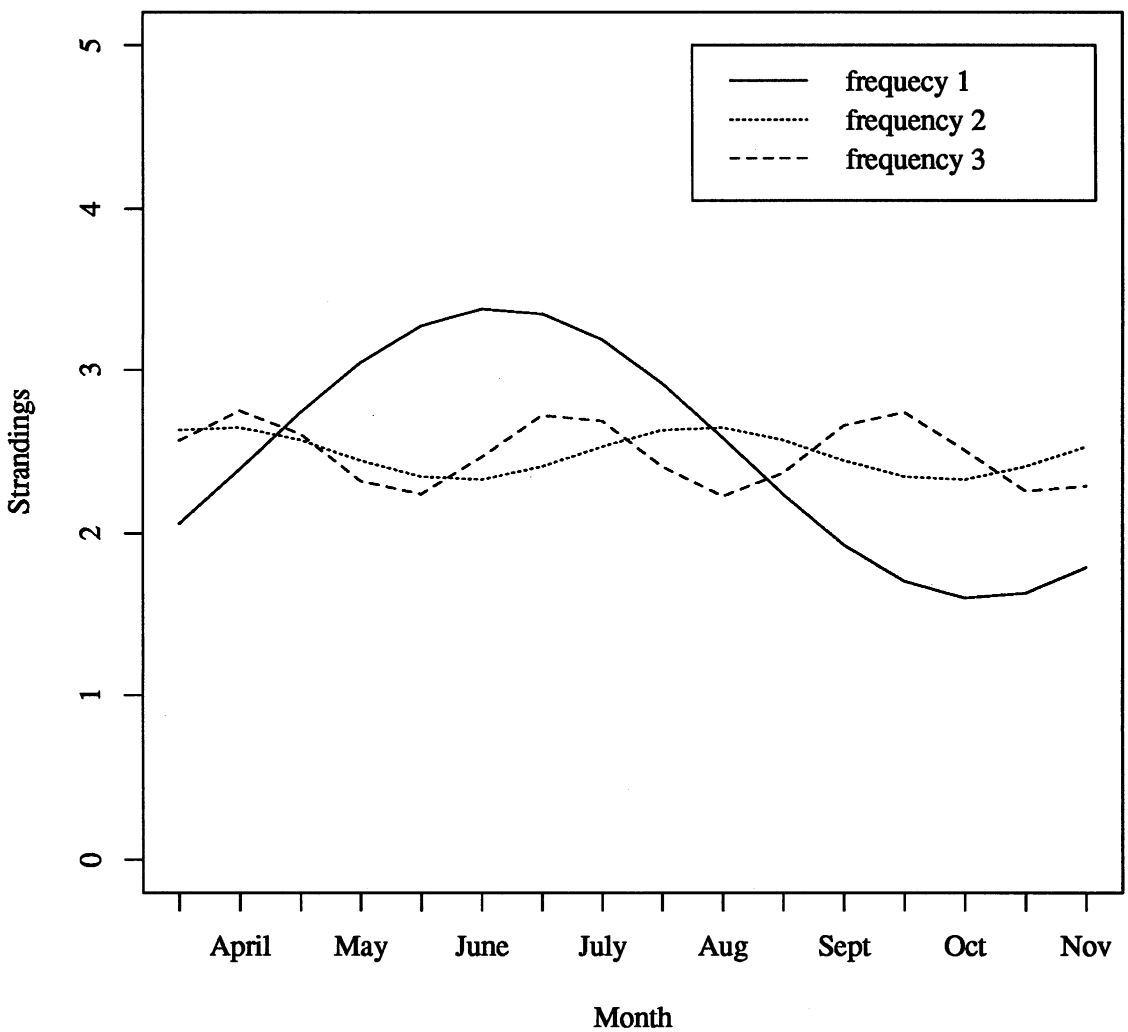

Figure 19: The individual periodic components of the strandings record.

be occurring in the population. The estimated trend based on the log strandings suggests that strandings will reach the mean level (*in logarithm*) seen in 1980 again in 1997. We attribute this to an increasing population as a result of TED use (Crowder et al. (1994)).

Sinusoids of 1, 2, and 3 cycles/year were fit. The strongest component represents that due to the increase in turtle abundance in the summer months. Early spring and late fall components due, respectively, to a sturgeon fishery during the first 7 years of the record and presumably the southward migration of turtles in the fall were also detectable in the data.

We feel that more work needs to be done concerning the relationship between the amount of shrimping effort and strandings. Although no strong relationship is obvious given shrimping season is in progress, it makes some sense to incorporate absolute effort into a model of strandings. Our major drawback at this point is the lack of data after 1990. This later data corresponds to 3 of the 4 full TED use years. Another possible area of work may involve modeling the *daily* strandings data as a non-stationary poisson process. This approach would remove several sources of error associated with combining the data into bi-weekly periods. Additionally, working with the true data as opposed to an aggregation of the data may provide more insight into the actual behavior of strandings over time. However daily strandings data are not readily available at this time.

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