

IMPROVING THE OUTLIER RESISTANCE AND ACCURACY
OF PRISM: DESCRIPTION AND SAMPLE ANALYSIS

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Abstract

It is well known that outliers (unusual or stray values) can and often do occur in actual consumption data. PRISM (PRInceton Scorekeeping Method), a statistical procedure which estimates weather-normalized energy consumption from actual consumption data, often has only twelve or fewer (monthly) data points and thus is susceptible to the influence of outliers. In this paper, enhancements of the PRISM model are developed to reduce the impact of outliers on the PRISM estimates.

The result is a robust version of PRISM, or Robust PRISM, which identifies and downweights outliers in the consumption data, and which gives results that are identical to those obtained from "ordinary" PRISM in the absence of outliers. A related feature of the method is the ability to adjust for unequal period lengths; the result is Weighted PRISM. In keeping with the objective that Robust PRISM be a direct extension of PRISM, a robust version of the R^2 statistic is developed. The formulae for Robust PRISM, whose theoretical underpinnings are developed and tested for this study, are natural extensions of the original formulae used in PRISM.

The performance of Robust PRISM is compared with PRISM by application to consumption data for several sets of houses. Electricity consumption data are used to test the method's resistance to outliers, and oil consumption data are used to examine the method's ability to adjust for unequal period lengths. Although the methodology is in a research stage of development, the results reported here illustrate the value of robustness in the PRISM model and the improvements that can ensue.

Note: To facilitate continued review of this methodology development, extremely detailed results are included in some of the tables and figures. Those tables and figures containing concise summaries of these results are indicated by asterisks in the text. For a cursory reading of the text, the reader may wish to emphasize the (asterisked) summaries.

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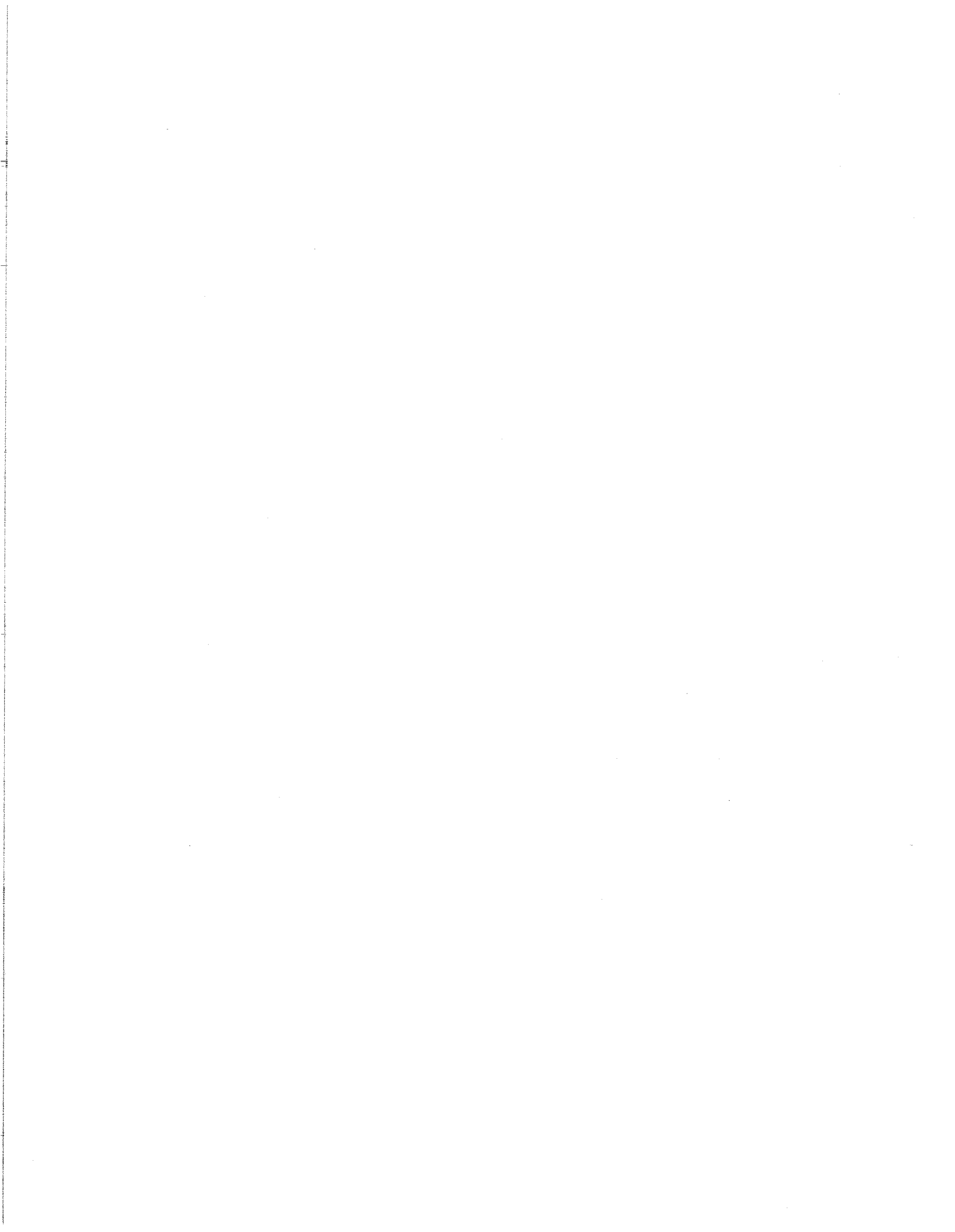
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I. INTRODUCTION

Increasing attention is being paid to the evaluation of energy savings based on actual energy consumption measurements. Actual consumption data, from gas or electricity meter readings or from fuel oil deliveries, tell the truth about how much energy has been saved, in a way that models based on simulated data cannot. While the structural component of a building's energy consumption may be accurately modeled, the effect of the occupants of the building on the energy consumption is far less quantifiable. Thus real-world data are essential for understanding how much energy has actually been saved.

PRISM, the PRInceton Scorekeeping Method, is a statistical procedure which uses actual consumption data to estimate weather-normalized energy consumption and savings. Generally applied to one year of approximately monthly data from before and after the conservation action of interest, PRISM has been found to be a productive tool for monitoring savings in all major fuel types (Fels, ed., 1986). Its main problem is its sensitivity to outliers (unusual or stray values) that often occur in actual consumption data; when there are few data points (12 or less, as is often the case in PRISM), and when the statistical procedure is based on least-squares regression (as it is in PRISM), a single outlier can have an undesirably strong influence on the results. A second problem is that of unevenly spaced meter readings which occur frequently with oil deliveries, for example. Both of these problems are inevitable artifacts of real-world data. The first problem especially will be encountered as long as people continue to live or work in the buildings being monitored.

In this paper, enhancements of PRISM are developed to reduce the impact of these problems on the PRISM estimates. Most of the work is devoted to development of a robust version of PRISM, to reduce the effect of outliers. From that, a version of PRISM to compensate for unequal period lengths

naturally follows. Before describing the new work, a brief synopsis of the original PRISM method is in order. For more detail, the reader is referred to an introductory paper on PRISM (Fels, 1986).

I.A. Synopsis of Ordinary PRISM

Three physical parameters result from PRISM applied to whole-house billing data for the heating fuel of an individual house (or building): base-level consumption α , providing a measure of the appliance (temperature-independent) usage in the house; reference temperature τ , corresponding to the average outdoor temperature above which no fuel is required for heating; and the heating slope β , giving the amount of fuel required for each incremental drop in outdoor temperature below τ . The house's index of consumption, NAC, or Normalized Annual Consumption, is obtained from these three parameters applied to a long-term annual (i.e., "typical year") average of heating degree-days.

The two data requirements for each period i included in the analysis are average daily consumption, F_i , and heating degree-days per day, $H_i(\tau)$, computed to reference temperature τ . F_i is generally computed from meter readings, and $H_i(\tau)$ from average daily temperatures from a nearby weather station (see Fels, 1986).

In ordinary PRISM (the version of PRISM currently being used by over 150 groups in the U.S. and other countries), the three parameters are found by a least-squares fit of the set of data points $\{F_i\}$ and $\{H_i\}$ to a linear model:

$$F_i = \alpha + \beta H_i(\tau) + \epsilon_i \quad (1)$$

where ϵ_i is the random error term. "Best τ " is found as the value of τ for which a plot of F_i vs. $H_i(\tau)$ is most nearly a straight line, or, formally in ordinary least-squares linear regression, for which the R^2 statistic is highest. The corresponding values of α and β are the best estimates of base level and heating slope. NAC is then determined from

$$\text{NAC} = 365\alpha + \beta H_0(\tau) \quad (2)$$

where $H_0(\tau)$ is the heating degree-days (base τ) for the typical year.

The NAC estimate provides a reliable consumption index from which energy savings may be accurately estimated. As shown in Table 1, its standard error is typically only 3-4% of the estimate. On the other hand, the individual parameters, β and τ , and also $\beta H_0(\tau)$, the heating part of NAC, are considerably less well determined, as the larger standard errors in Table 1* show. They are much more sensitive than NAC is to outliers or to the choice of which months were included in the estimation. It is the resulting instability of the individual PRISM parameters that motivates this work.

I.B. The Need for a Robust Version of PRISM

Outliers in energy consumption data arise either from corrupted data (e.g., incorrect meter readings, typing/transcription errors, etc.) or from accurate but atypical data (e.g., brief vacations, sporadic cooling, other temporary changes). Regardless of the cause, such outliers tend to have an adverse effect on the quality of the resulting PRISM estimates. Although the estimates of NAC seem to be relatively insensitive to outliers, the estimates of the individual parameters, α , β , and τ , can be strongly influenced by even a single bad point. Such an extreme sensitivity to outliers is undesirable: we would like our estimates to reflect the behavior of the bulk of the data, instead of being pulled away to accommodate a few unusual values.

One reasonable strategy for alleviating the problem is to identify the outliers (by inspecting plots of residuals, for example), and then to re-run the PRISM program with the outlier removed. This approach, however, has at least two substantial drawbacks. First, outlier identification is not as simple as one might think, particularly since PRISM tends to adjust the

An asterisk indicates a Table or Figure with summary results (e.g., Table 6, which summarizes the SAS Univariate output in Figures 2-5).

reference temperature to bring outliers as much in line as possible with the other points in the consumption vs. heating degree-day plot. Second, even if we could devise a method of deciding which points are outliers, it is not clear that we should simply throw away all of these points. It seems wasteful, for example, to discard points completely which are only slightly beyond some arbitrary cutoff value that defines them as outliers, especially since we often start with only 10 or 12 data points.

In our opinion, the problems caused by outliers, as well as the drawbacks of the expedient solution described above, warrant the development of a modified version of PRISM, which we call Robust PRISM, or RPRISM. It is specifically designed with three objectives: 1) to be robust (i.e., insensitive to outliers), without completely discarding any of the available information; 2) to give results which agree with those of PRISM itself when the data do not contain outliers; and 3) to take advantage of the years of development and application of the PRISM algorithm.

In Section II, we describe the RPRISM algorithm in fairly general terms, deferring the details to Appendix A, and we explain how RPRISM yields the useful by-product of automatic outlier identification. As we will show, RPRISM can be interpreted as automatically deciding how much weight to assign to each point, with the lowest weights going to the outliers. (Currently, PRISM computes ordinary unweighted least squares estimates.) Next, in Sections IIIA and IIIB we compare the performance of PRISM and RPRISM for two data sets. Each set consists of 50 electrically heated houses in New Jersey. The houses in the first set have no air conditioning, and the second have central air conditioning. The sporadic cooling found in many houses in heating-dominated climates has long been recognized as a nuisance to the heating-only PRISM method. The cooling points often appear as outliers in the consumption vs. heating degree-day plots, and tend to inflate the base-level estimate α . Therefore, the second data base offers RPRISM the

opportunity to remove some of the problems previously encountered with regular least-squares PRISM.

I.C. The Need for a Weighted Version of PRISM

Although not directly related to robustness, another problem with the PRISM approach is that PRISM gives equal weight (i.e., attaches equal importance) to all consumption values, regardless of the relative lengths of the corresponding periods. In the case of oil-heated homes, for which the periods between deliveries in the summer are typically much longer than those in the winter, this can lead to a lack of summer points and a correspondingly poor determination of the base level α . As we will describe in Section IV, statistical considerations suggest that it is sensible to take explicit account of the differing period lengths by weighting each point in proportion to the corresponding period length. This can be accomplished by extending PRISM to compute weighted least-squares estimates. Fortunately, the weighted least-squares (WPRISM) algorithm is easily created by making fairly minor alterations in the basic PRISM algorithm, and WPRISM is in fact one of the key elements in the fully robust version, RPRISM. Thus, the ability to handle unequal period lengths (or, in general, unequal error variances) comes as an additional benefit from the development of RPRISM.

In Section IV.A, we analyze a set of 69 oil-heated houses to examine the effectiveness of the correction for differing period lengths suggested above. Complete specifications of the new algorithms as well as pertinent mathematical derivations are given in Appendix A. These algorithms have been incorporated in a version of PRISM used for research at Princeton. The resulting software is described in Appendix B. In Appendix C, we discuss an additional possible application of the weighted PRISM (WPRISM) algorithm.

II. AN OVERVIEW OF THE RPRISM ALGORITHM

The key to robustifying PRISM lies in adapting the basic method to allow for weighted least squares, in which the estimates of α , β , and τ are chosen to minimize the sum of weighted squared residuals.

$$\sum_{i=1}^n w_i (Y_i - [\alpha + \beta X_i(\tau)])^2 \quad (3)$$

where w_1, \dots, w_n is a sequence of fixed nonnegative weights. The weighted least-squares algorithm is called weighted PRISM, or WPRISM. (In Appendix AIV, we describe the mathematical details of computing these WPRISM estimates.) Setting all weights to 1.0 and obtaining estimates to minimize Eq.(3) gives the basic PRISM method. Alternatively, if we give certain outlying points small weights while leaving the remaining weights at 1.0, then the WPRISM estimates will be less influenced by the outliers, and hence more robust, than the ordinary least-squares PRISM estimates. Further, if we allow the size of each weight to be determined by the severity of the outlier, we can progressively decrease the influence of a given outlier according to its severity. Thus, no point need be discarded (given zero weight), but progressively less attention will be paid to increasingly anomalous values.

The fully robust algorithm, RPRISM, proceeds automatically and iteratively, using WPRISM at each stage. A schematic is given in Figure 1.* The first step is to obtain the ordinary least squares (i.e., PRISM) estimates, $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$, as well as the residuals

$$r_i = y_i - [\hat{\alpha} + \hat{\beta} x_i(\hat{\tau})] \quad \text{for } i = 1, \dots, n. \quad (4)$$

Next, a set of weights $\{w_i\}$ is determined by the residuals $\{r_i\}$, through a simple formula. (See Appendix AII, step 4 for details.) The formula provides an automatic and objective way of downweighting the effect of

outliers. These weights are then used to obtain new provisional estimates $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$ by WPRISM. The RPRISM method proceeds iteratively, obtaining new provisional estimates at each stage by WPRISM, and then using the residuals from this fit to compute a new set of weights for use in the next stage. The algorithm converges after a few iterations (i.e., the provisional estimates at a given stage will be almost identical to the ones obtained at the previous stage), yielding the final robust estimates for α , β , and τ .

The final set of weights can be used for outlier detection: the outliers are the points with the smallest weights. Thus, RPRISM provides us not only with robust parameter estimates, but with an automatic outlier identification method as well.

If the final weights are all equal to 1.0, then the PRISM and RPRISM estimates will be identical. This situation, however, is relatively rare. More commonly, most of the weights are 1.0, and the remaining weights are reasonably large (e.g., ≥ 0.6). The resulting RPRISM estimates in this case typically differ only slightly from the PRISM estimates. Another possibility is that one or more of the weights is quite small (e.g., ≤ 0.4), indicating the presence of severe outliers. In this situation, the PRISM and RPRISM estimates can be quite different. More important, as will be shown, the RPRISM estimates in such cases often exhibit much more reasonable behavior than the corresponding PRISM estimates, since the latter are not resistant to the effects of outliers.

To preserve continuity with ordinary PRISM, we have developed a robust version of the R^2 statistic for use with RPRISM. In ordinary PRISM, $R^2(\tau)$ measures the percentage of data variability which can be explained by the fitted model at a given value of τ , and $R^2(\tau)$ is maximized by $\tau = \hat{\tau}$, the least-squares estimate. In RPRISM, for a given iteration of weighted least squares, the new statistic $R^2_w(\tau)$ is maximized by $\tau = \hat{\tau}_w$, the (provisional)

weighted least-squares estimate. When used with the final set of weights, R^2_w gives a robust measure of the percentage of explained variability. If the weights are all equal to 1.0, then R^2_w and R^2 will be identical, but if there are one or more strong outliers, R^2_w can be considerably larger than R^2 .

Approximate standard errors for the RPRISM estimates can be easily calculated. (See Appendix AIII for details.) The formulae used for the RPRISM standard errors can be justified from a theoretical point of view, and in addition they can be seen to be natural extensions of the formulae used in PRISM. Once again, when the final weights are all 1.0, the PRISM and RPRISM standard errors will be identical. Furthermore, where there are no severe outliers, the standard errors are reasonably similar. Finally, when there are one or more severe outliers, the RPRISM standard errors tend to be much smaller than those given by PRISM, indicating that in this case the RPRISM parameter estimates are much more reliable than the corresponding PRISM estimates.

III. SAMPLE ANALYSES OF ROBUST VS. ORDINARY PRISM

In the next two sections, we will compare the performance of PRISM and RPRISM for two sets of 50 electrically heated houses in New Jersey, one set reporting no air conditioning (Elec-H0), and the other reporting central air conditioning (Elec-AC). These sets of houses were studied previously in an adaptation of PRISM to houses with cooling (Stram and Fels, 1986). The consumption data for each of these houses consist of 12 monthly electricity bills from December 1978 to December 1979. The temperature data are from the Newark weather station (NOAA, 1970-81), and the normalized heating degree-days are based on the standard 12-year normalization period (1970-81) used in other PRISM studies done by Princeton researchers.

III.A. A Data Base of 50 Electrically Heated Homes without Air Conditioning

III.A.1 Comparison of PRISM and RPRISM

Several tables summarize the comparison of RPRISM with PRISM estimates for the Elec-H0 sample. Tables 2 and 3 give the house-by-house results for PRISM and RPRISM, respectively. Table 4^{*} gives the mean and median values of α , β , NAC, the heating part of NAC (i.e., $\beta H_0(\tau)$), R^2 , and the coefficients of variation for the parameters. Table 5 gives the percent differences for each estimate for all houses, defined as

$$\% \text{ Diff} = 100(\text{RPRISM Estimate} - \text{PRISM Estimate}) / \text{PRISM Estimate}.$$

Figures 2-5 give SAS Univariate summaries of the corresponding distributions. The mean, median, quartiles and extremes of the percent differences are given in Table 6^{*}. The quartiles are plotted in Figure 6^{*}.

The percent differences in any given parameter are typically quite small. For example, half of all the percent differences in α were between -0.3% and +0.8%. On the other hand, some notable exceptions are provided by houses J19, J23, J43, J45, and J47, which have differences in α of 171, -15, -12, -10, and 7%, respectively. Later, we will examine these houses in

* See footnote on page 3.

detail, and we will see that the discrepancies between PRISM and RPRISM can be attributed to outliers. It is significant that, for individual houses, the percent differences in NAC tend to be less than those in the other parameters. This is particularly true in houses for which one or more of the percent differences is large. This observation lends support to the finding that the PRISM NAC estimates are reasonably robust, while the PRISM estimates of the remaining parameters are definitely not robust.

In addition to analyzing differences between the PRISM and RPRISM estimates, we should also examine the differences between the standard errors provided by the two methods. A useful quantity for this purpose is the ratio of the PRISM and RPRISM coefficients of variation, which we call CVR, where $CVR = CV(\text{PRISM estimate})/CV(\text{RPRISM estimate})$. (The coefficient of variation, CV, of a parameter is defined as the ratio of the standard error of the parameter, to the parameter value itself.) If CVR is greater than 1.0 for a parameter for a given house, then we can conclude that the RPRISM estimate was better determined (i.e., more precise) than the corresponding PRISM estimate.

Table 7 gives the by-house CVRs for α , β , NAC, and the heating part of NAC. Figures 7-10 give summaries of the distributions of the CVRs. Table 8* gives the mean, median, quartiles and extremes of the CVRs for these same estimates. The corresponding quartiles are plotted in Figure 11.* Table 7 shows that, for a given house, the CVRs are fairly uniform across parameters. Comparison of Tables 7 and 5 shows that large CVRs often (but not always) correspond to large percent differences in the parameter estimates. The stemleaf diagrams of Figures 7-10 are all similar, since the rows of Table 7 are relatively constant. It therefore suffices to focus on NAC, as shown in Figure 9. The median CVR of this distribution is 1.11, while the mean CVR (1.31) is substantially larger. The discrepancy between the mean and median

is due to the skewness of the distribution: many ratios are reasonably far above 1.0, but no ratios are far below one. The interpretation is that the RPRISM NAC estimates are in many cases much better determined than the PRISM NAC estimates, and that the reverse situation has not occurred for any of the cases studied. The same phenomenon holds for the other parameters.

Next, we compare the PRISM and RPRISM results for the houses which show the largest difference between the two methods. These houses are J19, J43, J45 and J47.

House J19 provides an example of the dramatic improvement robust PRISM can offer. The results are summarized in Table 9. The PRISM estimates are rather ill-behaved: the estimate for τ is high, at 82°F, and the standard errors for α , τ , and the heating part of NAC are quite large. The RPRISM estimate for τ is down to 75.4°F, still a bit high, but with a standard error reduced from 13 to 2°F. The CVRs are relatively high (24.7, 2.6, 3.1, and 7.6 for α , β , NAC, and the heating part of NAC, respectively), indicating that the RPRISM estimates are much better determined than the corresponding PRISM estimates.

A look at outlying consumption data in the consumption and residuals plots for this house is instructive. Figures 12 and 13 give the consumption vs. heating degree-days (HDD) and residuals vs. HDD plots for PRISM, while Figures 14 and 15 give the analogous plots for RPRISM. Examination of the RPRISM plots shows that points H, E, C, and L are substantial outliers. The primary cause of the "high-TAU" difficulty in PRISM for this house is that the consumption for period H (Jul 20-Aug 19, 1979) is quite low -- lower than any other consumption point. The basic PRISM method adjusts τ to make the consumption vs. HDD plot as straight as possible. Indeed, in Figure 12 from PRISM, with $\tau = 82^\circ$ F, point H is somewhat more in line with the other points than it is in Figure 14 from RPRISM, with $\tau = 75^\circ$ F. In addition, since point

H (as the lowest consumption point) is from the hottest summer month, PRISM finds a very high τ so that H lies to the left of the other summer points. Thus, the fact that the PRISM parameters are estimated by least squares forces the intercept (α) of the best line to be unreasonably low, in order to accommodate this single point. In RPRISM, by contrast, point H is essentially ignored (Final Weight = 0.15), and the resulting τ and α are more reasonable. Note that RPRISM also pays little attention to two other outliers, points E and L (Final Weights = 0.13 and 0.14, respectively).

Comparison of the residual plots (Figures 13, 15) shows that RPRISM has succeeded in decreasing the scatter of the bulk of the residuals, while allowing a few residuals to be large. Furthermore, since the best PRISM line goes near point H, the corresponding residual for point H is fairly small. This demonstrates that examination of the residuals from a least squares fit provides no guarantee of finding all outliers. Indeed, outliers will generally not stand out as well in residual plots from least-squares fits (such as PRISM) as they will in residual plots from robust fits (such as RPRISM).

For house J43 (Figures 16-19), point C (Feb 16-Mar 18, 1979) is a very extreme outlier (Final Weight = 0.10). This forces the PRISM estimated value of τ down to 45.2°F. The RPRISM value of τ is higher, at 53.5°F. This higher value of τ allows points J, K, and D (which had few degree-days at $\tau = 45.2^\circ\text{F}$) to move to the right, making for a much better-defined line. This is the house with the highest CVR for NAC, 4.6. Note from the residual plots that point C is much further from the RPRISM line than it is from the PRISM line. This occurs since robust fitting methods do not strain to accommodate outliers at the expense of the bulk of the data. The resulting benefit for RPRISM is clear from the residual plots: the RPRISM residuals for all points except C and L are much smaller than the corresponding PRISM residuals.

For house J47 (Figures 20-23), point C (Feb 21-Mar 20, 1979) is a strong outlier (Final Weights of = 0.14); which in PRISM tends to exaggerate the heating slope, and lower R^2 (0.87 for PRISM, 0.96 for RPRISM). Indeed, the RPRISM slope is less than the PRISM slope by 5.3%. (Interestingly, the PRISM and RPRISM estimates of τ are only 1°F different.) By allowing points C and L to have large residuals, RPRISM manages to decrease the remaining residuals. The RPRISM estimates are much better determined than the PRISM estimates. The CVR of NAC, for example, is 2.8.

To assess the stability of RPRISM in the face of extreme outliers, we performed an experiment on house J44. The results are summarized in Table 10. In the original data, point D (Mar 2-Apr 20, 1979) is a moderate outlier (Final Weight = 0.38), and the only outlier; the resulting PRISM and RPRISM estimates are very similar. The experiment consisted of artificially increasing the consumption for point D from 1940 kwh to 3000 kwh. This has the effect of increasing the PRISM estimate of τ from 59.4 to 66.2°F, noticeably changing the estimated parameters, and markedly inflating the standard errors. By contrast, the RPRISM estimates and standard errors change hardly at all (for example, in the 6th decimal place of NAC). The weight for point D drops from 0.382 to 0.081, while all other weights remain at 1.0. The final comparison for J44 was with point D completely omitted. Not surprisingly, the resulting RPRISM and PRISM estimates are very close.

III.A.2. A Closer Look at the RPRISM Weights

The initial and final weights of the RPRISM runs on each house in this data set are listed in Table 11. (By "initial weights", we mean the weights computed after the first iteration of RPRISM, and thus the weights based on the residuals from PRISM least squares.) From this table, we see that the majority of all weights are 1.0. Furthermore, the initial and final weights for a given house often are not appreciably different, although there are

exceptions. (See, for example, J27, J45, J47.) For three of the houses (J7, J50, and J57), the weights were all equal to 1.0. Note that as long as the initial weights are all 1.0, the same will be true of all subsequent weights. In this case, the final results will be identical to those given by PRISM. Indeed, the PRISM and RPRISM results do match for houses J7, J50 and J57, although there are small discrepancies due to rounding errors.

As we have mentioned, the final weights can be used for outlier identification: the smaller the weight, the more severe the outlier. To make this relationship more precise, it is useful to know the frequency with which weights of various sizes are observed. The second column of Table 12^{*} gives the percentage of final weights (W) which are less than W , for various values of W . Thus, for example, 19.6% of the weights are less than 1.0, while only 1.5% are less than 0.3.

The observed final weights provide convincing evidence that least squares is not the optimal method for analyzing actual consumption data. This can be seen by comparing the observed weights with the weights that would be expected if the residuals from the robust fit had the normal ("bell-shaped curve") distribution.

We do this by using simulated data. Least-squares estimates are statistically optimal only if the error term ϵ_i in the model

$$Y_i = \alpha + \beta H_i(\tau) + \epsilon_i$$

has a Normal distribution. If, on the other hand, the error term (which we are approximating here by the residual from the robust fit) shows a higher proportion of outliers than admitted by the Normal distribution, then least squares is no longer optimal, in which case robust methods (such as RPRISM) often exhibit superior performance.

Column 3 of Table 12 summarizes the distribution of "weights" based on 200 simulated (computer generated) samples of Normal "residuals", each sample

of size 12. Comparison of columns 2 and 3 shows some significant differences. For example, only 0.25% of the simulated weights were less than 0.3, while fully 1.5% of the observed weights were this small. Thus, extreme outliers (with weights < 0.3) occurred six times as often in the observed data as we would expect under the idealized assumptions which would have guaranteed the optimality of least squares.

III.A.3. A Comparison of Robust and Ordinary R^2

An objective of RPRISM was to develop a robust analogue of the R^2 statistic used in ordinary (least-squares) PRISM. In Figure 24*, we compare the robust R^2_w given by RPRISM with the ordinary R^2 of PRISM, where w corresponds with the final set of weights used in RPRISM.

Perhaps the most striking aspect of Figure 24 is that R^2_w is greater than R^2 for all houses. The median difference is 0.52%. The points which lie farthest from the $R^2_w = R^2$ line correspond to houses J47, J43, J63 and J23, for which the differences are 9.9, 7.5, 6.4 and 3.4%, respectively. In each case, the discrepancy can be attributed to the presence of one or more small final weights (corresponding to outliers). For houses J7, J50 and J57, R^2_w and R^2 are identical, since the final weights (as observed previously) were all 1.0 for these houses. Finally, since most of the points in Figure 24 lie reasonably close to (although always above) the $R^2_w = R^2$ line, we conclude that for non-anomalous data sets the robust and ordinary R^2 statistics behave similarly.

III.B. A Data Base of 50 Electrically Heated Houses with Central Air Conditioning

The Elec-AC data base consists of 50 houses located in New Jersey, which have electric space heating and central air conditioning. Our previous studies (Stram and Fels, 1986) showed that the air conditioning usage in many of these houses is evidently weather dependent, but in many others it is sporadic. (In all houses, weather-dependent heating consumption dominates.) The sporadic cooling creates difficulties with the heating-only PRISM model, since it contributes unexplained variability to the data in the form of outliers in the cooling months¹. In particular, the sporadic cooling tends

¹ Also under study is a heating-plus-cooling (HC) version of (ordinary) PRISM in which the cooling component as well as the heating component of consumption are modeled. [More precisely, the term $\beta_c C_i(\tau_c)$ is added to the

to inflate the estimate of the base level, α . Thus, it is hoped that if RPRISM is run on these houses, the sporadic cooling months will be largely ignored, and that the weather dependence of the bulk of the non-winter months will be accurately captured. Since RPRISM is an automated method, its use in this situation is preferable to a segmented approach in which outliers are first identified and removed and then PRISM is run. In addition, using RPRISM here seems clearly preferable to an arbitrary rejection rule such as: "throw away all consumption periods ending in July and August." It must be recognized, however, that if there is a long and consistent cooling period, then the cooling months will no longer be outliers, and in such cases RPRISM and PRISM will behave similarly.

Tables 13 and 14 give a summary of the PRISM and RPRISM results, respectively. Table 15* gives the mean and median values of the parameters, R^2 , and coefficients of variation. Note that the RPRISM median value of α is 2.3% lower than the corresponding PRISM median value of α . With the exception of α , the PRISM and RPRISM average results are quite similar. Table 16 gives the percent differences for each house, and Figures 25-28 give the corresponding SAS Univariate summaries. Percent differences exceeding 10% occur for houses J2832, J2902, J2923, J3075, J3076, and J3112. The stemleaf diagram for the percent difference in α (Figure 25) shows a distribution which is clearly skewed towards low values: α from RPRISM is lower than the corresponding α from PRISM by as much as 13%, but higher by only as much as 2%. Thus, there is a clear tendency for α to decrease when RPRISM is applied, and this result is in agreement with intuition: if the sporadic cooling months are downweighted, α will go down. The skewness

model in Eq. (1)]. Although the resulting five-parameter model has been a useful research tool, there are stability problems that complicate the interpretation of the individual parameter estimates. Whether robustifying the HC model would alleviate these problems warrants consideration.

described above is also apparent in the plots of the quartiles of the percent differences, in Figure 29,* and in Table 17,* which gives the means, medians, quartiles, and extremes of the percent differences. We believe that the lower α , from RPRISM, is a more reliable estimate of base-level consumption, insofar as α is intended to represent the temperature-independent component of consumption and thus should exclude a cooling contribution.

The CVRs are listed in Table 18, and the corresponding SAS Univariate results are given in Figures 30-33. Table 19* gives the mean, median, quartiles and extremes of the CVRs. The quartiles of the CVRs are plotted in Figure 34.* The average CVRs are all greater than one, but are not as large as they were for the Elec-HO houses.

A scatterplot of robust versus ordinary R^2 shown in Figure 35* illustrates that robust R^2 i.e., R^2_w (median = 0.982) is systematically higher than ordinary R^2 (median = 0.975). Similar to the Elec-HO sample, R^2_w is systematically higher than R^2 for all houses.

To see whether the changes that RPRISM does produce can be linked to sporadic cooling, we now examine in detail three interesting cases. These are houses J2832, J3075 and J3076.

For house J2832, the consumption vs. period plot (Figure 36) indicates relatively strong cooling in period H (Jul 26-Aug 23, 1979). This is borne out in the PRISM consumption vs. HDD and residuals vs. HDD plots (Figures 37, 38). The corresponding RPRISM plots (Figures 39, 40) show that point H is indeed a strong outlier (Final Weight = .023). Other outliers are D, C and I, with Final Weights of 0.28, 0.42 and 0.67, respectively. Note that RPRISM achieves a very good linear relationship among the non-outlying points. The α estimate goes from 74.1 to 64.5 (down by 13%), and R^2 goes from 0.83 to 0.93.

For house J3075, the consumption vs. period plot (Figure 41) shows no indication of summer cooling. The PRISM and RPRISM consumption vs. HDD plots (Figures 42, 43) show that the discrepancies can be attributed to the outliers B and C (Final Weights = 0.54, and 0.61 respectively). The fact that α increases a small amount, from 41.3 to 42.9 (by 4%), should not worry us, since there was no evidence of cooling for this house.

For house J3076, the consumption vs. period plot (Figure 44) suggests an overwhelming cooling load in the single period I (Aug 2-Aug 30, 1979). The PRISM consumption vs. HDD and residuals vs. HDD plots (Figures 45, 46) show that point I is indeed a gross outlier. The corresponding RPRISM plots (Figures 47, 48) show that the downweighting of point I (Final Weight = 0.16) allows for a more reasonable intercept, and for smaller residuals in the non-outlying points. The α estimate decreases from 98.9 to 86.6 (by 12%), and R^2 increases from 0.82 to 0.95.

It is clear from these three houses that, in comparison with heating, the contribution to consumption from cooling in a climate such as New Jersey's can be weak and erratic. One motivation for this study was to explore whether a robust version of the heating-only PRISM model could reduce the interference of cooling on the heating estimates. The results for the Elec-AC sample, on average for the 50 houses and individually for these three cases, suggest a high degree of success. More work is needed to compare the RPRISM estimates with those resulting from our experimental heating-plus-cooling model. Ultimately a comparison with submetered heating and cooling consumption in houses heated and cooled by electricity would be desirable.

IV. THE MERITS OF WEIGHTED PRISM WHEN THE PERIOD LENGTHS DIFFER

The basic PRISM model assumes that all data values have the same variance, and hence are equally reliable. This is a reasonable assumption if the period lengths are all nearly identical. If the period lengths are radically different, however, then the most sensible assumption is that the variance of a given data point is inversely proportional to the length of the corresponding period. Thus, if the period lengths differ radically, as can be the case with oil-heated homes, the constant-variance assumption is inappropriate. In addition, even if we put aside robustness considerations, ordinary least-squares regression is no longer the optimal method of estimating the parameters. If we use PRISM in this case, the estimates will not be as well determined as they could be. Further, the PRISM standard errors will be incorrect since the theory used in PRISM relies on the equal variance assumption. It can be shown (see Appendix AV) that the optimal estimation technique here is weighted least squares with weights proportional to the period lengths. Thus, if we use weighted PRISM with these weights, then we can get better estimates and correct standard errors.

IV.A. A Data Base of 69 Oil-Heated houses: Ordinary vs. Weighted PRISM

We now present a comparison of ordinary and weighted PRISM (PRISM and OUTWTS, respectively) on a data base (OIL) of 69 oil-heated houses in New Jersey. Thirty-nine of these houses have an oil-fired hot water heater, and therefore have a theoretically positive oil base level. These houses are designated as "HW", vs. "H" for the remaining houses that use oil for heating only. (The application of regular PRISM to this data base was studied previously, in Fels et al., 1986.)

We use the name WPRISM to refer generally to weighted PRISM, and the name OUTWTS to refer specifically to WPRISM with weights proportional to the period lengths. This terminology stresses that here WPRISM is being run on

fixed outside weights that do not depend directly on consumption. Note that RPRISM, by contrast, consists of WPRISM run iteratively on robust or inside weights computed from the residuals. (See the schematics for OUTWTS and RPRISM, Figures 49* and 1,* respectively.) In the present study, we are concentrating on the effects of the outside weighting, and therefore do not use the robust option. In principle, outside weighting (OUTWTS) and robust PRISM (RPRISM) can be used simultaneously; one such case is presented later in this section.

Tables 20 and 21 give complete summaries of the PRISM and OUTWTS results, respectively. The water-heater indicator (HW,H) is included. Of the 39 houses with HW, negative α occurs consistently between PRISM and OUTWTS, i.e., the set of eight HW houses for which PRISM gave negative α is identical to the set for which OUTWTS gave negative α . (The HW indicator is a homeowner response and is not always an accurate indicator of the type of water heater. As indicated previously, several of these cases were miscoded.)

Table 22* gives the mean and median values of R^2 , the parameters, and their coefficients of variation (CV). For $CV(\alpha)$, the HW houses with positive α and finite $se(\alpha)$ (i.e., finite $se(\tau)^1$) are treated separately: there were 31 such houses for PRISM, 30 for OUTWTS. In our earlier study of the same data base, the PRISM parameters were generally less well determined for oil-heated houses than for electrically or gas-heated houses (Fels et al., 1986). A comparison of the CVs in Table 22 with those in either Table 4

¹When $se(\tau)$ is infinite, as it will be if "best TAU" is determined to be the maximum observed temperature in the time period used for estimation, then the corresponding $se(\alpha)$ is assumed to be infinite as well. In this data set, there were 3 such cases with OUTWTS and 5 such cases with PRISM where this occurred. All in all, there were 8 cases with large or infinite $se(\tau)$ (i.e., $se(\tau) > 20$), and they were the same set of 8 with both PRISM and OUTWTS.

or 15 is consistent with our earlier observations. Clearly, part of the discrepancy between oil and the other results is due to noneven period lengths in the oil data: weighted PRISM reduces the CV of NAC for the oil data base from a median of 6.8% to a median of 4.1%, thus bringing it more in line with the 3.0% CV typically seen for gas- and electrically heated houses.

Table 23 gives the by-house percent differences for the estimates, and the corresponding SAS Univariate outputs are given in Figures 50-53. The mean, median, quartiles and extremes are given in Table 24*. The quartiles of the percent differences are plotted in Figure 54*. Some of the percent differences in α are quite large because α , especially for houses without oil water heating, may be very close to zero. Still, the percent differences in the other parameters as well seem much greater than they were for the earlier comparisons of PRISM and RPRISM.

The CVRs are given in Table 25, with the corresponding SAS univariate output in Figures 55-58. The Univariate summaries for $CVR(\alpha)$ and $CVR(\text{heating part})$ are based on the 64 homes with finite $se(\tau)$. Table 26* gives the means, medians, quartiles and extremes of the CVRs. The quartiles of the CVRs are plotted in Figure 59*. For $CVR(\alpha)$, only the 30 HW houses with positive α and finite $se(\alpha)$ for both PRISM and OUTWTS are included. Again, some of the CVRs are very large, and the ranges are much larger than they were in the comparison of PRISM and RPRISM for electrically heated houses. The median value for $CVR(\alpha)$ was 1.46, and the mean was 3.76, vs. a median of 1.08 for both electricity data sets. Thus, α was substantially better determined by the OUTWTS method. A plausible explanation for this result is that many of the long periods fall in the summer (in which case there might be only one "summer" data point). Hence if these points are given large weights, as they are by the OUTWTS option, then the base level will be better determined. In addition, NAC is considerably improved by the weighting: the

median CVR(NAC) from OUTWTS vs. PRISM applied to oil-heated houses is 1.61, vs. the comparable medians of 1.11 and 1.08 from RPRISM vs. PRISM applied to electricity data sets Elec-HO and Elec-AC.

A scatterplot of R^2 (Figure 60)* shows that the R^2 values are consistently higher for OUTWTS than for PRISM. The median value was 0.982 for OUTWTS, up from 0.971 for PRISM. The large average values of CVR(α) and CVR(NAC), together with the increase in R^2 , indicate that the weighting procedure tried here is indeed reasonable.

Two houses which showed great differences between the PRISM and OUTWTS results were P76263 and P57490. We now examine these houses in detail.

For P76263, an HW house, the consumption versus period plot (Figure 61) shows a very erratic pattern, with consumption varying wildly from one period to the next. The PRISM consumption vs. HDD plot (Figure 62) shows a poor linear fit, with a particularly strong outlier at point B (Nov 12-Nov 12, 1979 and an unreasonably low value of $\tau=37.0^\circ\text{F}$. Interestingly, the period length corresponding to point B is just one day -- perhaps a data error, but an interesting test case for our purposes. (The second shortest period was F (Jan 11-Jan 24, 1980), with 14 days.) The OUTWTS consumption vs. HDD plot (Figure 63) shows a line which better fits the lower cluster of points (A,C,F,G,H,I). The change in τ was substantial, from 37.0 to 75.0°F , while R^2 increased from 0.20 to 0.65. The α estimate is cut in half, from 8.98 to 4.43 gal/day. Unfortunately, the standard error of α goes from 0.97 to indeterminate [$\text{se}(\tau) = \infty$, but this seems an acceptable price to pay for the improved model fit.

For house P57490, another HW house, the consumption vs. period plot is given in Figure 64. The summer points B (Apr 10-Aug 12, 1979) and J (Apr 23-Aug 27, 1980) have the longest periods. The PRISM consumption vs. HDD plot (Figure 65) shows a fairly good fit, with $R^2 = .965$. The corresponding

OUTWTS plot (Figure 66) is similar, except for a shift in the horizontal axis due to the change in τ from 76.5 to 72.0°F. The added weight placed on points B and J pulls the line closer to these points, and thereby brings α up from 0.02 to 0.45. The standard error of α decreases from 1.54 to 0.57, and R^2 increases from 0.965 to 0.973. Note that point I is a moderate outlier which is not downweighted by the OUTWTS method since it does not correspond to an unusually short period. Running the program with both the ROBUST and OUTWTS options changes α to 0.35, and increases R^2 to 0.988.

On the basis of the study described in this section, we can conclude that OUTWTS improves the model fit, as well as the determination of the parameters, for oil-heated houses having unequal period lengths. In particular, the determination of α (and therefore of NAC) is often improved due to the increased weights given to summer points. This phenomenon was illustrated in our study of house P57490. In addition, OUTWTS can improve the model fit by downweighting points with unusually short period lengths, as shown in our study of house P76263.

V. CONCLUSION

We have developed a robust version of PRISM as well as an automatic adjustment for unequal period lengths, and we have studied the performance of these new methods on over 150 houses. The new methods retain all of the features of ordinary PRISM (e.g., variable reference temperature, standard errors for the parameter estimates, R^2 statistic to summarize adequacy of model fit). The execution of the new computer algorithm is identical to that of PRISM, with the requirement of additional input commands.

By automatically finding and downweighting outliers, robust PRISM (RPRISM) can often improve the model fit as well as the determination of the parameters. Outliers can occur even in houses with no apparent problems, can

be difficult and time-consuming to detect by hand, and can severely deteriorate the corresponding PRISM results. Hence, the development of an objective and automatic method to deal with these problems is worthwhile. When there are no outliers, RPRISM and PRISM will give identical results.

For a set of 50 electrically heated houses without air conditioning, the median CV of NAC was 2.4% for RPRISM, versus 3.0% for PRISM. The RPRISM values of R^2 were systematically higher than those for PRISM: the median R^2 value was 0.981 for RPRISM, vs. 0.972 for PRISM. PRISM and RPRISM often give reasonably similar results, thereby reinforcing our confidence in PRISM as a useful tool. A study of individual problem houses, however, shows that RPRISM can make noticeable improvements.

For a set of 50 electrically heated houses with central air conditioning the overall gains of RPRISM were not as strong. The median CV of NAC was 2.7% for RPRISM, versus 3.0% for PRISM. Still, RPRISM was able to make strong improvements in some houses exhibiting sporadic cooling and other isolated outlier problems. In houses with sporadic cooling, PRISM generally overestimates the base level α . RPRISM, by automatically downweighting the outlying summer points, typically decreased (and thus improved) α . The median R^2 value was 0.982 for RPRISM, vs. 0.975 for PRISM; robustness systematically improved R^2 for this data set as well.

The adjustment for unequal period lengths (OUTWTS) can be justified on theoretical grounds, and provides a straightforward application of weighted PRISM. In a study of 69 oil-heated homes (many of which had periods of radically different lengths), OUTWTS was able to improve the model fit and accuracy (often dramatically so), by giving increased weight to the summer points and decreased weight to points with unusually short period lengths. The increased weighting of summer points improved the determination of α and hence of NAC. The median CV of NAC was 4.1% for OUTWTS, vs. 6.8% for PRISM.

R^2 was systematically improved by OUTWTS. The median R^2 value was 0.982 for OUTWTS, vs. 0.971 for PRISM.

The sample applications illustrate the improvements in reliability of PRISM estimates that can occur from a more robust treatment (internal weighting) of outliers in consumption data, and also from external weighting of different consumption period lengths. The improvements can be dramatic, particularly in cases with one or more extreme outliers (or extremely uneven period lengths). Yet, in the three samples presented here, and in samples we have analyzed elsewhere, such cases are the exception rather than the rule.

An important question for evaluators of conservation programs is whether ordinary PRISM is adequate for the determination of average savings. We believe that it generally is, particularly if robust statistics (e.g., median rather than mean values) are used to calculate the averages; improvement of a few anomalous cases in a sample of hundreds should not greatly affect the median. There are many examples of evaluations in which PRISM has produced highly reliable, and statistically significant, estimates of average savings (see, for example, Dutt et al., 1986). If, on the other hand, the concern is for as much reliability as possible for each individual house being analyzed, use of robust PRISM may substantially increase the quality of the study.

One such study, recently conducted by Princeton, was a pilot test of a Home Energy Report in which consumers were offered weather-adjusted estimates of their own consumption over the last two years (Layne et al., 1988). It was important to offer the estimates only if they were reliable, and to maximize the number of participants that received the estimates. For this reason, robust PRISM was used throughout the study. Although most of the participants (53 out of 64) would have received reliable weather adjustments with either PRISM or RPRISM, use of RPRISM made it possible to increase the number of participants receiving reliable information (from 53 to 60;

Reynolds and Fels, 1988). Figures 67* and 68* respectively show a plot of CV(NAC) and NAC for Robust vs. Ordinary PRISM. Whereas on average CV(NAC) improves only a little (for example, median CV(NAC) decreases from 0.033 with PRISM to 0.029 with RPRISM for the first year of data), a dramatic improvement in CV(NAC) for a few individual cases is evident. Nevertheless, NAC is not greatly changed by the robust version, on average or even at the level of individual cases. This is consistent with the findings of the Elec-HO and Elec-AC samples studied here (Figures 4 and 27). Robust PRISM seems to have a greater effect on the accuracy of the estimates than on the estimates -- a feature that could be particularly useful when individual-house or individual-building accuracy is of paramount importance.

The PRISM software currently being distributed (version 4.0, dated October 1986) contains regular PRISM, with a cooling-only as well as a heating-only option. Since the vast majority of applications seek a high level of reliability in average savings, this version seems to be meeting the needs of the more than 150 members of the PRISM Users Network. We hope at some time in the near future to be able to add robust and weighted PRISM, as options to the software package.

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AI: Description of RPRISM

The key to robustifying PRISM lies in modifying the original least squares method to allow for *weighted least squares*. Thus, if the heating degree days per day at base τ and the consumption are

$$(x_i(\tau), y_i)$$

for period $i, i = 1, \dots, n$, then we want to find $\hat{\alpha}, \hat{\beta}$, and $\hat{\tau}$ to minimize

$$\sum_{i=1}^n w_i (y_i - \hat{y}_i)^2, \quad (1)$$

where

$$\hat{y}_i = \hat{\alpha} + \hat{\beta} x_i(\tau),$$

and the w_i are a sequence of fixed nonnegative weights. Obviously, by setting all the weights to 1, we get regular PRISM. But if we arrange things so that "outliers" get small weights while the rest of the points get weights of 1, then the estimates from the weighted least squares version of PRISM will be insensitive to the outliers, and hence will be more robust than the estimates obtained from regular PRISM. To obtain the solution $\hat{\alpha}, \hat{\beta}, \hat{\tau}$ to the weighted least squares problem (1), we need to change the basic Newton's Method algorithm used by PRISM. We will give details of these modifications in Section AIV, but first we describe the complete RPRISM algorithm, of which weighted least squares is just a part.

RPRISM is an adaptation of the Huber M-Estimate, using iteratively reweighted least squares (IRLS) as the numerical method to obtain the estimate. In M-Estimation, the idea is to find estimates to minimize

$$\sum_{i=1}^n \rho \left(\frac{y_i - \hat{y}_i}{\hat{\sigma}} \right) \quad (2)$$

where ρ is a fixed function, and $\hat{\sigma}$ is a robust estimate of scale. If we put $\rho(r) = r^2$, we get least squares. If we put $\rho(r) = |r|$, we get least absolute deviations (the analog of the one-dimensional median). Huber proposes a compromise between these:

$$\rho(r) = \begin{cases} r^2/2 & |r| \leq H \\ H|r| - H^2/2 & |r| > H \end{cases} \quad H = 1.345.$$

The resulting estimates can be shown to be robust (even "optimally" robust, under certain assumptions). Unfortunately, the solutions to (2) cannot, in general, be written in closed form, so we must resort to iterative numerical techniques. We have chosen to use IRLS (which will be described presently) as that

numerical technique. It can be shown that the solution to IRLS converges to the solution to (2) as the number of iterations becomes large.

AII: Specification of the IRLS Algorithm For Computing RPRISM Estimates

The IRLS algorithm proceeds iteratively, and involves solving a weighted least squares problem (1) at each stage. The weights are determined by the residuals from the previous fit, through a simple formula.

We will describe IRLS in the context of PRISM:

- 1) Start with an ordinary least squares fit. Thus, find the solutions $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$ to (1) with $w_i = 1$, $i = 1, \dots, n$.
- 2) Using the current estimate $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$, compute the residuals $r_i = y_i - \hat{y}_i = y_i - (\hat{\alpha} + \hat{\beta}x_i(\tau))$.
- 3) To obtain a robust estimate of scale, compute the median absolute deviation (from the median) of the residuals:

$$MAD = \underset{i}{\text{med}} |r_i - \underset{j}{\text{med}}\{r_j\}| .$$

The final scale estimate is then

$$\hat{\sigma} = 1.48 MAD .$$

- 4) Obtain new weights from the residuals $\{r_i\}$ and the scale estimate $\hat{\sigma}$ by the formula

$$w_i = \begin{cases} 1 & |r'_i| \leq H \\ H/|r'_i| & |r'_i| > H \end{cases} ,$$

where $\{r'_i\}$ are the standardized residuals:

$$r'_i = \frac{r_i}{\hat{\sigma}} .$$

- 5) Get new estimates $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$ by weighted least squares (1) (see Section AIV), using the weights w_i from step 4).
- 6) If the current estimates are "sufficiently close" to the previous estimates, stop. Otherwise, go to step 2).

Of course, we use the estimates obtained in the final iteration. The weights that were used to obtain

these estimates (i.e., the "final weights") are useful for outlier detection: the "outliers" are the points with the small weights. The smaller the weight, the more extreme the outlier.

AIII: Standard Errors for the RPRISM Estimates

Given the robust estimates of α, β, τ, NAC and the heating part of NAC, we can obtain approximate standard errors for these estimates as follows:

1): The variance covariance matrix for

$$\begin{bmatrix} \hat{\alpha} \\ \hat{\beta} \\ \hat{\tau} \end{bmatrix}$$

is

$$\begin{bmatrix} \text{Var } \hat{\alpha} & \text{Cov}(\hat{\alpha}, \hat{\beta}) & \text{Cov}(\hat{\alpha}, \hat{\tau}) \\ \text{Cov}(\hat{\alpha}, \hat{\beta}) & \text{Var } \hat{\beta} & \text{Cov}(\hat{\beta}, \hat{\tau}) \\ \text{Cov}(\hat{\alpha}, \hat{\tau}) & \text{Cov}(\hat{\beta}, \hat{\tau}) & \text{Var } \hat{\tau} \end{bmatrix},$$

and it is estimated by

$$M = \frac{n}{n-3} \hat{\sigma}^2 (\hat{\eta}^T \hat{\eta})^{-1} \frac{\frac{1}{n} \sum \Psi^2(r'_i)}{\left[\frac{1}{n} \sum \Psi'(r'_i) \right]^2}.$$

The various quantities in this equation are defined below.

A) $\hat{\sigma}$ is the current robust scale estimate obtained from the IRLS routine.

B)

$$\hat{\eta} = \begin{bmatrix} 1 & x_1(\hat{\tau}) & \hat{\beta} F_1(\hat{\tau}) \\ 1 & x_2(\hat{\tau}) & \hat{\beta} F_2(\hat{\tau}) \\ \vdots & \vdots & \vdots \\ 1 & x_n(\hat{\tau}) & \hat{\beta} F_n(\hat{\tau}) \end{bmatrix}$$

where

$$F_i(\hat{\tau}) = \frac{d}{d\tau} x_i(\tau) \Big|_{\tau=\hat{\tau}}.$$

Note that η is the same matrix as defined on Page 74 of Goldberg (1982), Equation (4.13).

C)

$$r'_i = \frac{r_i}{\hat{\sigma}} \quad \text{where } r_i = y_i - (\hat{\alpha} + \hat{\beta}x_i(\hat{\tau})) .$$

D)

$$\Psi^2(r) = \begin{cases} r^2 & |r| \leq H \\ H^2 & |r| > H \end{cases} ,$$

$$\Psi'(r) = \begin{cases} 1 & |r| \leq H \\ 0 & |r| > H \end{cases} .$$

2): The standard errors of $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$ are

$$SE \hat{\alpha} = \sqrt{M(1,1)} , \quad SE \hat{\beta} = \sqrt{M(2,2)} , \quad SE \hat{\tau} = \sqrt{M(3,3)} .$$

3) The standard error of $NAC = 365.25(\hat{\alpha} + \hat{\beta}H_o(\hat{\tau}))$ is:

$$SE \hat{\Gamma} = 365.25(Var \hat{\alpha} + (H_o(\hat{\tau}))^2 Var \hat{\beta} + (\hat{\beta}F_o(\hat{\tau}))^2 Var \hat{\tau} \\ + 2H_o(\hat{\tau}) Cov(\hat{\alpha}, \hat{\beta}) + 2H_o(\hat{\tau}) \hat{\beta}F_o(\hat{\tau}) Cov(\hat{\beta}, \hat{\tau}) \\ + 2\hat{\beta}F_o(\hat{\tau}) Cov(\hat{\alpha}, \hat{\tau}))^{1/2} ,$$

where the covariances are found as the appropriate entries of the matrix M found in step 1. Note that $H_o(\hat{\tau})$ is the normalized heating degree days *per day* at base $\hat{\tau}$.

4) The standard errors for the heating part of $NAC (= 365.25 \hat{\beta}H_o(\hat{\tau}))$ is given by

$$SE \text{ Heating} = 365.25((H_o(\hat{\tau}))^2 Var \hat{\beta} + (\hat{\beta}F_o(\hat{\tau}))^2 Var \hat{\tau} \\ + 2\hat{\beta}F_o(\hat{\tau})H_o(\hat{\tau}) Cov(\hat{\beta}, \hat{\tau}))^{1/2} .$$

AIV: Implementation of WPRISM: Hilbert Space Approach

The WPRISM (weighted PRISM) problem is: find $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$ to minimize

$$\sum_{i=1}^n w_i (y_i - (\alpha + \beta H_i(\tau)))^2 ,$$

where the w_i are fixed weights, $0 < w_i \leq 1$, $i = 1, \dots, n$. The solutions to WPRISM are useful for at least two purposes: first, as a building block in the fully robust RPRISM algorithm; second, as a stand-alone method in situations where the period lengths are radically different.

Here, we will show that the solutions to WPRISM can be obtained from the ordinary PRISM algorithm if certain sums are changed to weighted sums. Our development hinges on a simple observation about vector space norms and inner products, which we haven't seen exploited elsewhere. Besides giving a simple solution to WPRISM, our idea leads to a new and previously unexplored generalization of the R^2 statistic having interesting geometrical and robustness properties.

Before presenting our idea, we will give some elementary background on norms and inner products of vectors, and on linear regression. If x and y are n -dimensional vectors $x = (x_1, \dots, x_n)^T$, $y = (y_1, \dots, y_n)^T$, then

$$(x, y) = \sum_{i=1}^n x_i y_i$$

is called the Euclidean inner product of x and y , and

$$\|x\| = \sqrt{\sum x_i^2} = \sqrt{(x, x)}$$

is called the Euclidean norm of x . If $(x, y) = 0$, then x and y are said to be *orthogonal*. If, in addition, $\|x\| = \|y\| = 1$, then x and y are said to be *orthonormal*.

The simple linear regression model can be written as

$$y_i = \alpha + \beta x_i + \epsilon_i \quad i = 1, \dots, n,$$

or

$$y = \alpha 1 + \beta x + \epsilon,$$

where $1 = (1, \dots, 1)^T$ and $x = (x_1, \dots, x_n)^T$. The least squares estimates $\hat{\alpha}$, $\hat{\beta}$ minimize $\|y - \hat{y}\|^2$, where $\hat{y} = \alpha 1 + \beta x$, as a function of α , β . As shown in Theorem 1 (which relies on vector space concepts), the solutions are

$$\hat{\alpha} = \bar{y} - \frac{SXY}{SXX} \bar{x}, \quad \hat{\beta} = \frac{SXY}{SXX},$$

where

$$SXX = \|x - \bar{x}\|^2, \quad SY = \|y - \bar{y}\|^2, \quad SXY = (x - \bar{x}, y - \bar{y}).$$

Now, the weighted least squares estimates, by definition, minimize

$$\sum_{i=1}^n w_i (y_i - \hat{y})^2.$$

Interestingly, the weighted least squares solutions can be expressed in formulas which have exactly the same form as those given above, if we replace the Euclidean norm $||x||$ and Euclidean inner product (x, y) by the *weighted* norm

$$||x||_w = \sqrt{\sum w_i x_i^2}$$

and the *weighted* inner product

$$(x, y)_w = \sum_{i=1}^n w_i x_i y_i .$$

The proof follows simply from Theorem 1 and from the fact that the weighted least squares estimates minimize $||y - \hat{y}'||_w^2$. For more details, see Theorem 2. Thus, if we define

$$\begin{aligned} S_w &= \sum w_i , \quad \bar{x}_w = \frac{\sum w_i x_i}{S_w} , \quad \bar{y}_w = \frac{\sum w_i y_i}{S_w} , \\ SXX &= ||x - \bar{x}_w||_w^2 = \sum_{i=1}^n w_i (x_i - \bar{x}_w)^2 , \\ SYY &= ||y - \bar{y}_w||_w^2 = \sum_{i=1}^n w_i (y_i - \bar{y}_w)^2 , \\ SXY &= (x - \bar{x}_w, y - \bar{y}_w)_w = \sum_{i=1}^n w_i (x_i - \bar{x}_w) (y_i - \bar{y}_w) , \end{aligned}$$

then the weighted least squares estimates are

$$\hat{\alpha} = \bar{y}_w - \frac{SXY}{SXX} \bar{x}_w , \quad \hat{\beta} = \frac{SXY}{SXX} .$$

Note that these formulas reduce to the unweighted case if all w_i are set to 1 .

We now turn to the PRISM model,

$$y = \alpha 1 + \beta H(\tau) + \varepsilon .$$

We will show that the ordinary PRISM estimates of α , β , τ are in fact the least squares estimates. If τ is fixed, $\hat{\alpha}$, $\hat{\beta}$ are the corresponding least squares estimates of α , β , and $\hat{y}' = \hat{\alpha} 1 + \hat{\beta} H(\tau)$, then the R^2 statistic is defined as

$$R^2(\tau) = 1 - \frac{||y - \hat{y}'(\tau)||^2}{||y - \bar{y}'||^2} = 1 - \frac{RSS(\tau)}{||y - \bar{y}'||^2} . \quad (1)$$

By Theorem 3 (with all weights set to 1), we can also write $R^2(\tau)$ as

$$R^2(\tau) = \frac{||\hat{y}' - \bar{y}'||^2}{||y - \bar{y}'||^2} . \quad (2)$$

Thus, $R^2(\tau)$ is the proportion of the total variability in y (i.e., $||y - \bar{y}||^2$) which can be explained by the least squares fit $\hat{y}(\tau)$. $R^2(\tau)$ is also the square of the correlation coefficient between y and $H(\tau)$, as shown in Theorem 3. As defined in most CEES reports, and as implemented in the original PRISM program, the PRISM estimate of τ is the value $\hat{\tau}$ which maximizes $R^2(\tau)$. But since $||y - \bar{y}||^2$ does not depend on τ , (1) implies that $\hat{\tau}$ can equivalently be characterized as the value which minimizes $RSS(\tau)$. Now, it follows easily that the PRISM estimates are the least squares estimates, i.e., that they minimize $||y - (\alpha + \beta H(\tau))||^2$ as a function of all three parameters α, β, τ . To see this, note that the minimizer $\hat{\tau}$ of $RSS(\tau)$ and the corresponding least squares estimates $\hat{\alpha}$ and $\hat{\beta}$ give the best least squares fit which can be obtained by holding τ at some fixed value. If there were some other numbers $\alpha^*, \beta^*, \tau^*$ which gave a better fit than $\hat{\alpha}, \hat{\beta}, \hat{\tau}$, then the least squares estimates of α and β corresponding to τ^* would have to also give a better fit than $\hat{\alpha}, \hat{\beta}, \hat{\tau}$, and this possibility is ruled out by the discussion given above.

Thus for a given value of τ , the corresponding least squares estimates $\hat{\alpha}, \hat{\beta}$ are given by

$$\hat{\alpha} = \bar{y} - \frac{SHY}{SHH} \bar{H}, \quad \hat{\beta} = \frac{SHY}{SHH}$$

where

$$SHH = ||H(\tau) - \bar{H}(\tau)||^2, \quad SY = ||y - \bar{y}||^2, \quad SHY = (H - \bar{H}, y - \bar{y}).$$

Furthermore,

$$\hat{Y} = \hat{\alpha} + \hat{\beta}H(\tau), \quad RSS(\tau) = ||y - \hat{y}||^2, \\ R^2(\tau) = 1 - \frac{RSS(\tau)}{||y - \bar{y}||^2} = \frac{SHY^2}{SHH SY} = \hat{\beta}^2 \frac{SHH}{SY}.$$

$\hat{\tau}$ is determined by maximizing $R^2(\tau)$, or, equivalently, by minimizing $RSS(\tau)$. In PRISM, this maximization is accomplished through a combination of Newton's Method and a grid search.

We will now show that the WPRISM estimates can be obtained from the original PRISM algorithm, provided that $\bar{H}, \bar{y}, || ||, (,)$ are changed to $\bar{H}_w, \bar{y}_w, || ||_w, (,)_w$. Thus, if we make these simple changes, we can use the existing PRISM software to solve the WPRISM problem. We will also discuss some of the properties of R_w^2 , a new version of the R^2 statistic which is appropriate for WPRISM. First, it follows from Theorem 2 that for τ fixed, the weighted least squares estimates of α and β are given by

$$\hat{\alpha} = \bar{y}_w - \frac{SHY}{SHH} \bar{H}_w, \quad \hat{\beta} = \frac{SHY}{SHH},$$

where

$$SHH = ||H(\tau) - \bar{H}_w(\tau)||_w^2, \quad SYY = ||y - \bar{y}_w||_w^2, \quad SHY = (H - \bar{H}_w, y - \bar{y}_w)_w.$$

Define

$$\hat{y} = \hat{\alpha} 1 + \hat{\beta} H(\tau), \quad RSS(\tau) = ||y - \hat{y}||_w^2 = \sum w_i (y_i - \hat{y}_i)^2,$$

$$R_w^2(\tau) = 1 - \frac{RSS(\tau)}{||y - \bar{y}_w||_w^2}. \quad (3)$$

R_w^2 is a statistic which has not, so far as we know, been previously studied. Since by Theorem 3,

$$R_w^2 = \frac{||\hat{y} - \bar{y}_w||_w^2}{||y - \bar{y}_w||_w^2},$$

we can think of R_w^2 as measuring the proportion of the total "variability" in y (i.e., $||y - \bar{y}_w||_w^2$) which can be explained by the weighted least squares fit. Here, variability is measured in terms of the w -norm. As shown in Theorem 3, $R_w^2(\tau)$ is also the square of the correlation coefficient between y and $H(\tau)$, with respect to the w -norm and w -inner product. This guarantees that $0 \leq R_w^2(\tau) \leq 1$, and allows us to write $R_w^2(\tau)$ as

$$R_w^2(\tau) = \frac{SHY^2}{SHH SYY} = \hat{\beta}^2 \frac{SHH}{SYY},$$

in exact analogy to the unweighted case. By virtue of (3), the WPRISM estimate $\hat{\tau}$ can be found by maximizing $R_w^2(\tau)$. The final WPRISM estimates are then the weighted least squares estimates $\hat{\alpha}$, $\hat{\beta}$ corresponding to $\hat{\tau}$, along with $\hat{\tau}$ itself.

So far, we have shown that for fixed τ , PRISM can be changed to WPRISM by simply changing the appropriate sums, norms and inner products to weighted sums, weighted norms, and weighted inner products. We have also shown that the WPRISM estimate of τ can be obtained by maximizing $R_w^2(\tau)$, in exact analogy to the ordinary PRISM case. To prove that the above changes will transform the full PRISM algorithm (in which τ is not necessarily fixed) into the full WPRISM algorithm, we still need to show that if the above changes are made, the formulas used in the PRISM Newton's Method will yield a valid Newton's Method for WPRISM. The proof is given in Theorem 4, which closely parallels the development for PRISM given in Goldberg (1982), pp. 237-239.

We now give Theorems 1-4.

Theorem 1: For simple linear regression, the least squares solution $\hat{\alpha}$, $\hat{\beta}$ which minimizes $||y - (\alpha 1 + \beta x)||^2$ is

$$\hat{\beta} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} = \frac{SXY}{SXX}, \quad \hat{\alpha} = \bar{y} - \hat{\beta}\bar{x}.$$

Proof: Define

$$v = \frac{1}{\sqrt{n}} 1, \quad SXX = ||x - \bar{x}||^2, \quad SY = ||y - \bar{y}||^2, \quad SXY = (x - \bar{x}, y - \bar{y}), \quad u = \frac{x - \bar{x}}{\sqrt{SXX}}.$$

Then u and v are orthonormal and y can be expressed uniquely as

$$y = (y, v)v + (y, u)u + \sum_{j=3}^n (y, v_j)v_j,$$

where v_j $j=3, \dots, n$ are orthonormal vectors each of which is also orthonormal to v and u . Note that any linear combination of 1 and x can be uniquely expressed as a linear combination of v and u (and *vice versa*). It can be shown that the minimizer $\hat{y} = \hat{\alpha}1 + \hat{\beta}x$ of $||y - (\alpha 1 + \beta x)||^2$ is characterized by $(y - \hat{y}, z) = 0$ for any linear combination z of 1 and x (or equivalently, for any linear combination z of v and u). We will now prove that the minimizer \hat{y} is given by

$$\hat{y} = (y, v)v + (y, u)u.$$

To prove it, we must show that $(y - \hat{y}, u) = 0$ and $(y - \hat{y}, v) = 0$. But these relations follow easily since

$$(y - \hat{y}, u) = \left(\sum_{j=3}^n (y, v_j)v_j, u \right) = \sum_{j=3}^n (y, v_j)(v_j, u) = 0$$

and

$$(y - \hat{y}, v) = \left(\sum_{j=3}^n (y, v_j)v_j, v \right) = \sum_{j=3}^n (y, v_j)(v_j, v) = 0.$$

We have now proved that $\hat{y} = (y, v)v + (y, u)u$. Since $(y, v)v = \bar{y}$ and since

$$(y - \bar{y}, u) = (y, u) - (\bar{y}, u) = (y, u) - (y, v)(v, u) = (y, u),$$

we have

$$\begin{aligned} \hat{y} &= \bar{y} + (y - \bar{y}, u)u = \bar{y} + \frac{SXY}{\sqrt{SXX}} \frac{x - \bar{x}}{\sqrt{SXX}} \\ &= \left[\bar{y} - \frac{SXY}{SXX} \bar{x} \right] + \frac{SXY}{SXX} x. \end{aligned}$$

Thus,

$$\hat{\beta} = \frac{SXY}{SXX} \quad \text{and} \quad \hat{\alpha} = \bar{y} - \frac{SXY}{SXX} \bar{x} .$$

Theorem 2: For simple linear regression, the weighted least squares solution $\hat{\alpha}, \hat{\beta}$ which minimizes $||y - (\alpha 1 + \beta x)||_w^2$ is

$$\hat{\beta} = \frac{\sum w_i (x_i - \bar{x}_w) (y_i - \bar{y}_w)}{\sum (x_i - \bar{x}_w)^2} = \frac{SXY}{SXX} , \quad \hat{\alpha} = \bar{y}_w - \hat{\beta} \bar{x}_w ,$$

where

$$\bar{x}_w = \frac{1}{S_w} \sum w_i x_i , \quad \bar{y}_w = \frac{1}{S_w} \sum w_i y_i , \quad S_w = \sum w_i .$$

Proof: In the proof of Theorem 1, change all occurrences of $|| ||$ to $|| ||_w$ and $(,)$ to $(,)_w$.

Change \bar{x} to \bar{x}_w and \bar{y} to \bar{y}_w . Finally, change v to

$$v = \frac{1}{\sqrt{S_w}} 1 .$$

All steps of the proof of Theorem 1 will still be correct if these changes are made. Thus the conclusion of Theorem 1, with the indicated changes, is correct as well.

Theorem 3: For simple weighted linear regression, if R_w^2 is defined by

$$R_w^2 = 1 - \frac{RSS}{SYY} ,$$

then the following relations hold:

$$R_w^2 = \frac{||\hat{y} - \bar{y}_w||_w^2}{||y - \bar{y}_w||_w^2} , \quad RSS = SYY - \frac{SXY^2}{SXX} , \quad R_w^2 = \frac{SXY^2}{SXX SYY} .$$

Proof: The weighted least squares estimates are $\hat{\beta} = \frac{SXY}{SXX}$, $\hat{\alpha} = \bar{y}_w - \hat{\beta} \bar{x}_w$, and the corresponding

vector of fitted values is

$$\hat{y} = [\bar{y}_w - \frac{SXY}{SXX} \bar{x}_w] + \frac{SXY}{SXX} x . \quad (1)$$

Clearly,

$$y - \bar{y}_w = (\hat{y} - \bar{y}_w) + (y - \hat{y}) .$$

Since the two parenthesized vectors on the right are orthogonal with respect to $(,)_w$, we have

$$SYY = ||\hat{y} - \bar{y}_w||_w^2 + RSS \quad (2)$$

Thus, we can write

$$R_w^2 = 1 - \frac{RSS}{SYY} = \frac{||\hat{y} - \bar{y}_w||_w^2}{||y - \bar{y}_w||_w^2} \quad (3)$$

Using (1) and (2), we can also write

$$RSS = SYY - ||\hat{y} - \bar{y}_w||_w^2 = SYY - \frac{SXY^2}{SXX} \quad (4)$$

Finally, (4) implies that

$$R_w^2 = 1 - \frac{RSS}{SYY} = \frac{SXY^2}{SXX SYY} ,$$

the squared correlation coefficient between x and y with respect to $(\cdot)_w$.

Theorem 4: If $\bar{x}, \bar{y}, ||\cdot||, (\cdot)$ are changed to $\bar{x}_w, \bar{y}_w, ||\cdot||_w, (\cdot)_w$, then the Newton's Method algorithm for PRISM described on pages 237-239 of Goldberg (1982) will be a valid algorithm for WPRISM.

Proof: From Theorem 3, for a given τ ,

$$R_w^2(\tau) = \frac{SXY^2(\tau)}{SXX(\tau)SYY}$$

We seek the value τ such that

$$\frac{d}{d\tau} R_w^2(\tau) = 0$$

Since SYY does not depend on TAU , it suffices to find τ such that

$$\frac{d}{d\tau} \frac{SXY^2}{SXX} = 0$$

Let $F(\tau) = \frac{d}{d\tau} H(\tau)$. Thus, we want

$$\begin{aligned} 0 &= \frac{d}{d\tau} \frac{SXY^2}{SXX} = (SXX \cdot 2 SXY SFY - SXY^2 \cdot 2 SXF) / SXX^2 |_{\tau} \\ &= \frac{2 SXY}{SXX^2} (SFY SXX - SXY SXF) |_{\tau} , \end{aligned}$$

so it suffices to find τ such that

$$(SFY SXX - SXY SXF) |_{\tau} = 0 \quad (1)$$

Now, put $\delta = \tau - \tau_0$, and approximate $x(\tau)$ by

$$x(\tau) = x(\tau_0) + \delta F(\tau_0) .$$

Also, approximate $SFY(\tau)$ by $SFY(\tau) = SFY(\tau_0)$. To this order of approximation, then,

$$SXX(\tau) = SXX(\tau_0) + \delta^2 SFF(\tau_0) + 2\delta SXF(\tau_0)$$

$$SXY(\tau) = SXY(\tau_0) + \delta SFY(\tau_0)$$

$$SXF(\tau) = SXF(\tau_0) + SFF(\tau_0) .$$

Now, (1) implies that

$$SFY(SXX + \delta^2 SFF + 2\delta SXF) |_{\tau} = (SXY + \delta SFY)(SXY + \delta SFF) |_{\tau}$$

and hence

$$[SFY SXX + 2\delta SFY SXF]_{\tau} = [SXY SXF + \delta(SFY SXF + SXY SFF)]_{\tau}$$

and hence, finally,

$$\delta = \left[\frac{SXY SXF - SFY SXX}{SFY SXF - SXY SFF} \right]_{\tau} .$$

This agrees exactly with Goldberg (1982), p. 239.

Hence if the value of τ after the i 'th iteration of Newton's Method is $\tau^{(i)}$, the value after the $i+1$ 'th iteration is

$$\tau^{(i+1)} = \tau^{(i)} + \delta .$$

AV: The Merits of Using Weighted PRISM When the Period Lengths Differ

The basic PRISM model

$$y = \alpha + \beta H(\tau) + \varepsilon \quad \varepsilon \sim (0, \sigma^2 I_n) \quad (1)$$

is reasonable if the period lengths are nearly the same. If the period lengths are radically different, however, the error terms should not be assumed to have equal variances. Instead, the reasonable assumption is that the variance of ε_i is inversely proportional to the length of period i . This conclusion follows logically if we start with the model (1) with each period having length *one day*, and then average both sides of the equation over blocks of days. Thus, if $\sigma_i^2 = [\text{length of period } i]^{-1} = w_i^{-1}$, and W is a diagonal matrix with (i, i) element w_i , then the appropriate model if the period lengths are unequal is

$$y = \alpha + \beta H(\tau) + \varepsilon \quad \varepsilon \sim (0, \sigma^2 W^{-1}) . \quad (2)$$

The most appropriate regression method for fitting such a model is not least squares, but *weighted* least

squares with weights proportional to the period lengths. To see this, transform (2) into a model for which ordinary least squares is appropriate: let \sqrt{W} be a diagonal matrix with (i, i) element $\sqrt{w_i} = \sigma_i^{-1}$. Then (2) is equivalent to

$$\sqrt{W} y = \sqrt{W} \eta(\theta) + \sqrt{W} \varepsilon, \quad \sqrt{W} \varepsilon \sim (0, \sigma^2 I_n),$$

where

$$\eta(\theta) = \alpha + \beta H(\tau).$$

Since the errors $\sqrt{W} \varepsilon$ in this transformed model have equal variances, it is appropriate to fit $\sqrt{W} \eta(\theta)$ to the data $\sqrt{W} y$ by least squares, thereby minimizing

$$\| \sqrt{W} (y - \eta(\theta)) \|^2 = \sum_{i=1}^n w_i (y_i - \eta_i(\theta))^2.$$

Clearly, this method is equivalent to fitting $\eta(\theta)$ by weighted least squares with weights w_i .

Thus, if one is faced with data having substantially different period lengths, weighted PRISM with weights proportional to the period lengths is preferable to ordinary PRISM. Using PRISM when WPRISM is called for can adversely affect the quality of the estimates, although it will not introduce any systematic bias. Another hazard of using PRISM when WPRISM is called for is that the PRISM standard errors will be incorrect, due to the incorrectness of the PRISM model.

We now derive the theoretical variance-covariance matrix for $\hat{\theta}$ when WPRISM is correctly used.

Start with the model

$$y = \eta(\theta) + \varepsilon, \quad \varepsilon \sim (0, \sigma^2 W^{-1}).$$

Carrying out a first order Taylor series expansion of $\eta(\theta)$ about the weighted least squares estimate $\hat{\theta}$, we obtain

$$\eta(\theta) = \eta(\hat{\theta}) + \dot{\eta}(\hat{\theta})(\theta - \hat{\theta}).$$

Treating $\hat{\theta}$ as fixed, the model becomes

$$y - \eta(\hat{\theta}) + \dot{\eta}(\hat{\theta})\hat{\theta} = \dot{\eta}(\hat{\theta})\theta + \varepsilon,$$

or equivalently,

$$\sqrt{W} (y - \eta(\hat{\theta}) + \dot{\eta}(\hat{\theta})\hat{\theta}) = \sqrt{W} \dot{\eta}(\hat{\theta})\theta + \sqrt{W} \varepsilon.$$

Since $\sqrt{W} \varepsilon \sim (0, \sigma^2 I_n)$, we have, to this order of approximation,

$$\text{Varcov}(\hat{\theta}) = \sigma^2 (\dot{\eta}(\hat{\theta})^T W \dot{\eta}(\hat{\theta}))^{-1} \quad (3)$$

For estimating σ^2 in (3), we should use $\hat{\sigma}_w^2$, the error variance produced by WPRISM.

AVI: Combining RPRISM With the Unequal Period Length Adjustment, OUTWTS

Here, we describe the algorithm used in the latest version of the PRISM software if both the ROBUST and OUTWTS options are set to ON. The method given here simultaneously takes account of unequal period lengths and robustness. This is accomplished by using two sets of weights. The outside weights W_i keep track of the period lengths: W_i is the number of days in period i . The inside weights w_i account for robustness.

The most appropriate regression model can be written as

$$\sqrt{W_i} y_i = \sqrt{W_i} (\alpha + \beta H_i(\tau)) + \varepsilon_i, \quad i = 1, \dots, n, \quad (1)$$

where $\text{var } \varepsilon_i = \sigma^2 = \text{constant}$ for all i . The algorithm described here can be thought of as giving robust estimates for the model (1):

- 1) Estimate α, β, τ by WPRISM with weights W_i . Denote the fitted values by \hat{y}_i .
- 2) Use the values $\sqrt{W_i}(y_i - \hat{y}_i)$, which are the "residuals" from the equal-variance model (1), to obtain robustness weights w_i .
- 3) Obtain new provisional estimates $\hat{\alpha}, \hat{\beta}, \hat{\tau}$ by WPRISM with weights $W_i w_i$. (This is equivalent to fitting the model (1) by weighted least squares with weights w_i .) Denote the fitted values by \hat{y}_i .
- 4) Repeat steps 2) and 3) until the current estimates are sufficiently close to the previous estimates. Use the current estimates as the final estimates.

Note that if all period lengths are equal, then the algorithm described here reduces exactly to the RPRISM (IRLS) algorithm described in Section AII. Note also that the outside weights are never changed.

AVII: Proposed Algorithm To Compensate for Systematic Nonconstant Variability, Unequal Period Lengths, and Isolated Outliers

The algorithm described here has not been implemented in the current version of the PRISM software. It is more general than the algorithm described in Section AVI since it allows for systematic non-constant variability.

- 1) Run RPRISM with OUTWTS ON. Obtain $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$, \hat{y}_i .
- 2) Given \hat{y}_i , compute a new set of outside weights proportional to (length of period i)/ \hat{y}_i .
- 3) Run RPRISM with the current set of outside weights. Obtain new provisional values of $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$, \hat{y}_i .
- 4) Repeat steps 2) and 3) until convergence is reached
- 5) Stop. Use the current values of $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$ as the final estimates.

Appendix B. Summary of New Additions to the PRISM Software

The developments described in this paper have been incorporated in an earlier research version of the PRISM software. Specifically, this preliminary version of Robust PRISM now has two new options, controlled by the 'SET' command. The ROBUST option, which is OFF by default, causes the execution of the Robust PRISM (RPRISM) algorithm. The OUTWTS option, which is also OFF by default, runs weighted PRISM (WPRISM), with weights proportional to the period lengths. If desired, both options may be set to ON. This would simultaneously provide the user with robustness and with the unequal period-length adjustment. If both options are set to OFF (the default settings), then the ordinary PRISM algorithm will be executed.

All runs of RPRISM done for this paper used six iterations of WPRISM (see schematic for RPRISM, Figure 1). Subsequently, the algorithm has been revised to stop if the weights converge (to within a tolerance of .01) before six iterations. If the ROBUST option is used, the initial and final (inside) weights for each house will be written to Fortran Unit 11.

Appendix C: Using Weighted PRISM to Compensate for Another Kind of
Nonconstant Variability

In developing models for electrical consumption, Latta (1983) has suggested that the variance of the consumption may be approximately proportional to the fitted consumption value. Thus, according to Latta's proposal the variance is nonconstant, and increases with fitted consumption. Although Latta's models differ from the PRISM model in many ways, the assumed pattern of variability may be a good approximation to the truth for PRISM as well. (Indeed, this type of pattern has often been proposed by statisticians as a realistic one for many commonly encountered regression data sets.)

To formalize the idea, write the (modified) PRISM model as

$$y_i = \alpha_i + \beta H_i(\tau) + \epsilon_i$$

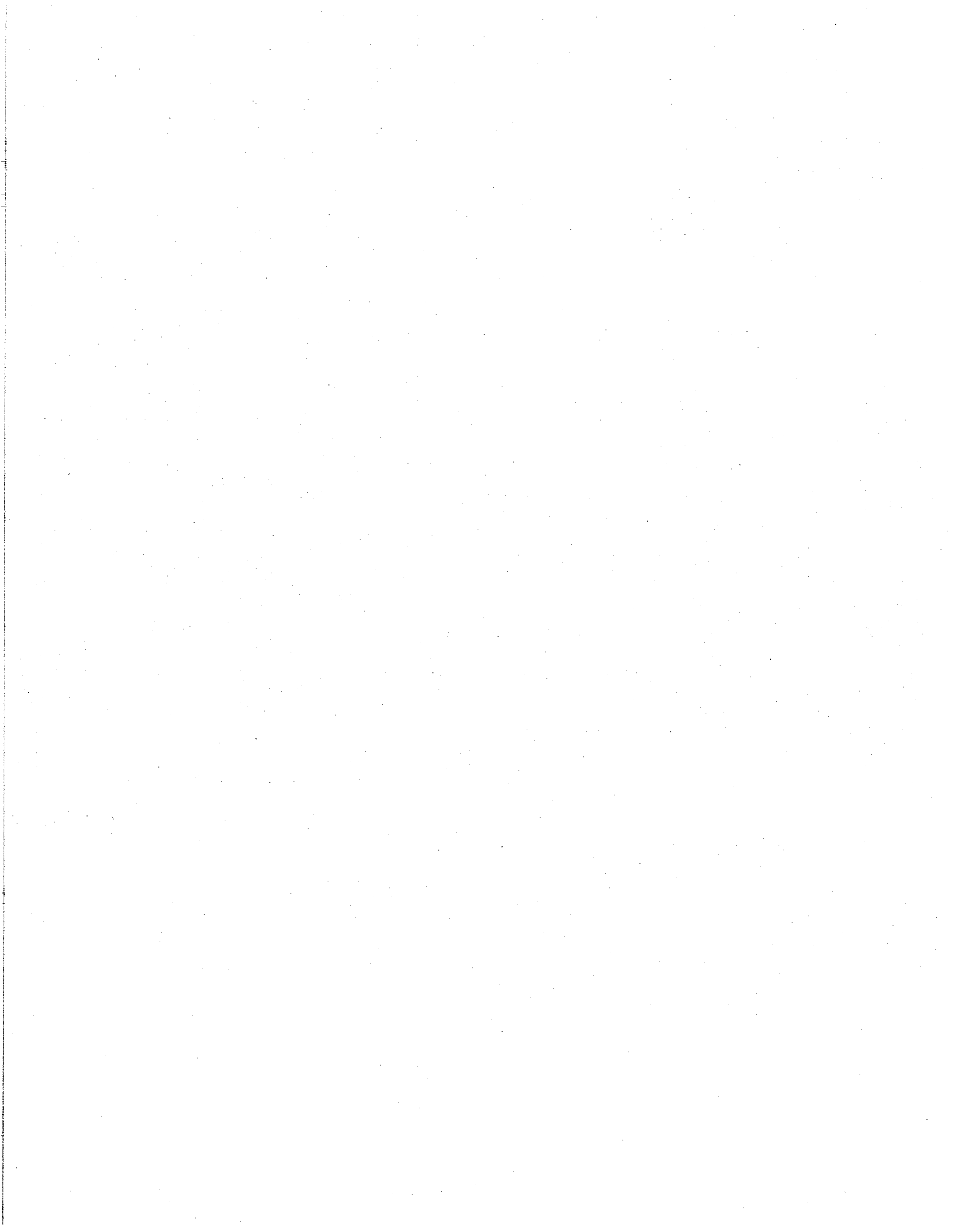
where the ϵ_i are independent zero mean random variables with variances σ_i^2 , to be determined. For simplicity, suppose that the period lengths are all identical. Now, assume that $\text{var}(y_i) = \sigma_i^2$ is proportional to $\alpha + \beta H_i(\tau)$, the (theoretical) average consumption according to the true model. This is a reasonable assumption, under which variance increases with average consumption. Thus, if α , β , and τ were known, the optimal fitting method would be weighted least squares (i.e., WPRISM), with weights inversely proportional to $\alpha + \beta H_i(\tau)$. Unfortunately, α , β , and τ are unknown, and so the best we can do is to obtain preliminary estimates $\hat{\alpha}$, $\hat{\beta}$, $\hat{\tau}$ (e.g., by using ordinary PRISM), and then to assume that $\text{var}(y_i)$ is proportional to the fitted consumption, $\hat{y}_i = \hat{\alpha} + \hat{\beta} H_i(\hat{\tau})$. Thus, the second stage in the fitting process would be to apply WPRISM to the original data, with weights inversely proportional to \hat{y}_i . This would yield new estimates, as well as new fitted values.

We could stop here, and use the current values as the final estimates. Alternatively, if desired, we could iterate the fitting process, at each stage computing new weights from the present fit and then running WPRISM with

these weights. The iterations could be stopped when the fitted values at a given stage are sufficiently close to the fitted values at the previous stage.

Note that the iterative scheme proposed above is analogous, though not identical, to the iterations used in calculating RPRISM estimates. The difference is that the weights computed for RPRISM are designed to directly compensate for the effects of outliers, while the weights computed for the present scheme are designed to compensate for an assumed global pattern of variability.

It would be relatively easy to incorporate the compensation discussed in this section with the previously described compensation for unequal period lengths (OUTWTS) and the compensation for outliers (RPRISM). A specification of the complete algorithm is given in Appendix AVI.



Tables and Figures

Note: To facilitate continued review of this methodology development, extremely detailed results are included in some of the tables and figures (in the form of Univariate summaries from SAS, house-by-house PRISM output, and individual-house plots of consumption data). Those tables and figures containing concise summaries of the detailed results are indicated by asterisks in the text. For a cursory reading of the text, the reader may wish to emphasize the (asterisked) summaries.

Table 1. Summary of median accuracy measures from ordinary PRISM^a.

Heating fuel:	Electricity (i)	Gas (ii)	Oil (iii)
# houses	50	276	207

R ²	0.972	0.990	0.971
se(α)/ α	0.123	0.160	0.476 ^b
se(β)/ β	0.098	0.076	0.105
se(τ) (°C)	1.7	1.2	3.0
se(NAC)/NAC	0.030	0.025	0.073

a. Median R² values and standard errors from ordinary PRISM applied to three New Jersey samples of houses are shown:

- i) a set of 50 houses from our General Public Utilities data base, which are heated but not cooled by electricity (Stram and Fels, 1986)
- ii) gas-heated houses in the Modular Retrofit Experiment (a pre- and a post-retrofit period for each of 138 houses) (Dutt et al., 1986)
- iii) a set of 207 oil-heated houses (Fels et al., 1986).

Standard errors of α , β , and NAC are expressed as fractions of the estimate:

- b. Since all houses in the other two samples have their water heated by the space heating fuel, the median of se(α)/ α for the oil sample corresponds to the subset of 133 houses with oil-fired water heaters.

Results in this table are reproduced from an earlier paper (Fels et al., 1986, Table 2).

Table 2. By-house PRISM results for 50 electrically heated homes in New Jersey (Elec-HO sample). Units for PRISM parameters are as follows: τ (TREF) = °F; α (BASELEVEL) = kWh/day; β (SLOPE) = kWh/°F-day; NAC(Normalized Annual Consumption) = kWh/year; βH_0 (HEATING PART) = kWh/year.

UNIT ID	# PDS	# DAYS	RAW CONS	# ITS RXR	TREF	BASELEVEL X PER DAY	SLOPE X PER HDD	NAC X PER YEAR	HEATING PART
J3	12	365	15889	3	59.7 (2.8)	18.61 (2.58)	2.528 (0.272)	16279.92 (591.68)	9483.9 (782.2)
J4	12	365	23279	5	50.9 (1.2)	29.06 (1.98)	5.975 (0.339)	23579.34 (503.88)	12964.8 (565.0)
J5	12	365	41639	4	70.0 (2.3)	51.42 (5.37)	3.788 (0.179)	42208.88 (646.24)	23428.2 (1726.6)
J6	12	365	27979	3	64.5 (1.6)	26.33 (2.77)	3.932 (0.195)	28526.00 (513.06)	18908.7 (981.3)
J7	12	365	28519	3	61.9 (3.2)	51.19 (3.20)	2.434 (0.269)	28935.67 (668.48)	10238.3 (981.3)
J10	12	366	30339	3	61.9 (4.5)	44.26 (3.73)	3.426 (0.321)	30581.97 (779.55)	14417.0 (1137.5)
J11	12	366	17989	3	61.6 (4.7)	28.32 (3.55)	1.929 (0.303)	18358.97 (379.62)	8010.8 (1088.9)
J16	12	365	17949	3	60.4 (1.7)	23.12 (1.73)	2.553 (0.164)	18379.12 (374.47)	9934.9 (528.6)
J17	12	366	22051	3	66.0 (2.7)	27.90 (3.24)	1.380 (0.171)	22474.81 (512.06)	12285.4 (1043.4)
J18	12	367	13279	4	61.0 (5.3)	17.79 (6.37)	5.313 (0.339)	13455.32 (798.25)	6957.7 (1100.1)
J19	12	365	59429	7	82.0 (13.3)	19.79 (63.72)	1.732 (0.371)	60022.26 (1860.89)	52793.1 (23385.2)
J20	12	365	8575	5	57.5 (4.7)	7.22 (2.88)	1.840 (0.362)	8739.71 (686.59)	6102.8 (864.1)
J22	12	367	38299	4	58.0 (2.4)	55.56 (4.95)	5.377 (0.629)	38613.22 (1157.20)	18320.3 (1478.7)
J23	12	365	43169	4	66.1 (3.5)	28.66 (11.35)	6.530 (0.615)	44362.91 (1819.59)	33894.6 (3636.4)
J24	12	365	31219	4	59.6 (4.6)	38.92 (7.57)	4.725 (0.840)	31839.25 (1705.52)	17622.4 (2324.8)
J25	12	365	21999	3	64.4 (3.4)	24.19 (4.52)	2.866 (0.297)	22520.50 (853.35)	13686.5 (1422.7)
J26	12	365	30739	3	64.7 (4.0)	36.60 (6.41)	3.693 (0.457)	31267.29 (1222.00)	17900.4 (2024.4)
J27	12	365	26059	3	60.2 (2.5)	26.62 (2.47)	4.367 (0.411)	26556.09 (944.24)	16833.8 (1284.8)
J28	12	365	20219	1	59.0 (4.2)	24.76 (2.47)	3.199 (0.274)	20375.04 (557.01)	11533.3 (757.4)
J29	12	365	10476	3	23.0 (2.2)	28.05 (2.47)	1.486 (7.264)	10355.92 (854.05)	108.0 (562.5)
J30	12	367	19059	3	60.9 (2.0)	25.77 (2.02)	2.529 (0.184)	19458.17 (446.53)	10117.6 (611.0)
J32	12	365	33799	4	65.2 (2.1)	35.76 (4.32)	4.259 (0.264)	34259.31 (758.81)	21196.7 (1371.4)
J33	12	365	25229	4	64.0 (2.0)	30.41 (3.31)	3.861 (0.250)	29201.95 (648.64)	18093.6 (1025.6)
J34	12	365	22009	3	67.4 (3.9)	24.25 (6.30)	3.080 (0.293)	25849.05 (900.95)	16992.3 (2014.5)
J38	12	365	25479	3	63.3 (5.3)	27.33 (6.57)	2.772 (0.467)	22549.16 (1278.83)	12565.6 (2045.5)
J39	12	365	27269	4	61.2 (2.8)	31.33 (3.98)	3.564 (0.363)	25926.55 (860.10)	14484.4 (1212.9)
J40	12	365	26599	3	65.8 (1.5)	14.94 (3.14)	4.420 (0.192)	28067.22 (543.46)	22609.7 (998.0)
J41	12	365	24779	2	63.1 (1.7)	33.99 (2.47)	3.284 (0.187)	27137.64 (474.96)	14724.3 (770.9)
J43	12	365	22909	3	55.4 (6.5)	41.94 (6.42)	3.353 (0.964)	25087.87 (1514.06)	9770.7 (1912.1)
J44	12	365	20339	3	59.4 (1.6)	29.04 (1.65)	2.735 (0.166)	22906.89 (1568.98)	9780.4 (1614.0)
J45	12	365	26869	3	64.7 (3.4)	28.29 (5.27)	3.532 (0.369)	27479.96 (993.53)	10097.4 (501.7)
J46	12	366	20109	3	68.1 (3.4)	20.65 (4.40)	2.282 (0.187)	20508.37 (626.22)	17147.0 (1663.6)
J47	12	365	24099	5	70.6 (9.5)	24.98 (13.95)	2.435 (0.467)	24555.00 (1692.84)	15429.5 (4487.7)
J48	12	365	35839	3	61.4 (2.6)	43.19 (4.95)	4.638 (0.448)	36488.96 (1070.63)	19034.4 (1505.5)
J49	12	367	22599	4	59.0 (3.8)	47.79 (2.70)	1.942 (0.285)	22777.74 (604.94)	7000.9 (827.6)
J51	12	365	22259	3	69.1 (1.3)	16.66 (2.21)	2.793 (0.083)	22720.55 (305.18)	16636.0 (700.6)
J54	12	365	22399	4	51.6 (3.7)	45.07 (2.32)	2.695 (0.487)	22588.97 (576.72)	6125.4 (706.0)
J55	12	365	18980	2	62.8 (3.3)	27.25 (2.97)	2.134 (0.242)	19349.84 (606.09)	9397.0 (918.0)
J57	12	365	36379	3	63.5 (2.1)	41.21 (4.62)	4.852 (0.323)	37197.82 (883.89)	22144.9 (1439.4)
J58	12	365	28619	5	66.4 (3.0)	34.22 (4.67)	3.184 (0.245)	29258.22 (720.28)	16758.4 (1503.1)
J60	12	367	18509	4	55.9 (0.9)	21.18 (1.09)	3.741 (0.136)	18994.35 (263.81)	11256.9 (319.7)
J62	12	365	29069	4	67.0 (4.8)	32.74 (3.37)	3.078 (0.314)	24282.05 (724.00)	12323.7 (1024.1)
J63	12	365	25399	4	58.8 (6.4)	37.84 (7.37)	2.921 (0.342)	29619.67 (1053.95)	15798.1 (2356.6)
J64	12	365	23849	4	70.5 (6.2)	33.26 (9.32)	3.918 (0.981)	26108.77 (2147.61)	13959.0 (2782.6)
J65	12	365	21759	3	61.6 (1.4)	23.73 (12.26)	3.295 (0.409)	29461.89 (1476.04)	20793.2 (3943.6)
J67	12	367	42739	5	68.0 (4.2)	31.50 (1.43)	2.569 (0.127)	42895.33 (934.81)	16592.0 (2162.4)
J69	12	365	27319	2	62.2 (3.0)	72.01 (6.77)	2.931 (0.291)	27850.84 (979.37)	15825.4 (1440.7)
J70	12	365	24389	3	65.0 (1.1)	23.36 (1.67)	3.347 (0.109)	24979.45 (308.99)	16447.9 (525.6)

Table 3. By-house RPRISM results for Elec-HO sample. See Table 2 caption.

UNIT ID	#	# PDS	TIME PERIOD	# DAYS	RAW CONS	# ITS RXR	TREF	BASELEVEL X PER DAY	SLOPE X PER HDD	X PER YEAR	MAC	HEATING PART
J3	12	12	12/4/78-12/4/79	365	15889	2	0.977	18.73(1.81)	2.629(0.191)	16397.70(414.87)	9558.0(548.5)	
J4	12	12	12/20/78-12/20/79	365	23279	1	0.995	29.44(1.59)	5.808(0.258)	23474.59(405.86)	12723.2(465.6)	
J5	12	12	12/26/78-12/26/79	365	41639	2	0.992	51.73(2.57)	3.810(0.208)	42138.15(733.23)	23243.8(1772.7)	
J6	12	12	12/11/78-12/11/79	365	27979	2	0.993	26.07(2.76)	3.871(0.195)	28371.84(512.17)	18850.6(876.7)	
J7	12	12	12/19/78-12/19/79	365	28519	3	0.966	51.19(3.20)	2.434(0.269)	28935.67(668.49)	10238.3(981.3)	
J10	12	12	12/22/78-12/24/79	367	30339	3	0.976	44.24(3.05)	3.403(0.340)	30537.96(825.12)	14380.1(1204.0)	
J11	12	12	12/27/78-12/28/79	366	17989	2	0.959	27.91(3.05)	1.810(0.220)	18587.02(586.40)	8394.0(953.9)	
J16	12	12	12/14/78-12/14/79	365	17949	1	0.990	23.02(1.89)	2.524(0.178)	18417.42(407.55)	10007.6(575.3)	
J17	12	12	12/27/78-12/28/79	366	22051	1	0.995	28.19(1.42)	1.378(0.084)	22284.07(242.52)	11988.1(454.3)	
J18	12	12	12/22/78-12/24/79	367	13279	3	0.926	18.51(2.79)	1.877(0.300)	13154.87(655.45)	6395.9(820.3)	
J19	12	12	12/19/78-12/19/79	365	59429	2	0.992	53.68(6.99)	5.354(0.146)	61013.75(611.16)	41406.6(2424.8)	
J20	12	12	12/5/78-12/5/79	365	8575	2	0.931	7.37(2.97)	1.739(0.340)	8906.63(702.52)	6213.9(886.3)	
J21	12	12	12/17/78-12/3/79	367	38299	2	0.984	54.82(3.84)	5.292(0.411)	38055.41(898.63)	18031.9(1148.3)	
J22	12	12	12/13/78-12/13/79	365	43169	2	0.974	28.88(9.52)	6.827(0.581)	44932.43(1645.80)	34383.5(3022.4)	
J23	12	12	12/12/78-12/12/79	365	31219	1	0.965	33.21(6.97)	4.200(0.487)	32326.46(1287.41)	20198.3(2210.4)	
J24	12	12	11/30/78-11/30/79	365	21999	2	0.967	24.29(4.55)	2.880(0.299)	22482.84(858.52)	13612.2(1431.4)	
J25	12	12	12/5/78-12/5/79	365	30739	2	0.958	36.55(6.95)	3.698(0.494)	31253.70(1323.71)	17904.9(2192.9)	
J26	12	12	12/7/78-12/7/79	365	26059	2	0.982	27.57(3.73)	4.708(0.431)	26805.00(862.50)	16735.9(1118.8)	
J27	12	12	12/11/78-12/11/79	365	20219	2	0.992	24.73(1.32)	3.262(0.157)	20160.40(301.23)	11126.5(398.1)	
J28	12	12	12/28/78-12/28/79	365	10476	3	0.179	27.02(1.48)	1.172(0.202)	10052.43(495.75)	184.1(622.4)	
J29	12	12	12/20/78-12/20/79	365	19059	1	0.987	25.65(2.06)	2.536(0.188)	19406.60(455.07)	10038.0(622.7)	
J30	12	12	12/17/78-12/3/79	367	33799	2	0.989	36.61(4.59)	4.258(0.280)	34362.32(806.05)	20990.7(1456.8)	
J32	12	12	12/7/78-12/7/79	365	28699	2	0.992	30.58(2.75)	3.897(0.208)	28813.80(539.42)	17644.4(852.9)	
J33	12	12	12/26/78-12/26/79	365	25229	2	0.990	24.77(3.37)	3.108(0.177)	25568.60(519.50)	16520.2(1084.1)	
J34	12	12	12/28/78-12/28/79	365	22009	2	0.944	28.24(3.87)	2.881(0.326)	21911.83(815.99)	11597.9(1185.1)	
J38	12	12	12/6/78-12/6/79	365	25479	2	0.975	31.45(4.36)	3.592(0.397)	26052.31(941.58)	14566.3(845.9)	
J39	12	12	12/13/78-12/13/79	365	27269	2	0.996	13.88(2.64)	4.369(0.143)	27994.51(423.25)	22923.1(1327.8)	
J40	12	12	12/12/78-12/12/79	365	26599	1	0.991	33.97(2.36)	3.248(0.178)	27044.83(453.61)	14638.0(736.2)	
J41	12	12	12/11/78-12/11/79	365	24779	2	0.877	41.87(5.64)	3.292(0.847)	25058.34(1330.06)	9765.6(1679.7)	
J43	12	12	12/15/78-12/17/79	367	22909	2	0.984	31.75(1.51)	5.116(0.230)	24837.74(367.87)	13242.7(430.8)	
J44	12	12	12/19/78-12/19/79	365	20339	1	0.994	29.33(1.14)	2.851(0.121)	20508.72(265.59)	9796.5(339.1)	
J45	12	12	12/4/78-12/4/79	365	26869	2	0.980	25.45(4.59)	3.187(0.223)	27033.50(701.28)	17738.8(1458.6)	
J46	12	12	12/27/78-12/28/79	366	20109	2	0.979	20.00(4.34)	2.207(0.163)	20457.43(584.90)	13153.4(1380.6)	
J47	12	12	12/19/78-12/19/79	365	24099	2	0.959	26.68(4.34)	2.306(0.184)	23197.67(616.69)	13451.5(1387.4)	
J48	12	12	12/5/78-12/5/79	365	35839	2	0.983	47.68(4.45)	4.445(0.371)	36846.83(924.99)	19430.2(1376.1)	
J49	12	12	12/15/78-12/17/79	367	22599	2	0.957	43.26(2.59)	2.043(0.290)	22841.31(592.54)	7041.5(777.2)	
J50	12	12	11/30/78-11/30/79	365	22259	1	0.996	16.66(2.21)	2.793(0.083)	22720.55(305.09)	16636.0(700.3)	
J51	12	12	12/3/78-12/13/79	365	22399	2	0.966	45.20(2.21)	2.666(0.464)	22674.26(548.98)	6164.9(672.1)	
J54	12	12	12/4/78-12/4/79	365	18980	2	0.971	27.37(2.07)	2.165(0.169)	19322.86(422.26)	9326.7(639.6)	
J55	12	12	12/18/78-12/18/79	365	36379	2	0.986	41.16(5.25)	4.818(0.366)	37145.00(1003.94)	22111.4(1634.9)	
J57	12	12	12/26/78-12/26/79	365	28619	1	0.982	34.22(4.67)	3.184(0.245)	29258.22(720.21)	16758.4(1503.0)	
J58	12	12	12/28/78-12/28/79	365	18509	3	0.997	21.19(1.14)	3.721(0.133)	19010.09(273.78)	11269.7(330.9)	
J60	12	12	12/15/78-12/17/79	367	23978	2	0.988	32.85(2.16)	2.947(0.187)	23909.30(444.77)	11911.5(666.0)	
J62	12	12	12/26/78-12/26/79	365	29069	2	0.969	36.47(7.43)	2.894(0.345)	29146.49(1062.41)	15826.5(2375.5)	
J63	12	12	12/18/78-12/18/79	365	25399	2	0.961	33.48(7.46)	3.755(0.666)	26730.18(1607.29)	14500.0(2263.6)	
J64	12	12	12/26/78-12/26/79	365	28849	2	0.961	34.99(9.23)	3.452(0.387)	29277.95(1271.28)	20150.2(2957.4)	
J65	12	12	12/4/78-12/4/79	365	21759	2	0.994	31.32(1.50)	2.575(0.133)	22232.21(319.81)	10794.1(454.9)	
J67	12	12	12/22/78-12/24/79	367	42739	1	0.971	61.8(1.4)	2.909(0.283)	42686.69(861.08)	16357.0(1902.7)	
J69	12	12	12/6/78-12/6/79	365	27319	2	0.969	72.94(5.96)	3.716(0.423)	27867.24(1056.82)	15836.1(1554.6)	
J70	12	12	12/18/78-12/18/79	365	24389	2	0.997	23.37(1.79)	3.348(0.117)	24974.71(332.61)	16438.4(565.8)	

Table 4. Summary statistics of PRISM vs. RPRISM parameters for Elec-HO sample.

	MEDIAN		MEAN		
	REGULAR	ROBUST	REGULAR	ROBUST	
ALPHA	28.85	29.39	31.53	32.03	kWh/day
BETA	3.24	3.22	3.42	3.36	kWh/°F-day
BHO	14451	14440	15043	14844	kWh/year
NAC	25469	25314	26561	26544	kWh/year
R-SQUARE	.972	.981	.945	.959	
CV ALPHA	.123	.108	.217	.127	
CV BETA	.098	.077	.204	.120	
CV BHO	.090	.075	.209	.111	
CV NAC	.030	.024	.034	.027	

Table 5. By-house percent differences for each estimate for Elec-HO sample. Percent difference is defined as:

$$\left[\frac{(\text{RPRISM estimate} - \text{PRISM estimate}) / \text{PRISM estimate}}{\right] * 100.$$

	HOUSELET	PCALPHA	PCBETA	PCNAC	PCBHO
J3	0.645	3.995	0.7235	0.781	0.781
J4	1.308	-2.795	-0.4442	-1.864	-1.864
J5	0.603	0.581	-0.1676	-0.787	-0.787
J6	-0.987	-1.551	-0.5404	-0.307	-0.307
J7	0.000	0.000	0.0000	0.000	0.000
J10	-0.045	-0.671	-0.1439	-0.256	-0.256
J11	-1.483	-6.169	1.2422	4.784	4.784
J16	-0.433	-1.136	0.2084	0.732	0.732
J17	1.039	-0.084	-0.8487	-2.420	-2.420
J18	4.047	8.372	-2.2329	-8.075	-8.075
J19	171.248	0.772	1.6519	-21.568	-21.568
J20	2.078	-5.489	1.9099	1.820	1.820
J21	-1.332	-1.581	-1.4446	-1.574	-1.574
J22	0.768	4.548	1.2838	1.442	1.442
J23	-14.671	-11.111	1.5302	14.617	14.617
J24	0.413	0.488	-0.1672	-0.543	-0.543
J25	-0.137	0.135	-0.0435	0.025	0.025
J26	3.569	7.809	0.9373	-0.582	-0.582
J27	-0.121	1.969	-2.0153	-3.527	-3.527
J28	-3.706	-21.131	-2.9306	70.463	70.463
J29	0.313	0.277	-0.2650	-0.787	-0.787
J30	2.377	-0.023	0.3007	-0.972	-0.972
J32	0.559	0.932	-1.3292	-2.483	-2.483
J33	2.144	0.909	-1.0850	-2.778	-2.778
J34	3.330	3.932	-2.8264	-7.701	-7.701
J38	0.383	0.786	0.4851	0.565	0.565
J39	-7.095	-1.154	-0.2591	1.386	1.386
J40	-0.059	-1.096	-0.3420	-0.586	-0.586
J41	-0.167	-1.819	-0.1177	-0.052	-0.052
J43	-11.658	-27.750	8.4291	35.400	35.400
J44	0.999	4.241	-0.9475	-2.980	-2.980
J45	-10.039	-9.768	-1.6247	3.451	3.451
J46	-3.148	-3.287	-0.2484	1.448	1.448
J47	6.805	-5.298	-5.5277	-12.820	-12.820
J48	-0.230	-4.161	0.9808	2.079	2.079
J49	0.162	5.201	0.2791	0.580	0.580
J50	0.000	0.000	0.0000	0.000	0.000
J51	0.288	-1.076	0.3776	0.645	0.645
J54	0.440	1.453	-0.1394	-0.748	-0.748
J55	-0.121	-0.701	-0.1420	-0.151	-0.151
J57	0.000	0.000	0.0000	0.000	0.000
J58	0.047	-0.535	0.0829	0.114	0.114
J60	0.336	-4.256	-1.5351	-3.345	-3.345
J62	-3.621	-0.924	-1.5975	0.180	0.180
J63	0.661	-4.160	2.3801	3.876	3.876
J64	5.310	4.765	-0.6243	-3.092	-3.092
J65	-0.571	0.234	0.3149	1.291	1.291
J67	0.111	-0.751	-0.4864	-1.416	-1.416
J69	0.061	0.351	0.0589	0.068	0.068
J70	0.043	0.030	-0.0190	-0.058	-0.058

Table 6. Summary statistics of percent differences of PRISM vs. RPRISM parameters for Elec-HO sample. (See Figures 2-5.)

	MIN	Q1	MED	Q3	MAX	MEAN
ALPHA	-14.7	-.28	.086	.825	171	3.01
BETA	-27.8	-2.1	-.054	.816	8.37	-1.33
NAC	-5.5	-.87	-.141	.331	8.43	-.138
HEATING	-22	-1.6	-.055	.91	70.5	1.29

Table 7. By-house summary of the ratio of the coefficients of variation (CVR) for PRISM vs. RPRISM estimates for Elec-HO sample. $CVR = CV(PRISM\ estimate)/CV(RPRISM\ estimate)$.

	HOUSELET	CVRALPHA	CVRBETA	CVRNAC	CVRBHO
J3	1.4346	1.48098	1.43650	1.43721	1.43721
J4	1.2616	1.27723	1.23600	1.19087	1.19087
J5	0.9699	0.86557	0.87988	0.96633	0.96633
J6	0.9937	0.98449	0.99632	0.99863	0.99863
J7	1.0000	1.00000	0.99999	1.00000	1.00000
J10	0.9439	0.93778	0.94341	0.94235	0.94235
J11	1.1467	1.29231	1.27696	1.19613	1.19613
J16	0.9114	0.91088	0.92075	0.92555	0.92555
J17	2.3054	2.03400	2.09349	2.24114	2.24114
J18	1.3612	1.22460	1.19067	1.23281	1.23281
J19	24.7267	2.56071	3.09515	7.56411	7.56411
J20	0.9898	1.00626	0.99599	0.99270	0.99270
J21	1.2719	1.26676	1.26914	1.26746	1.26746
J22	1.2014	1.10666	1.11979	1.22050	1.22050
J23	0.9267	1.53320	1.34504	1.20549	1.20549
J24	0.9975	0.99816	0.99232	0.98853	0.98853
J25	0.9210	0.92635	0.92276	0.92339	0.92339
J26	1.1856	1.02806	1.10503	1.14169	1.14169
J27	1.8689	1.77959	1.81185	1.83543	1.83543
J28	1.6071	2.83618	1.67226	3.27926	3.27926
J29	0.9837	0.98143	0.97863	0.97349	0.97349
J30	0.9635	0.94264	0.94422	0.93223	0.93223
J32	1.2104	1.21313	1.18649	1.17263	1.17263
J33	1.9095	1.67042	1.71545	1.80660	1.80660
J34	1.7542	1.48884	1.52292	1.59309	1.59309
J38	0.9163	0.92154	0.91790	0.91863	0.91863
J39	1.1050	1.32717	1.28069	1.19616	1.19616
J40	1.0460	1.03905	1.04349	1.04100	1.04100
J41	1.1364	1.11743	1.13700	1.13776	1.13776
J43	3.3816	6.50247	4.62454	5.07280	5.07280
J44	1.4618	1.43009	1.39962	1.43542	1.43542
J45	1.0329	1.49308	1.39372	1.17991	1.17991
J46	0.9819	1.10953	1.06799	1.03587	1.03587
J47	3.4330	2.40358	2.59330	2.81995	2.81995
J48	1.1098	1.15730	1.16880	1.11678	1.11678
J49	1.0442	1.03387	1.02378	1.07102	1.07102
J50	1.0000	1.00000	1.00029	1.00043	1.00043
J51	1.0528	1.03827	1.05450	1.05721	1.05721
J54	1.4411	1.45275	1.43335	1.42453	1.42453
J55	0.8789	0.87633	0.87917	0.87909	0.87909
J57	1.0000	1.00000	1.00010	1.00007	1.00007
J58	0.9566	1.01709	0.96438	0.96725	0.96725
J60	1.5654	1.60768	1.60282	1.48626	1.48626
J62	0.9560	0.98214	0.97619	0.99383	0.99383
J63	1.2576	1.41169	1.36797	1.27692	1.27692
J64	1.3988	1.10720	1.15382	1.29223	1.29223
J65	0.9479	0.95712	0.95829	0.96771	0.96771
J67	1.1372	1.02055	1.08034	1.12039	1.12039
J69	0.9272	0.92997	0.92726	0.92736	0.92736
J70	0.9334	0.93190	0.92881	0.92841	0.92841

Table 8. Summary statistics of CVRs of PRISM vs. RPRISM parameters for Elec-HO sample. (See Figures 7-10.)

	MIN	Q1	MED	Q3	MAX	MEAN
ALPHA	.88	.97	1.08	1.41	24.7	1.74
BETA	.87	.98	1.11	1.46	6.50	1.36
NAC	.88	.98	1.11	1.40	4.62	1.31
HEATING	.88	.98	1.13	1.33	7.56	1.45

Table 9. PRISM and RPRISM results for House J19 from Elec-HO sample.

PRISM

ESTIMATION FOR HOUSE J19 , PERIOD: DEC 19, 1978 TO DEC 19, 1979

REFERENCE TEMPERATURE	HEATING SLOPE	BASE LEVEL	NORM ANNUAL CONSUMPTION	R-SQUARE	NUM OF OBS
82.00 (13.34)	5.3130 (0.3713)	19.7923 (63.7163)	60022.2617 (1860.8901)	0.9699	12

HEATING PART OF NAC: 52793.1328 (23385.1953) % OF NAC 88.0 ENERGY UNITS:

CORRELATION MATRIX FOR ESTIMATES	INTERCEPT SLOPE REF TEMP	INTERCEPT SLOPE REFERENCE TEMP
	1.0	1.0
	0.4270	-0.5433
	-0.9882	1.0

ERROR VARIANCE: 308.3 NUMBER OF ITERATIONS: 7

TECHNICAL CODES: G RMF 0.000 RTF 0.000 FBT 0.000 MKP 0.000 TRT 0.000

RPRISM

ESTIMATION FOR HOUSE J19 , PERIOD: DEC 19, 1978 TO DEC 19, 1979

REFERENCE TEMPERATURE	HEATING SLOPE	BASE LEVEL	NORM ANNUAL CONSUMPTION	R-SQUARE	NUM OF OBS
75.38 (1.83)	5.3545 (0.1456)	53.6814 (6.9918)	61013.7539 (611.1587)	0.9920	12

HEATING PART OF NAC: 41406.6406 (2424.7996) % OF NAC 67.9 ENERGY UNITS:

CORRELATION MATRIX FOR ESTIMATES	INTERCEPT SLOPE REF TEMP	INTERCEPT SLOPE REFERENCE TEMP
	1.0	1.0
	0.3828	-0.6746
	-0.9172	1.0

ERROR VARIANCE: 55.45 NUMBER OF ITERATIONS: 2

TECHNICAL CODES: RMF 0.000 RTF 0.000 FBT 0.000 MKP 0.000 TRT 0.000

Table 10. PRISM and RPRISM results for House J44 from Elec-HO sample. House identifiers in column 1 are defined as follows: J44 - original data were run; K44 - Point D from data was inflated from 1940 kWh to 3000 kWh; O44 - Point D was removed from the data.

METHOD	OR	SAMP	TIME PERIOD	# PDS	# DAYS	RAW CONS	# ITS	RXR	TREF	BASELEVEL X PER DAY	SLOPE X PER HDD	NAC X PER YEAR
J44	CELL	12/19/78-12/19/79	12	365	20339	3	0.990	59.4(1.6)	29.04(1.65)	2.735(0.166)	20704.90(375.28)	
J44	CELL	12/19/78-12/19/79	12	365	20339	2	0.994	58.1(1.0)	29.33(1.14)	2.851(0.121)	20508.59(265.58)	
K44	CELL	12/19/78-12/19/79	12	365	21399	3	0.882	66.2(7.3)	26.58(8.61)	2.318(0.454)	21776.91(1393.56)	
K44	CELL	12/19/78-12/19/79	12	365	21399	1	0.983	58.1(1.0)	29.33(1.14)	2.850(0.121)	20508.74(265.59)	
O44	CELL	12/19/78-12/19/79	11	335	18399	5	0.998	56.9(0.9)	29.59(0.81)	2.981(0.106)	20316.54(206.61)	
O44	CELL	12/19/78-12/19/79	11	335	18399	2	0.998	56.8(1.2)	29.62(1.10)	2.974(0.143)	20287.43(279.46)	

Table 12. Distribution of final and simulated weights for Elec-HO sample using RPRISM (W = weight). Simulated weights are defined as the weights which would be observed if the residuals had a normal distribution.

W	DISTRIBUTION OF SIMULATED WEIGHTS (200 IDEAL SAMPLES OF SIZE 12)	
	% OF ACTUAL WEIGHTS < W	% OF SIMULATED WEIGHTS < W
1	19.6	21.38
.95	18.4	19.38
.90	17.0	17.17
.85	15.6	15.58
.80	15.1	13.83
.75	13.9	11.58
.70	12.1	9.21
.60	8.5	5.92
.50	6.6	3.29
.40	4.5	1.42
.30	1.5	.25
.20	.87	.04

Table 13. By-house PRISM results for 50 electrically heated and cooled homes in New Jersey (Elec-AC sample). Units for PRISM parameters are as follows: τ (TREF) = °F; α (BASELEVEL) = kWh/day; β (SLOPE) = kWh/°F-day; NAC(Normalized Annual Consumption) = kWh/year; β H₀(HEATING PART) = kWh/year.

ID	TIME PERIOD	# PDS	# DAYS	RAW ITS	RXR	TREF	BASELEVEL X PER DAY	SLOPE X PER HDD	NAC X PER YEAR	HEATING PART
J2810	12/13/78-12/13/79	12	365	20599	3	0.989	27.68(1.88)	3.029(0.207)	21091.89(421.75)	10980.0(579.0)
J2815	12/28/78-12/28/79	12	365	22739	4	0.976	24.13(3.88)	3.595(0.327)	23443.89(818.20)	14628.9(1188.3)
J2827	12/19/78-12/19/79	12	365	21329	3	0.925	18.87(8.66)	2.680(0.404)	21729.59(1300.86)	14838.7(2758.6)
J2827	12/28/78-12/28/79	12	365	29839	5	0.952	47.96(4.82)	3.820(0.509)	30534.96(1127.85)	13017.6(1430.4)
J2831	12/26/78-12/26/79	12	365	34469	4	0.983	40.80(4.42)	5.912(0.474)	35349.95(1033.03)	20448.8(1307.2)
J2832	12/26/78-12/26/79	12	365	42299	4	0.833	74.08(11.84)	4.395(1.206)	43136.22(2679.26)	16078.1(3599.8)
J2833	12/18/78-12/18/79	12	365	34109	3	0.917	67.00(6.60)	5.717(0.747)	43638.31(1568.83)	19167.4(1951.7)
J2836	12/28/78-12/28/79	12	365	19929	4	0.951	65.83(5.73)	4.310(0.862)	34660.31(1412.22)	10615.2(1674.3)
J2855	12/13/78-12/13/79	12	365	23519	5	0.963	28.28(3.61)	2.939(0.466)	20327.00(848.85)	9996.5(1089.9)
J2873	12/1/78-12/3/79	12	367	37519	3	0.977	29.18(4.32)	3.735(0.475)	24123.74(970.23)	13465.4(1332.0)
J2901	12/27/78-12/28/79	12	366	26669	7	0.881	53.94(4.56)	5.020(0.465)	37921.39(1049.62)	18219.0(1380.2)
J2902	12/4/78-12/4/79	12	365	27559	5	0.913	33.83(10.45)	3.012(0.619)	27174.64(1780.16)	14818.9(3334.8)
J2903	12/22/78-12/24/79	12	367	46759	5	0.983	36.09(7.52)	3.945(0.713)	28211.73(1680.10)	15029.6(2253.8)
J2906	12/22/78-12/24/79	12	367	21259	6	0.917	81.03(3.95)	3.970(0.310)	47006.64(787.82)	17411.7(1225.2)
J2923	12/5/78-12/5/79	12	365	16969	3	0.869	19.36(10.51)	2.307(0.356)	21338.59(1247.32)	14266.5(3380.4)
J2929	12/13/78-12/13/79	12	365	14239	3	0.981	18.85(6.35)	2.809(0.685)	17292.29(1483.21)	10407.6(1919.1)
J2933	12/5/78-12/5/79	12	365	33339	3	0.993	16.32(2.04)	3.145(0.305)	14522.86(478.75)	8560.5(591.9)
J2937	12/18/78-12/18/79	12	365	39559	5	0.975	32.20(2.93)	5.312(0.265)	34015.10(634.19)	22252.5(891.8)
J2956	12/28/78-12/28/79	12	365	33029	3	0.970	47.94(4.12)	4.907(0.482)	32790.19(973.29)	15279.2(1202.8)
J2959	11/30/78-11/30/79	12	365	26989	3	0.983	44.46(6.93)	3.901(0.388)	33866.09(1026.29)	14454.4(1947.8)
J2975	12/15/78-12/17/79	12	367	35539	3	0.983	34.11(3.47)	3.362(0.245)	27628.53(679.01)	15169.4(1076.1)
J2984	12/12/78-12/12/79	12	365	37239	3	0.989	52.06(3.74)	5.537(0.474)	35927.96(871.93)	16914.5(1104.5)
J2994	12/22/78-12/24/79	12	367	17869	4	0.874	51.37(3.36)	6.488(0.498)	37842.44(795.38)	19078.9(994.9)
J2995	12/22/78-12/24/79	12	367	19039	3	0.995	28.00(4.80)	2.558(0.570)	17971.90(162.64)	7746.2(1377.3)
J3000	12/19/78-12/19/79	12	365	30759	3	0.981	16.83(1.62)	3.138(0.139)	19316.95(317.56)	13168.4(492.6)
J3015	12/11/78-12/11/79	12	365	14589	3	0.991	28.97(2.70)	3.254(0.278)	22819.61(617.84)	12239.1(814.4)
J3023	12/13/78-12/13/79	12	365	34119	3	0.988	64.09(9.22)	7.356(0.672)	30545.85(2630.96)	7137.9(2550.6)
J3033	12/21/78-12/21/79	12	365	35699	3	0.882	16.28(1.42)	2.117(0.129)	14872.33(295.38)	8924.8(437.2)
J3040	12/28/78-12/28/79	12	365	38689	3	0.912	50.36(3.13)	4.063(0.278)	34828.97(645.25)	16436.1(964.3)
J3054	12/28/78-12/28/79	12	365	22089	4	0.979	69.51(7.50)	4.942(0.933)	39411.52(1808.27)	14024.6(2120.6)
J3061	12/18/78-12/18/79	12	365	25339	3	0.986	28.93(2.89)	3.461(0.305)	22680.07(676.30)	12115.1(857.7)
J3070	12/18/78-12/18/79	12	365	20309	3	0.985	36.27(2.66)	4.597(0.337)	25813.52(635.12)	12566.7(753.5)
J3075	12/19/78-12/19/79	12	365	28599	5	0.823	23.67(2.47)	3.812(0.289)	20784.57(583.79)	12137.6(721.5)
J3076	12/1/78-12/3/79	12	367	50679	5	0.819	41.28(13.55)	2.611(0.631)	29200.22(2034.98)	14122.9(4315.4)
J3078	12/1/78-12/3/79	12	367	39719	4	0.971	98.50(13.20)	7.174(2.610)	50835.78(3248.72)	14711.9(3891.6)
J3082	12/14/78-12/14/79	12	365	22709	3	0.975	61.45(5.17)	5.749(0.623)	40113.20(1228.88)	17737.7(1523.0)
J3087	11/30/78-11/30/79	12	365	38619	4	0.983	31.45(4.18)	2.529(0.237)	23191.51(625.82)	11703.1(1019.1)
J3107	12/6/78-12/6/79	12	365	61059	3	0.980	55.14(3.26)	5.123(0.408)	39511.53(954.90)	19373.1(1273.2)
J3112	12/28/78-12/28/79	12	365	10749	3	0.931	101.88(5.95)	5.528(0.461)	61857.50(192.11)	24646.6(1845.8)
J3113	12/28/78-12/28/79	12	365	35749	3	0.931	13.04(6.92)	1.626(0.576)	11095.67(1399.62)	6332.2(1923.4)
J3120	12/28/78-12/28/79	12	365	15699	3	0.987	18.24(1.86)	2.299(0.157)	16159.68(391.68)	9497.0(2025.6)
J3133	12/22/78-12/24/79	12	367	22559	3	0.974	34.18(2.82)	3.748(0.358)	22705.92(688.97)	10220.9(788.8)
J3143	12/1/78-12/3/79	12	367	53959	4	0.969	87.21(6.47)	6.133(0.659)	54352.79(1487.35)	22501.0(1955.8)
J3144	12/1/78-12/3/79	12	367	34069	4	0.989	62.44(2.20)	5.067(0.412)	34145.24(540.39)	11339.2(671.5)
J3171	12/19/78-12/19/79	12	365	26269	4	0.989	31.65(2.77)	3.809(0.233)	26869.25(577.71)	15310.6(848.0)
J3176	12/28/78-12/28/79	12	365	29269	4	0.983	47.15(2.75)	3.633(0.290)	29846.89(642.90)	12623.9(815.3)
J3178	12/18/78-12/18/79	12	365	14069	5	0.844	21.69(5.10)	3.322(0.950)	14187.59(1315.55)	6264.2(1439.7)

Table 14. By-house RPRISM results for Elec-AC sample. See Table 13 caption.

UNIT ID	# PDS	# DAYS	RAW CONS	# ITS	RXR	TREF	BASELEVEL X PER DAY	SLOPE X PER HDD	NAC X PER YEAR	HEATING PART
J2810	12	365	20599	2	0.992	59.4(1.8)	26.79(1.88)	3.040(0.207)	20993.99(422.44)	11210.2(580.0)
J2815	12	365	22739	3	0.981	61.0(2.2)	24.19(1.85)	3.568(0.274)	23180.68(685.21)	14344.6(995.2)
J2827	12	365	21329	1	0.937	67.7(6.1)	18.60(8.74)	2.701(0.407)	21912.51(1311.74)	15117.5(2781.7)
J2831	12	365	29839	3	0.956	57.0(3.4)	48.32(4.96)	3.918(0.563)	30247.76(1188.21)	12597.3(1460.1)
J2832	12	365	34469	1	0.984	58.5(2.4)	41.19(5.27)	5.846(0.564)	35247.18(1227.77)	20464.6(1553.6)
J2833	12	365	42259	2	0.933	64.5(4.6)	64.47(8.42)	3.951(0.560)	42520.91(1563.86)	18972.4(2651.1)
J2836	12	365	42909	2	0.974	59.3(2.3)	67.69(4.68)	5.271(0.467)	44092.61(1053.37)	19367.8(1425.9)
J2839	12	365	34109	2	0.924	52.8(5.9)	66.38(7.59)	4.276(1.143)	34810.76(1872.14)	10564.5(2219.5)
J2855	12	365	19929	2	0.956	58.2(3.9)	27.76(3.99)	2.957(0.469)	20311.59(913.59)	10173.8(1208.3)
J2855	12	365	23519	3	0.975	60.0(1.8)	50.78(3.71)	3.707(0.362)	23719.52(1812.71)	14123.9(1143.7)
J2873	12	367	37519	3	0.986	60.0(1.8)	32.16(3.25)	3.023(0.668)	37500.89(832.42)	18951.7(1109.7)
J2901	12	366	26669	3	0.882	65.0(7.8)	33.78(11.27)	3.023(0.668)	27212.65(1919.56)	14875.7(3596.0)
J2902	12	365	27559	2	0.986	58.4(1.8)	81.61(3.20)	4.878(0.354)	28759.86(747.91)	17012.6(958.6)
J2903	12	367	46749	2	0.964	63.3(2.2)	19.52(10.34)	3.855(0.280)	47289.38(744.31)	17482.9(1192.2)
J2906	12	367	21259	3	0.926	70.0(7.4)	16.83(5.67)	2.328(0.250)	21527.42(1227.98)	14398.9(3327.9)
J2929	12	365	16969	2	0.888	64.4(5.9)	14.69(2.06)	2.181(0.404)	16554.70(1080.54)	10406.8(1790.1)
J2933	12	365	14239	2	0.988	55.0(2.0)	32.52(2.29)	3.083(0.207)	14170.79(483.24)	8803.7(619.9)
J2937	12	365	33339	2	0.995	61.0(1.1)	45.39(2.71)	4.942(0.317)	34341.00(495.19)	22462.8(696.3)
J2949	12	365	32179	1	0.986	56.8(1.5)	69.99(6.93)	5.414(0.927)	32320.16(641.28)	15742.7(792.5)
J2956	12	365	39559	1	0.926	54.0(3.8)	43.00(3.24)	3.928(0.249)	40017.87(1728.23)	14454.4(1947.4)
J2959	12	365	26989	2	0.985	62.7(1.9)	32.82(3.70)	3.351(0.261)	32932.08(654.58)	17225.9(1008.1)
J2975	12	367	35539	1	0.985	63.7(2.5)	52.50(4.05)	5.488(0.261)	27501.09(724.65)	15512.4(1148.4)
J2984	12	365	37239	1	0.991	55.9(1.7)	51.19(3.11)	6.283(0.461)	36070.10(944.52)	16895.7(1196.5)
J2994	12	367	17869	2	0.901	54.4(4.4)	28.57(4.35)	2.697(0.552)	37612.08(735.72)	18914.4(920.2)
J2995	12	367	19039	2	0.995	61.9(1.3)	16.73(1.72)	3.136(0.148)	17825.59(1063.36)	7390.3(1217.4)
J3000	12	367	22549	1	0.983	59.5(2.3)	28.81(2.89)	3.280(0.297)	22904.27(359.47)	13193.6(524.5)
J3015	12	365	30759	1	0.768	41.5(7.8)	62.98(9.39)	7.374(3.737)	30260.70(2677.16)	12172.2(2595.4)
J3027	12	365	14589	2	0.993	62.1(1.2)	49.71(2.74)	2.087(0.085)	14833.18(206.34)	8905.3(318.6)
J3033	12	365	35699	3	0.884	60.8(1.9)	67.62(7.87)	4.140(0.264)	34631.42(593.19)	16474.6(834.7)
J3040	12	365	38689	2	0.944	55.5(4.3)	67.58(7.28)	4.839(1.138)	36017.16(1980.32)	11319.7(2250.3)
J3054	12	365	22089	1	0.985	59.1(1.8)	27.30(2.37)	4.948(0.905)	39205.90(1758.06)	14523.4(2130.4)
J3061	12	365	25339	1	0.994	55.2(1.1)	33.88(1.68)	3.439(0.213)	22451.25(545.60)	12479.7(717.0)
J3070	12	365	20309	1	0.991	57.9(1.3)	22.62(1.75)	3.653(0.198)	20647.53(415.58)	13046.3(492.7)
J3076	12	367	50679	2	0.853	64.8(7.8)	86.62(6.86)	2.900(0.691)	29408.99(1976.61)	12386.6(517.0)
J3078	12	367	39719	2	0.977	56.6(2.0)	59.63(4.03)	6.714(1.004)	48937.80(1647.55)	17300.1(1999.9)
J3082	12	365	22709	2	0.992	65.9(2.3)	30.87(1.74)	2.430(0.105)	39696.73(957.04)	17916.6(1186.1)
J3107	12	365	61059	1	0.988	59.1(1.7)	55.12(4.51)	5.124(0.440)	39532.91(1029.93)	19400.1(3305.1)
J3112	12	365	38619	1	0.983	59.9(2.3)	99.22(4.03)	5.612(0.338)	48937.80(1647.55)	17300.1(1999.9)
J3120	12	365	10749	2	0.949	58.7(5.7)	12.97(4.11)	1.918(0.434)	61092.07(845.52)	24852.2(1243.8)
J3133	12	365	35749	2	0.990	62.4(3.6)	60.24(6.07)	5.623(0.914)	35787.65(1497.29)	6808.1(1221.4)
J3143	12	365	15699	1	0.990	62.4(3.6)	18.01(1.70)	2.239(0.131)	16271.64(342.60)	13786.2(1775.6)
J3144	12	367	53959	3	0.976	54.3(2.8)	34.15(3.13)	3.747(0.398)	22700.55(765.58)	10227.9(876.5)
J3171	12	367	34069	1	0.993	60.0(1.5)	88.01(7.01)	5.960(0.646)	54849.07(1570.79)	22700.6(2094.1)
J3176	12	365	26269	2	0.992	61.8(1.6)	62.32(1.95)	5.326(0.385)	33870.36(478.85)	11109.0(573.6)
J3178	12	365	29269	2	0.984	58.2(2.4)	31.77(2.43)	3.711(0.204)	27133.88(506.75)	15530.1(743.9)
J3178	12	365	14069	2	0.871	47.8(5.4)	47.66(3.32)	3.635(0.351)	29925.01(777.71)	12515.9(986.3)
J3178	12	365	14069	2	0.871	47.8(5.4)	20.71(4.16)	3.307(0.956)	13238.96(1122.69)	5673.9(1159.9)

Table 15. Summary statistics of PRISM vs. RPRISM parameters for Elec-AC sample.

	MEDIAN		MEANS		
	REGULAR	ROBUST	REGULAR	ROBUST	
ALPHA	38.54	37.67	44.22	43.19	KWh/day
BETA	3.86	3.88	4.14	4.13	KWh/°F-day
BHO	14195	14234	14035	14257	KWh/Year
NAC	29524	29667	30186	30033	KWh/Year
R-SQUARE	.975	.982	.941	.957	
CV ALPHA	.101	.096	.140	.126	
CV BETA	.098	.092	.140	.122	
CV BHO	.084	.073	.119	.104	
CV NAC	.030	.027	.040	.035	

Table 16. By-house percent differences for each estimate for Elec-AC sample. Percent difference is defined as:

$$\left[\frac{(\text{RPRISM estimate} - \text{PRISM estimate})}{\text{PRISM estimate}} \right] * 100.$$

	HOUSELET	PCALPHA	PCBETA	PCNAC	PCBHO
J2810	-3.215	0.363	-0.4642	2.0965	
J2815	0.249	-0.751	-1.1227	-1.9434	
J2822	-1.431	0.784	0.8418	1.8789	
J2827	0.751	2.565	-0.9406	-3.2287	
J2831	0.956	-1.116	0.4533	0.0773	
J2832	-12.972	-10.102	-1.4264	18.0015	
J2833	1.030	-7.801	1.0411	1.0455	
J2836	0.835	-0.789	0.4341	-0.4776	
J2839	-1.839	0.612	-0.0758	1.7736	
J2855	-9.973	-0.750	-1.6756	4.8903	
J2873	-5.858	-0.896	-1.1089	4.0216	
J2901	-0.148	0.365	0.1399	0.3833	
J2902	-10.889	23.650	1.9429	13.1940	
J2903	0.716	-2.897	0.6015	0.4089	
J2906	0.826	0.910	0.8849	0.9280	
J2923	-10.716	-22.357	-4.2654	-0.0077	
J2929	-9.988	-1.971	-2.4242	2.8410	
J2933	0.994	5.083	0.9581	0.9451	
J2937	-5.319	0.713	-1.4334	3.0335	
J2949	0.000	0.000	0.0000	0.0000	
J2956	-3.284	0.692	-2.7580	-2.2766	
J2959	-3.782	-0.327	-0.4613	2.2611	
J2975	0.845	-0.885	0.3956	-0.1111	
J2984	-0.350	3.160	-0.6087	-0.8622	
J2994	2.036	5.434	-0.8141	-4.5945	
J2995	-0.594	-0.064	-0.0656	0.1914	
J3000	-0.552	0.799	-0.5443	-0.5466	
J3015	-1.732	0.245	-0.9335	1.6798	
J3023	-0.307	-1.417	-0.2632	-0.2185	
J3027	-1.291	1.895	-0.5672	0.2342	
J3033	-0.221	-0.165	-0.2042	-0.1552	
J3040	-2.777	0.121	-0.5217	3.5566	
J3054	-5.634	-0.636	-1.0089	3.0095	
J3061	-6.589	-1.849	-1.5201	3.8164	
J3070	-4.436	-4.171	-0.6593	2.0515	
J3075	1.502	11.069	0.7150	-0.1204	
J3076	-12.417	-6.412	-3.7336	17.5926	
J3078	-2.661	-0.609	-1.0382	1.0086	
J3082	-1.844	-3.915	0.3195	2.4498	
J3087	-0.036	0.020	0.0541	0.1425	
J3107	-2.611	1.520	-1.2375	0.8342	
J3112	-0.537	17.958	4.0519	7.5156	
J3113	1.585	8.846	-1.9080	-6.9970	
J3120	-1.261	-2.610	0.6928	2.0712	
J3133	-0.088	-0.027	-0.0237	0.0685	
J3143	0.917	-2.821	0.9131	0.9048	
J3144	-0.192	5.112	-0.8050	-2.0301	
J3171	0.379	-2.573	0.9849	1.4336	
J3176	1.082	0.055	0.2617	-0.8555	
J3178	-4.518	-0.452	-6.6863	-9.4234	

Table 17. Summary statistics of percent differences of PRISM vs. RPRISM parameters for Elec-AC sample. (See Figures 25-28.)

	MIN	Q1	MED	Q3	MAX	MEAN
ALPHA	-13.0	-3.9	-.57	.72	2.04	-2.3
BETA	-22.4	-1.9	-.11	.79	23.7	.146
NAC	-6.7	-1.1	-.46	.44	4.05	-.512
HEATING	-9.4	-.17	.86	2.3	18.0	1.45

Table 18. By-house summary of the ratio of the coefficients of variation (CVR) for PRISM vs. RPRISM estimates for Elec-AC sample. $CVR = CV(PRISM \text{ estimate})/CV(RPRISM \text{ estimate})$.
HOUSELET CVRALPHA CVRBETA CVRNAC CVRBHO

J2810	0.96785	1.00363	0.99373	1.01921
J2815	1.19681	1.18447	1.18068	1.17083
J2822	0.97667	1.00041	1.00005	1.01033
J2831	0.84995	0.92728	0.94027	0.94803
J2832	1.22376	0.83104	0.84520	0.84205
J2833	1.42478	1.93601	1.68880	1.60229
J2836	0.76125	1.47478	1.50485	1.38306
J2839	0.88813	0.74821	0.75761	0.75076
J2855	1.03712	0.99969	0.92843	0.91801
J2873	1.15710	1.30232	1.17382	1.22160
J2901	0.92587	1.34746	1.24694	1.29378
J2902	2.09410	0.93003	0.92868	0.93092
J2903	1.03332	2.49047	2.29004	2.66135
J2906	1.02484	1.07507	1.06482	1.03188
J2923	0.99992	1.02640	1.02474	1.02520
J2929	0.89138	1.31648	1.31411	1.07198
J2933	1.29219	0.97708	0.96669	0.98196
J2937	1.43943	1.34526	1.29297	1.29287
J2949	1.00000	1.53135	1.49597	1.56377
J2956	1.62985	1.00000	1.00003	1.00005
J2959	0.90237	1.56902	1.57713	1.64611
J2975	0.93126	0.93563	0.93270	0.95823
J2984	1.07660	0.91580	0.92680	0.92208
J2994	1.12591	1.04613	1.07451	1.07186
J2995	0.93626	1.08872	1.08446	1.07937
J3015	0.96489	0.93859	0.93843	0.94098
J3023	1.38788	0.98501	0.97357	0.99925
J3027	1.12759	1.49614	1.42775	1.36926
J3033	0.93566	1.07299	1.08159	1.15797
J3040	1.00161	0.93519	0.93511	0.93558
J3054	1.15070	1.03219	1.02319	1.03080
J3061	1.47900	1.27337	1.22705	1.23223
J3070	1.34882	1.55290	1.55790	1.58769
J3075	1.31111	1.39872	1.39550	1.42418
J3076	1.68528	1.01424	1.03689	1.30411
J3078	1.24874	2.43291	1.89823	2.28823
J3082	1.83901	1.27672	1.27071	1.29699
J3107	0.92649	2.16878	2.07757	1.88937
J3112	1.43788	0.92745	0.92765	0.92850
J3113	1.53914	1.38463	1.39247	1.49638
J3120	1.15810	1.56553	1.51216	1.69310
J3133	0.90017	1.02535	1.09510	1.06127
J3143	0.93143	1.16720	1.15118	1.10061
J3144	1.12604	0.89926	0.89972	0.90056
J3171	1.14424	0.99135	0.95553	0.94241
J3176	0.83727	1.12483	1.11943	1.14691
J3178	1.17057	1.11277	1.15126	1.15628
J3178	0.82667	0.82667	0.82882	0.81955
J3178	0.98924	1.09343	1.09343	1.12426

Table 19. Summary statistics of CVRs of PRISM vs. RPRISM parameters for Elec-AC sample. (See Figures 30-33.)

	MIN	Q1	MED	Q3	MAX	MEAN
ALPHA	.76	.93	1.08	1.30	2.09	1.15
BETA	.75	.97	1.06	1.36	2.49	1.21
NAC	.76	.94	1.08	1.33	2.29	1.18
HEATING	.75	.95	1.08	1.32	2.66	1.20

Table 20. By-house PRISM results for 69 oil-heated homes in New Jersey (OIL). Units for PRISM parameters are as follows: τ (TREF) - °F; α (BASELEVEL) = gallons/day; β (SLOPE) = gallons/°F-day; NAC(Normalized Annual Consumption) = gallons/year; β_{H_0} (HEATING PART) = gallons/year.

UNIT ID	# PDS	# DAYS	CON RAW	HW	RXR	TREF	BASELEVEL X PER DAY	SLOPE X PER HDD	NAC X PER YEAR	HEATING PART
P18646	11	1541	1845	H	0.984	59.1(4.9)	0.04(0.19)	0.101(0.013)	384.11(22.77)	368.0(60.2)
P24939	13	790	4573	HW	0.957	68.9(7.1)	0.64(1.29)	0.287(0.031)	1922.39(132.30)	1688.3(399.0)
P45584	9	823	2950	HW	0.961	57.6(7.3)	1.76(0.59)	0.219(0.048)	1214.49(83.35)	728.0(171.2)
P56368	12	1147	6853	HW	0.984	61.1(4.8)	1.33(0.69)	0.338(0.038)	2008.90(81.33)	1367.0(217.9)
P61454	15	756	2508	HW	0.975	58.5(2.9)	0.79(0.37)	0.240(0.019)	1130.32(62.96)	842.8(93.3)
P64773	9	414	3078	HW	0.970	62.7(4.4)	2.67(1.01)	0.415(0.050)	2795.51(144.89)	1820.1(264.8)
P69085	13	742	7688	HW	0.966	69.3(6.5)	-1.34(2.95)	0.683(0.064)	3601.62(282.79)	4090.6(910.7)
P76263	9	159	1462	HW	0.205	37.0(20.9)	8.98(0.97)	0.223(0.498)	3418.03(276.21)	137.1(118.3)
P88006	12	756	1744	H	0.937	55.9(5.4)	0.33(0.57)	0.223(0.037)	790.92(102.59)	671.4(136.4)
P01249	12	1150	4129	HW	0.993	62.9(2.3)	1.31(0.18)	0.169(0.009)	1230.78(26.57)	750.9(56.5)
P07232	14	760	2371	H	0.972	80.0(26.3)	-1.96(4.40)	0.192(0.017)	1055.99(76.22)	1773.4(1618.2)
P07234	14	760	2294	H	0.984	91.0(-9.9)	-3.78(-9.90)	0.183(0.007)	1028.41(52.09)	2409.2(-9.9)
P11122	9	91	1675	HW	0.979	52.0(20.2)	6.71(9.91)	0.548(0.045)	3734.54(1902.14)	1281.9(1721.4)
P15920	12	825	1650	H	0.881	61.9(11.2)	-0.23(0.98)	0.177(0.053)	660.09(126.56)	745.1(277.3)
P38343	16	740	2971	HW	0.982	60.6(2.6)	1.31(0.33)	0.244(0.016)	1437.71(50.83)	960.3(87.0)
P45522	12	1060	4088	HW	0.911	60.1(7.0)	1.58(0.77)	0.223(0.043)	1430.54(120.19)	852.4(209.0)
P53095	13	790	2263	H	0.957	72.1(10.1)	-0.66(1.25)	0.174(0.019)	940.73(86.14)	1181.1(139.1)
P64672	12	1178	1984	HW	0.979	64.4(5.0)	-0.33(0.47)	0.223(0.016)	702.26(52.06)	821.6(139.2)
P65868	11	781	2121	HW	0.938	64.6(6.5)	0.71(0.52)	0.139(0.020)	929.14(70.59)	1181.1(139.1)
P75223	12	479	3069	HW	0.930	74.3(32.3)	0.89(7.40)	0.293(0.078)	1840.41(425.68)	669.5(146.6)
P12537	14	523	1831	HW	0.952	69.5(8.3)	0.69(0.82)	0.251(0.017)	1170.09(71.44)	2165.9(2469.0)
P43660	11	1125	3603	HW	0.980	67.3(6.6)	0.53(0.52)	0.164(0.021)	1094.84(45.34)	917.3(255.9)
P60414	14	751	2091	HW	0.970	59.6(3.7)	0.11(0.53)	0.245(0.021)	956.35(38.11)	899.9(178.4)
P67590	9	919	3027	HW	0.988	63.3(3.6)	0.86(0.29)	0.171(0.016)	1086.17(83.09)	773.0(133.1)
P73573	12	1055	2046	HW	0.990	72.2(5.5)	-0.12(0.41)	0.113(0.007)	724.90(24.89)	85.9(140.9)
P01990	13	724	1923	HW	0.954	56.8(4.4)	-0.04(0.70)	0.302(0.037)	948.04(116.77)	768.6(140.9)
P08723	4	977	3772	HW	0.983	60.8(6.2)	0.68(0.54)	0.218(0.030)	791.96(65.19)	962.6(164.5)
P34601	12	1140	3078	HW	0.936	61.5(11.0)	0.60(0.61)	0.139(0.034)	1114.42(56.19)	572.3(205.0)
P36769	9	479	3115	H	0.964	66.1(7.4)	-0.28(1.99)	0.381(0.044)	2084.53(220.77)	866.6(175.4)
P40687	11	1015	1709	HW	0.971	73.5(11.4)	-0.58(0.96)	0.234(0.019)	1077.70(55.29)	1981.4(553.1)
P54641	12	1140	2125	H	0.960	66.0(9.8)	0.58(0.96)	0.122(0.014)	660.29(50.40)	1167.1(173.1)
P63320	12	1049	2088	HW	0.988	64.3(4.4)	0.02(0.30)	0.155(0.023)	747.62(32.50)	665.8(211.0)
P74200	9	76	1614	H	0.983	50.0(4.9)	6.36(2.56)	0.689(0.051)	3724.60(504.67)	738.5(92.2)
P96389	12	973	3978	HW	0.976	65.4(3.5)	1.19(0.43)	0.226(0.018)	1560.50(62.23)	1400.1(443.8)
P96538	16	534	2548	HW	0.940	71.4(5.7)	0.17(0.85)	0.226(0.017)	1547.11(68.04)	1124.8(130.6)
P97666	17	536	2750	HW	0.955	64.0(5.5)	0.16(1.23)	0.335(0.033)	1626.86(159.26)	1484.8(279.6)
P07303	9	426	5377	HW	0.955	62.3(4.9)	4.54(1.95)	0.685(0.098)	4613.74(285.29)	1567.8(336.3)
P08396	12	1128	3231	HW	0.941	65.0(12.8)	0.06(1.21)	0.190(0.041)	956.60(88.54)	2954.6(404.1)
P23555	9	1522	2757	H	0.955	47.6(5.6)	0.52(0.29)	0.248(0.069)	611.53(51.42)	933.8(404.1)
P55178	13	1061	2274	HW	0.970	62.3(4.3)	1.04(0.41)	0.137(0.013)	792.12(43.77)	421.5(81.9)
P74022	12	1087	4671	HW	0.996	63.5(10.9)	-0.32(0.68)	0.252(0.015)	1535.06(31.44)	588.3(90.1)
P02952	11	1070	1774	HW	0.880	46.0(8.3)	0.97(0.28)	0.179(0.092)	544.60(44.91)	662.6(236.3)
P19896	11	1549	3831	H	0.993	91.0(-9.9)	-3.52(-9.90)	0.159(0.005)	809.64(26.19)	265.0(68.5)
P37925	14	772	2113	H	0.969	61.1(4.4)	-0.13(0.59)	0.232(0.021)	888.20(82.91)	2093.9(-9.9)
P57490	14	707	2401	HW	0.965	76.5(13.0)	0.02(1.54)	0.158(0.016)	1285.04(58.86)	937.2(158.9)
P81425	14	772	2395	H	0.977	70.7(6.2)	-0.25(0.75)	0.177(0.013)	1035.79(62.21)	1277.6(550.4)
P83519	9	351	1678	HW	0.976	61.8(3.6)	1.93(0.51)	0.257(0.027)	1783.94(80.64)	1127.9(235.0)
P83818	11	1133	3730	HW	0.984	78.0(18.5)	-1.66(3.04)	0.199(0.017)	1096.90(65.92)	1080.2(128.6)

Table 20 (cont'd).

P03401	2/ 5/79-	2/23/81	15	749	2320	HW	0.934	64.2(6.5)	1.15(0.49)	0.141(0.019)	1085.48(65.90)	666.0(147.4)
P18951	10/23/78-	2/ 3/81	12	834	1970	H	0.956	65.2(6.7)	-0.22(0.68)	0.169(0.021)	762.30(78.19)	841.6(197.5)
P19700	12/14/78-	2/13/81	13	792	1910	H	0.965	61.5(4.8)	-0.15(0.56)	0.198(0.020)	761.93(79.87)	815.6(147.7)
P19848	4/19/76-	1/ 9/81	10	1726	3409	HW	0.974	61.1(7.0)	0.44(0.36)	0.137(0.024)	712.67(36.57)	552.0(122.3)
P21045	3/ 4/78-	2/16/81	12	1080	2151	H	0.982	74.0(11.2)	-0.43(0.95)	0.121(0.012)	722.91(35.51)	881.6(332.3)
P31218	11/28/78-	5/30/80	9	549	3178	HW	0.957	58.8(8.0)	2.01(1.04)	0.321(0.073)	1877.72(137.89)	1142.1(286.6)
P35704	11/ 5/79-	2/20/81	18	473	3248	HW	0.916	68.4(6.9)	0.92(1.41)	0.301(0.035)	2073.55(162.46)	1739.3(417.7)
P39899	11/ 3/72-	9/14/73	9	315	1453	H	0.983	64.6(3.3)	-0.55(0.80)	0.403(0.078)	1742.72(109.48)	1942.1(206.0)
P48572	4/12/79-	2/19/81	15	679	4734	H	0.894	70.1(12.2)	-1.10(4.15)	0.494(0.035)	2669.30(353.08)	3070.1(1292.8)
P71306	12/10/77-	1/16/81	11	1133	3597	H	0.980	62.1(5.1)	0.16(0.59)	0.235(0.025)	1059.90(71.02)	1000.9(178.2)
P91342	3/ 8/79-	2/16/81	14	697	2391	H	0.950	66.9(5.8)	0.81(0.62)	0.188(0.022)	1307.80(75.67)	1011.9(187.5)
P03009	5/ 3/79-	2/16/81	16	655	2863	HW	0.989	68.7(2.7)	0.17(0.49)	0.270(0.011)	1641.41(53.96)	1579.7(146.8)
P05292	5/12/76-	9/ 2/80	10	1574	2023	HW	0.287	58.0(55.9)	2.14(0.56)	-0.078(0.218)	517.35(140.17)	-264.8(207.8)
P13631	4/14/76-	1/17/81	10	1739	3136	H	0.990	56.4(4.2)	0.11(0.22)	0.193(0.025)	637.58(27.30)	597.2(78.3)
P40400	5/ 1/78-	1/27/81	12	1002	2470	HW	0.989	67.3(6.2)	-0.07(0.55)	0.179(0.018)	951.36(38.44)	978.1(188.6)
P48878	5/17/77-	1/23/81	11	1347	3870	HW	0.972	65.5(5.7)	-0.19(0.68)	0.223(0.023)	1052.12(76.09)	1122.9(218.5)
P78349	3/22/78-	5/ 6/80	9	776	4730	HW	0.909	89.0(-9.9)	-4.72(-9.90)	0.317(0.038)	2226.38(215.23)	3952.0(-9.9)
P02626	1/15/79-	1/29/81	13	745	2031	H	0.977	63.8(4.2)	-0.37(0.61)	0.231(0.018)	939.12(80.05)	1073.0(166.3)
P05616	3/ 5/79-	2/11/81	15	709	2685	H	0.986	75.0(6.8)	-0.77(1.17)	0.223(0.012)	1416.92(54.78)	1698.4(405.6)

Table 21. By-house OUTWTS results for OIL sample. See Table 20 caption.

UNIT ID	# PDS	# DAYS	RAW CONS	HW	RXR	TREF	BASELEVEL X PER DAY	SLOPE X PER HDD	NAC X PER YEAR	HEATING PART
P18646	11	1541	1845	H	0.987	57.8 (5.0)	0.08 (0.14)	0.105 (0.016)	383.85 (15.39)	353.5 (50.9)
P24939	13	790	4573	HW	0.973	69.8 (5.5)	0.52 (0.80)	0.281 (0.028)	1914.32 (83.14)	1726.0 (278.1)
P45584	9	823	2950	HW	0.969	54.5 (5.4)	1.51 (0.36)	0.242 (0.051)	1220.25 (57.38)	667.9 (110.1)
P56368	12	2/77-4/21/80	6853	HW	0.989	63.7 (4.0)	1.45 (0.49)	0.321 (0.030)	2011.99 (55.06)	1482.1 (172.6)
P61454	15	756	2508	HW	0.983	58.1 (2.1)	0.82 (0.18)	0.241 (0.018)	1125.97 (39.05)	826.6 (56.6)
P64773	9	414	3078	HW	0.978	60.7 (3.1)	0.295 (0.52)	0.438 (0.054)	2813.85 (102.23)	1736.5 (148.8)
P69085	13	742	7688	HW	0.985	70.6 (4.9)	-1.72 (1.69)	0.665 (0.056)	3599.00 (146.76)	4227.9 (594.9)
P76263	9	159	1462	HW	0.655	75.0 (-9.9)	4.43 (-9.90)	0.140 (0.039)	2687.69 (222.80)	1069.8 (-9.9)
P88006	12	756	1744	H	0.952	55.2 (5.3)	0.27 (0.35)	0.229 (0.044)	758.78 (65.85)	659.9 (115.2)
P01249	12	1150	4129	HW	0.990	63.3 (2.4)	1.23 (0.17)	0.170 (0.011)	1219.95 (24.91)	770.6 (57.0)
P07232	14	760	2371	H	0.989	91.0 (-9.9)	-3.91 (-9.90)	0.188 (0.006)	1056.48 (34.43)	2485.1 (-9.9)
P07234	14	760	2294	H	0.994	91.0 (-9.9)	-3.76 (-9.90)	0.182 (0.004)	1022.50 (25.56)	2397.6 (-9.9)
P11122	9	91	1675	HW	0.979	52.0 (22.7)	6.73 (10.98)	0.546 (0.059)	3736.19 (2095.06)	1278.0 (1917.6)
P15920	12	825	1650	H	0.951	59.8 (6.3)	-0.12 (0.39)	0.182 (0.034)	640.46 (56.27)	685.2 (127.9)
P38343	16	740	2971	HW	0.988	61.6 (2.4)	1.24 (0.20)	0.237 (0.017)	1434.24 (32.19)	982.8 (65.9)
P45522	12	1060	4088	HW	0.941	59.8 (5.6)	1.56 (0.40)	0.229 (0.046)	1431.05 (74.05)	861.6 (128.6)
P53095	13	790	2263	H	0.978	70.3 (5.6)	-0.44 (0.37)	0.165 (0.017)	700.50 (27.31)	861.3 (134.0)
P64672	12	1062	1984	H	0.988	66.2 (5.1)	-0.50 (0.55)	0.178 (0.015)	933.27 (43.72)	1114.3 (193.7)
P65868	11	781	2121	HW	0.991	64.8 (5.0)	0.69 (0.28)	0.138 (0.019)	922.80 (44.05)	671.3 (92.5)
P75223	9	479	3069	HW	0.903	76.1 (32.9)	-1.16 (6.86)	0.278 (0.070)	1794.11 (239.88)	2216.1 (2449.2)
P12537	14	523	1831	HW	0.975	70.7 (6.5)	0.61 (0.52)	0.147 (0.015)	1163.89 (38.97)	940.0 (182.8)
P43660	11	1125	3603	H	0.984	66.7 (6.0)	0.58 (0.40)	0.166 (0.021)	1097.64 (35.49)	886.0 (144.4)
P60414	14	751	2091	H	0.982	59.5 (2.9)	0.08 (0.25)	0.247 (0.022)	942.96 (44.23)	914.2 (83.5)
P67590	9	919	3027	HW	0.991	63.2 (3.2)	0.87 (0.21)	0.171 (0.016)	1086.27 (27.94)	769.0 (66.4)
P01990	12	1055	2046	HW	0.994	70.8 (3.3)	-0.04 (0.21)	0.116 (0.006)	724.20 (14.55)	740.1 (72.9)
P08723	13	724	1923	H	0.977	56.6 (3.1)	0.52 (0.56)	0.133 (0.034)	786.74 (49.11)	597.4 (206.3)
P34601	11	1412	3078	HW	0.937	63.1 (11.2)	0.84 (0.35)	0.227 (0.032)	1114.39 (36.87)	805.9 (127.2)
P36769	9	479	3115	H	0.976	58.7 (5.1)	0.44 (0.91)	0.394 (0.051)	2080.44 (122.05)	1919.3 (282.7)
P39089	12	1140	3736	H	0.980	64.8 (5.1)	-0.36 (0.42)	0.228 (0.018)	1076.63 (29.86)	1209.5 (152.9)
P40687	11	1015	1709	HW	0.981	71.4 (7.5)	-0.44 (0.51)	0.124 (0.014)	654.26 (29.96)	815.1 (181.9)
P54641	12	1099	2125	H	0.993	67.0 (9.4)	-0.01 (0.53)	0.127 (0.021)	680.81 (28.74)	685.0 (192.6)
P63320	12	1049	2088	HW	0.986	62.8 (3.1)	0.10 (0.18)	0.161 (0.013)	745.90 (19.59)	710.6 (396.3)
P74200	9	76	1614	H	0.986	50.0 (4.4)	6.20 (2.23)	0.049 (0.049)	3681.67 (432.06)	1417.1 (396.3)
P96389	12	973	3978	HW	0.982	62.7 (3.4)	0.53 (0.17)	0.136 (0.013)	1552.16 (47.64)	1128.2 (95.6)
P96538	16	534	2548	HW	0.985	70.7 (4.0)	1.16 (0.28)	0.223 (0.018)	1539.71 (44.94)	1450.1 (165.5)
P97666	17	536	2750	H	0.968	63.8 (3.5)	0.25 (0.47)	0.227 (0.016)	1602.16 (81.68)	1563.9 (162.2)
P07303	9	426	5377	HW	0.976	64.3 (3.9)	4.04 (1.07)	0.338 (0.031)	4594.11 (174.79)	3118.2 (319.9)
P08396	12	1128	3231	HW	0.957	63.7 (10.1)	0.21 (0.75)	0.656 (0.086)	4594.11 (174.79)	887.5 (273.4)
P23555	9	1522	2757	H	0.954	66.0 (10.1)	-0.28 (0.59)	0.193 (0.041)	963.17 (56.58)	710.0 (209.1)
P55178	13	1061	2274	H	0.982	62.7 (3.4)	0.53 (0.17)	0.136 (0.013)	790.67 (25.44)	596.7 (58.6)
P74022	12	1087	4671	HW	0.996	63.4 (3.4)	0.252 (0.16)	0.252 (0.016)	1533.10 (23.13)	1150.7 (130.1)
P75517	11	1099	1725	H	0.983	64.6 (9.1)	-0.23 (0.48)	0.129 (0.023)	541.70 (26.75)	624.7 (174.1)
P02952	11	1070	1774	HW	0.887	58.8 (11.3)	0.70 (0.29)	0.099 (0.040)	607.89 (45.73)	624.7 (174.1)
P19896	11	1549	3831	H	0.991	91.0 (-9.9)	-3.48 (-9.90)	0.158 (0.005)	812.69 (21.32)	2083.4 (-9.9)
P37925	14	772	2113	H	0.985	61.5 (3.2)	-0.19 (0.27)	0.231 (0.019)	882.28 (43.72)	950.0 (93.6)
P57490	14	707	2401	HW	0.973	72.0 (6.5)	0.45 (0.57)	0.164 (0.017)	1268.69 (39.05)	1104.1 (203.8)
P81425	14	772	2395	H	0.990	69.9 (4.1)	-0.20 (0.38)	0.180 (0.012)	1034.80 (30.15)	1108.7 (132.9)
P83519	9	351	1678	HW	0.983	62.7 (3.0)	1.80 (0.29)	0.253 (0.028)	1771.14 (57.39)	1112.5 (87.7)
P83818	11	1133	3730	HW	0.988	70.6 (6.2)	-0.68 (0.73)	0.212 (0.018)	1096.43 (40.95)	1345.1 (260.5)

Table 21 (cont'd).

P03401	2/ 5/79-	2/23/81	15	749	2320	HW	0.967	61.8(4.1)	1.22(0.22)	0.152(0.018)	1087.53(37.92)	640.9(74.7)
P18951	10/23/78-	2/ 3/81	12	834	1970	H	0.980	67.4(6.6)	-0.35(0.50)	0.161(0.020)	757.84(37.86)	885.7(172.6)
P19700	12/14/78-	2/13/81	13	792	1910	H	0.981	62.5(4.3)	-0.24(0.31)	0.193(0.020)	752.24(40.76)	840.0(109.5)
P19848	4/19/76-	1/ 9/81	10	1726	3409	HW	0.976	59.6(6.9)	0.49(0.29)	0.144(0.028)	716.17(27.94)	537.2(106.8)
P21045	3/ 4/78-	2/16/81	12	1080	2151	H	0.990	71.8(6.6)	-0.28(0.44)	0.123(0.011)	721.42(20.35)	825.4(156.7)
P31218	11/28/78-	5/30/80	9	549	3178	HW	0.965	55.5(5.8)	2.33(0.61)	0.354(0.078)	1894.17(96.52)	1041.8(177.3)
P35704	11/ 5/79-	2/20/81	18	473	3248	HW	0.993	65.7(4.1)	1.13(0.59)	0.321(0.034)	2042.51(96.68)	1629.4(191.5)
P39899	11/ 3/72-	9/14/73	9	315	1453	H	0.956	63.4(2.5)	-0.46(0.34)	0.418(0.037)	1733.29(57.75)	1900.7(107.8)
P48572	4/12/79-	2/19/81	15	679	4734	H	0.984	68.4(6.8)	-0.75(1.63)	0.508(0.069)	2647.06(165.69)	2922.1(581.5)
P71306	12/10/77-	1/16/81	11	1133	3597	H	0.984	63.2(5.1)	0.06(0.47)	0.230(0.026)	1057.52(46.96)	1034.7(165.7)
P91342	3/ 8/79-	2/ 2/81	14	697	2391	H	0.956	66.4(4.9)	0.83(0.41)	0.190(0.024)	1299.56(60.02)	997.8(138.8)
P03009	5/ 3/79-	2/16/81	16	655	2863	HW	0.995	69.2(1.8)	0.11(0.24)	0.268(0.010)	1644.08(29.57)	1603.0(85.1)
P05292	5/12/76-	9/ 2/80	10	1574	2023	HW	0.264	85.0(***)	2.42(35.58)	-0.038(0.032)	461.83(131.93)	-420.4(12955.3)
P13631	4/14/76-	1/17/81	10	1739	3136	H	0.986	56.5(4.7)	0.13(0.22)	0.190(0.029)	639.73(24.12)	593.4(85.1)
P40400	5/ 1/78-	1/27/81	12	1002	2470	HW	0.993	70.3(6.1)	-0.34(0.54)	0.171(0.015)	946.92(24.26)	1071.8(195.6)
P48878	5/17/77-	1/23/81	11	1347	3870	HW	0.974	67.7(5.7)	-0.35(0.55)	0.212(0.024)	1053.88(51.35)	1183.5(202.2)
P78349	3/22/78-	5/ 6/80	9	776	4730	HW	0.945	89.0(-9.9)	-5.19(-9.90)	0.329(0.030)	2210.05(153.26)	4106.3(-9.9)
P02626	1/15/79-	1/29/81	13	745	2031	H	0.988	62.8(3.2)	-0.28(0.28)	0.234(0.019)	930.07(38.79)	1031.6(98.5)
P05616	3/ 5/79-	2/11/81	15	709	2685	H	0.992	74.3(4.9)	-0.67(0.73)	0.225(0.012)	1413.31(30.70)	1659.8(264.6)

Table 22. Summary statistics of PRISM vs. OUTWTS parameters for OIL sample.

	REGULAR		OUTWTS		
	MEDIANS	MEANS	MEDIANS	MEANS	
ALPHA	.16	.475	.13	.381	gal/day
BETA	.219	.239	.212	.237	gal/°F-day
BHO	963	1197	998	1215	gal/year
NAC	1086	1371	1086	1354	gal/year
R-SQUARE	.971	.942	.982	.961	
CV ALPHA	.393	1.53	.241	-.953	
	(HW=.487)	(HW=4.40)	(HW=.410)	(HW=1.22)	
CV BETA	.106	.113	.104	.107	
CV BHO	.198	.247	.141	-.274	
CV NAC	.068	.081	.041	.055	

Table 23. By-house percent differences for each estimate for OIL sample. Percent difference is defined as:

$$\left[\frac{(\text{RPRISM estimate} - \text{PRISM estimate})}{\text{PRISM estimate}} \right] * 100.$$

; HOUSELET PCALPHA PCBETA PCNAC PCBHO HOT WATER

	PCALPHA	PCBETA	PCNAC	PCBHO	HOT WATER
P18646	100.00	3.960	-0.068	-3.940	H
P24939	-18.75	-2.091	-0.420	2.233	HW
P45584	13.53	10.502	0.474	-8.255	HW
P56368	-17.61	-5.030	0.154	8.420	HW
P61454	3.80	0.417	-0.385	-1.922	HW
P64773	10.49	5.542	0.656	-4.593	HW
P69085	28.36	-2.635	-0.073	3.356	HW
P76263	-50.67	-37.220	-21.367	680.306	HW
P88006	-18.18	2.691	-4.064	-1.713	H
P01249	-6.11	0.592	-0.880	2.624	HW
P07232	99.49	-2.083	0.046	40.132	H
P07234	-0.53	-0.546	-0.575	-0.481	H
P11122	0.30	-0.365	0.044	-0.304	HW
P15920	-47.83	2.825	-2.974	-8.039	H
P38343	-5.34	-2.869	-0.241	2.343	HW
P45522	-1.27	2.691	0.036	1.079	HW
P53095	33.33	-3.509	-0.251	4.832	H
P64672	-24.24	2.299	-0.793	-5.656	H
P65868	-2.82	-0.719	-0.682	0.269	HW
P75223	30.34	-5.119	-2.516	2.318	HW
P12537	-11.59	-2.649	-0.530	2.475	HW
P43660	9.43	1.220	0.256	-1.545	HW
P60414	-27.27	0.816	-1.400	-0.087	H
P67590	1.16	0.000	0.009	-0.517	HW
P73573	-66.67	2.655	-0.097	-3.708	HW
P01990	-75.00	-0.331	-0.294	-1.444	H
P08723	-13.33	-4.317	-0.659	4.386	HW
P34601	23.53	4.128	-0.003	-7.004	HW
P36769	57.14	3.412	-0.196	-3.134	H
P39089	50.00	-2.564	-0.099	3.633	H
P40687	-24.14	1.639	-0.913	-6.707	HW
P54641	-125.00	-1.550	-0.169	2.884	H
P63320	400.00	3.871	-0.230	-3.778	HW
P74200	-2.52	1.306	-1.153	1.214	H
P96389	-2.52	-0.446	-0.534	0.302	HW
P96538	47.06	0.442	-0.478	-2.337	HW
P97666	-37.50	0.896	-1.518	-0.249	H
P07303	-11.01	-4.234	-0.425	5.537	HW
P08396	250.00	1.579	0.687	-4.958	HW
P23555	-153.85	-44.355	-0.476	68.446	H
P55178	-5.36	-0.730	-0.183	1.428	H
P74022	0.96	0.000	-0.128	-0.355	HW
P75517	-28.12	1.575	-0.533	-5.720	H
P02952	-27.84	-44.693	-2.013	32.491	HW
P19896	-1.14	-0.629	0.377	-0.501	H
P37925	46.15	-0.431	-0.667	1.366	H
P57490	2150.00	3.797	-1.272	-13.580	HW
P81425	-20.00	1.695	-0.096	-1.702	H
P83519	-6.74	-1.556	-0.718	2.990	HW
P83818	-59.04	6.533	-0.043	-21.081	HW
P03401	6.09	7.801	0.189	-3.769	HW
P18951	59.09	-4.734	-0.585	5.240	H
P19700	60.00	-2.525	-1.272	2.992	H
P19848	11.36	5.109	0.491	-2.681	HW

Table 23 (cont'd).

	HOUSELET	PCALPHA	PCBETA	PCNAC	PCBHO	HOT WATER
P21045	-34.884	1.653	-0.206	-6.3748	H	
P31218	15.920	10.280	0.876	-8.7821	HW	
P35704	22.826	6.645	-1.497	-6.3186	HW	
P39899	-16.364	3.722	-0.541	-2.1317	H	
P48572	-31.818	2.834	-0.833	-4.8207	H	
P71306	-62.500	-2.128	-0.225	3.3770	H	
P91342	2.469	1.064	-0.630	-1.3934	H	
P03009	-35.294	-0.741	0.163	1.4750	HW	
P05292	13.084	-51.282	-10.732	58.7613	HW	
P13631	18.182	-1.554	0.337	-0.6363	H	
P40400	385.714	-4.469	-0.467	9.5798	HW	
P48878	84.211	-4.933	0.167	5.3967	HW	
P78349	9.958	3.785	-0.733	3.9044	HW	
P02626	-24.324	1.299	-0.964	-3.8583	H	
P05616	-12.987	0.897	-0.255	-2.2727	H	

Table 24. Summary statistics of percent differences of PRISM vs. RPRISM parameters for OIL sample. (See Figures 50-53.)

	MIN	Q1	MED	Q3	MAX	MEAN
ALPHA	-154	-24.2	-1.3	23.2	2150	42.5
BETA	-51.3	-2.3	.42	2.7	10.5	-1.9
NAC	-21.4	-.76	-.38	-.023	.876	-.92
HEATING	-21	-3.17	-.35	2.99	680	11.73

Table 25. By-house summary of the ratio of the coefficients of variation (CVR) for PRISM vs. RPRISM estimates for OIL sample. $CVR = CV(PRISM\ estimate)/CV(RPRISM\ estimate)$.

HOUSELET CVRALPHA CVRBETA CVRNAC CVRBHO HOT WATER

P18646	2.7143	0.84468	1.47853	1.13611	H
P24939	1.3102	1.08400	1.58461	1.46677	HW
P45584	1.8607	1.04002	1.45949	1.42658	HW
P56368	1.1601	1.20296	1.47939	1.36875	HW
P61454	2.1336	1.05995	1.60609	1.61672	HW
P64773	2.1460	0.97724	1.42659	1.69783	HW
P69085	2.2406	1.11274	1.92549	1.58223	HW
P76263	-0.0483	8.01656	0.97483		HW
P88006	1.3325	0.86353	1.49463	1.16375	H
P01249	0.9942	0.82302	1.05725	1.01723	HW
P07232	-0.8866	2.77431	2.21479		H
P07234	0.9947	1.74044	2.02624		H
P11122	0.9052	0.89503	0.90832	0.89495	HW
P15920	1.3110	1.36092	2.18227	1.99380	H
P38343	1.5618	0.91418	1.57525	1.35111	HW
P45522	1.9006	0.95993	1.62367	1.64274	HW
P53095	1.6937	0.90815	1.90148	1.08822	H
P64672	1.7218	1.29579	1.95464	2.01255	H
P65868	1.8048	1.04506	1.59156	1.58913	HW
P75223	1.4060	1.05724	1.72991	1.03145	HW
P12537	1.3941	1.10331	1.82273	1.43453	HW
P43660	1.4226	1.01220	1.28081	1.21637	HW
P60414	1.5418	0.96234	1.85273	1.59262	H
P67590	1.3970	1.00000	1.36340	1.28698	HW
P73573	0.6508	1.19764	1.70900	1.86112	HW
P01990	0.6250	1.08463	2.16205	1.79341	H
P08723	0.9440	0.95683	1.31868	1.03728	HW
P34601	1.9059	0.97620	1.52396	1.28235	HW
P36769	3.4364	0.89218	1.80530	1.89517	H
P39089	1.9643	1.02849	1.84980	1.17324	H
P40687	1.4280	1.01639	1.66688	1.69404	HW
P54641	-0.3019	1.07826	1.82642	1.12713	H
P63320	8.3333	0.95881	1.65519	1.43555	HW
P74200	1.1191	1.05441	1.15459	1.13346	H
P96389	1.4970	0.99554	1.29927	1.37024	HW
P96538	2.6596	1.06720	1.50678	1.64994	HW
P97666	1.5375	1.07405	1.92020	2.06821	H
P07303	1.6217	1.09129	1.62524	1.63535	HW
P08396	5.6467	1.01579	1.57561	1.40477	HW
P23555	-0.2647	1.23855	1.26017	0.65977	H
P55178	1.7815	0.99270	1.71737	1.55950	H
P74022	1.1498	0.93750	1.35754	1.07074	HW
P75517	1.0182	0.97159	1.66994	1.27963	H
P02952	0.6968	1.27207	1.25992	0.93467	HW
P19896	0.9886	0.99371	1.23305		H
P37925	3.1937	1.10050	2.10902	1.72084	H
P57490	60.7895	0.97692	1.32917	2.33393	HW
P81425	1.5789	1.10169	2.06138	1.73815	H
P83519	1.6402	0.94928	1.39504	1.51021	HW
P83818	1.7059	1.00614	1.60908	3.35430	HW
P03401	2.3628	1.13790	1.74115	1.89886	HW
P18951	2.1636	1.00030	2.05316	1.20422	H
P19700	2.8903	0.97475	1.93460	1.38921	H
P19848	1.3824	0.90094	1.31530	1.11443	HW

Table 25 (cont'd).

	HOUSELET	CVRALPHA	CVRBETA	CVRNAC	CVRBHO	HOT WATER
P21045	1.40592	1.10894	1.74137	1.98543	H	
P31218	1.97635	1.03211	1.44113	1.47451	HW	
P35704	2.93534	1.09781	1.65523	2.04338	HW	
P39899	1.96791	0.98115	1.88550	1.87021	H	
P48572	1.73592	1.16247	2.11321	2.11604	H	
P71306	0.47074	0.94108	1.50895	1.11175	H	
P91342	1.54953	0.92642	1.25280	1.33204	H	
P03009	1.32108	1.09185	1.82779	1.75047	HW	
P05292	0.01780	3.31891	0.94844	0.02546	HW	
P13631	1.18182	0.84867	1.13566	0.91424	H	
P40400	4.94709	1.14637	1.57711	1.05658	HW	
P48878	2.27751	0.91106	1.48427	1.13893	HW	
P78349	1.09958	1.31462	1.39404		HW	
P02626	1.64865	0.95967	2.04379	1.62318	H	
P05616	1.39459	1.00897	1.77982	1.49804	H	

Table 26. Summary statistics of CVRs of PRISM vs. RPRISM parameters for OIL sample. (See Figures 55-58.)

	MIN	Q1	MED	Q3	MAX	MEAN
ALPHA	.018	.99	1.46	1.96	60.8	3.76
BETA	.82	.96	1.02	1.10	8.02	1.20
NAC	.91	1.38	1.61	1.84	2.21	1.61
HEATING	.025	1.14	1.44	1.72	3.35	1.47

Schematic for RPRISM

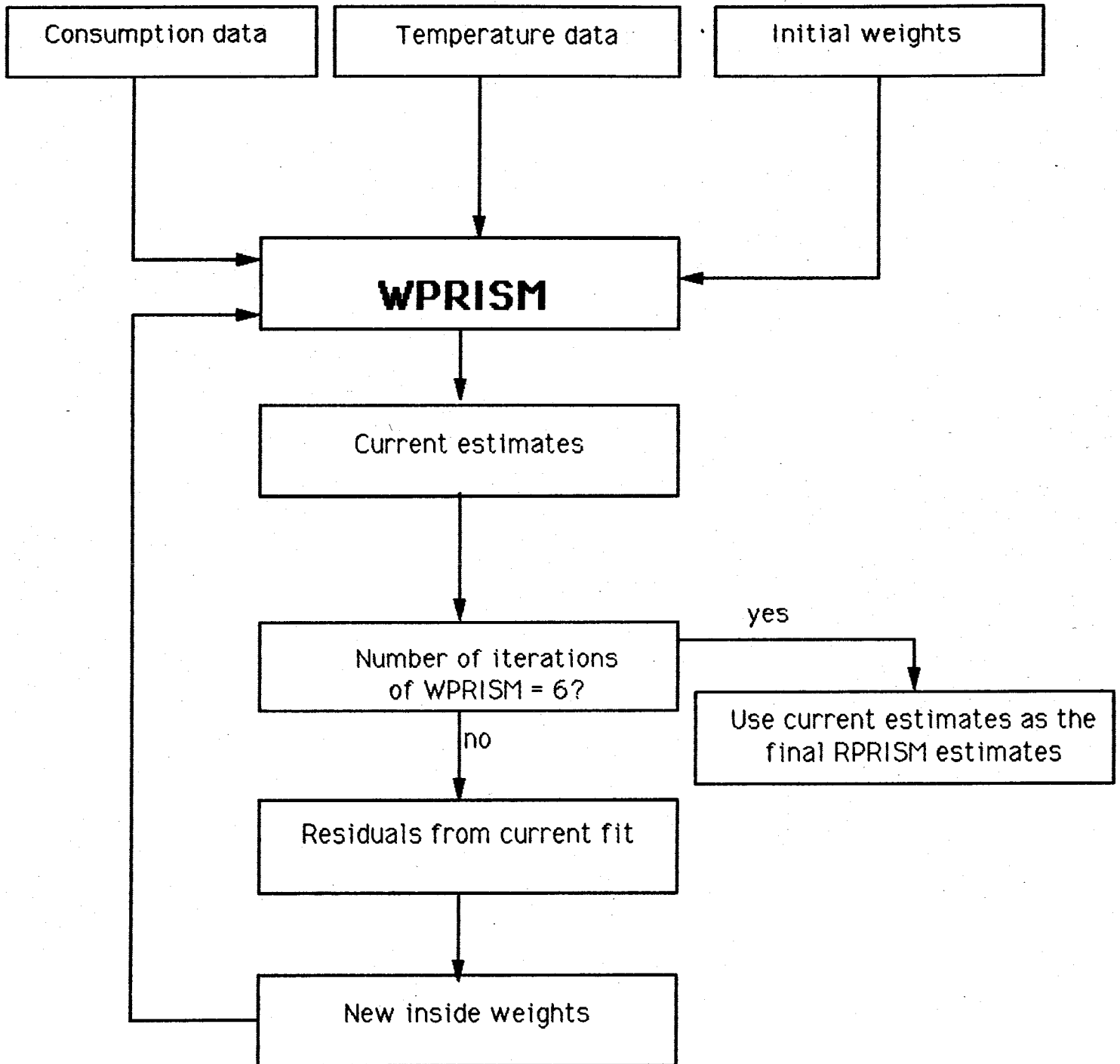


Figure 1. Schematic of Robust PRISM (RPRISM) algorithm.

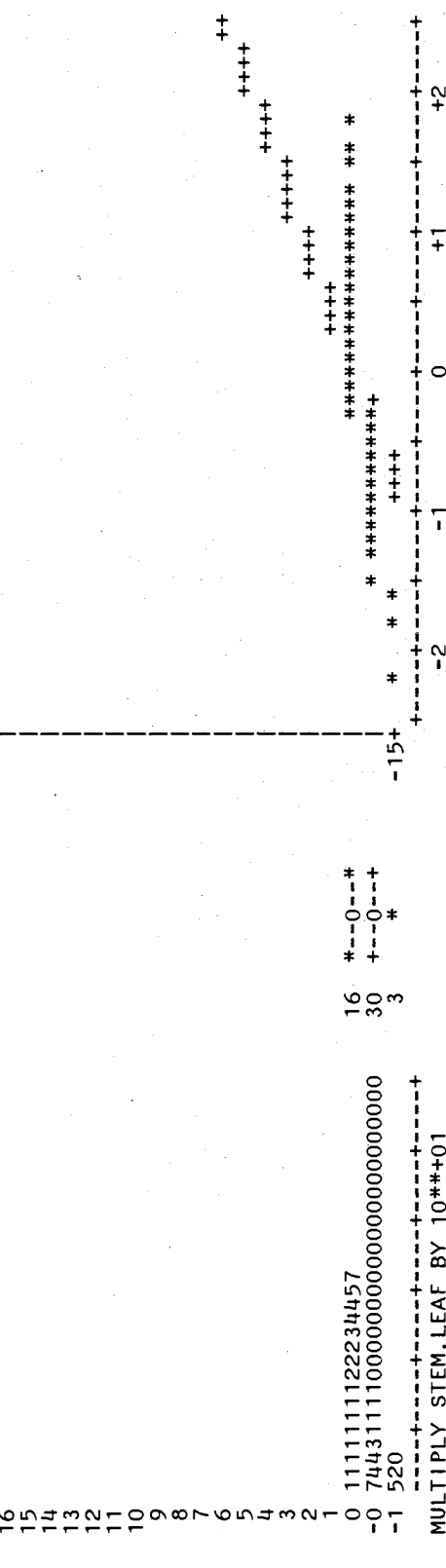
VARIABLE=PCALPHA

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	50	100% MAX	171.248	LOWEST	HIGHEST
MEAN	3.00927	75% Q3	0.825371	-14.6711	3.56875
STD DEV	24.5589	50% MED	0.0859245	-11.6583	4.04722
SKEWNESS	6.81459	25% Q1	-0.280762	-3.69776	5.30973
CV	30006.6	0% MIN	-14.6711	-10.7676	6.80544
T:MEAN=0	816.109	RANGE	185.919	-3.70634	171.248
SGN RANK	0.866437	Q3-Q1	1.10613		
NUM	95	MODE	0		
NUM	47				

STEM LEAF 175+
 17 1
 16
 15
 14
 13
 12
 11
 10
 9
 8
 7
 6
 5
 4
 3
 2
 1

NORMAL PROBABILITY PLOT

BOXPLOT *
 1



16 *-0--*
 30 +--0--*
 3
 0 1111111122234457
 -0 7443111100000000000000000000
 -1 520
 -----+-----+-----+-----+-----+
 MULTIPLY STEM.LEAF BY 10***01

Figure 2. SAS Univariate summary of distribution of percent difference for α (PCALPHA) from Elec-HO sample: RPRISM vs. PRISM

VARIABLE=PCBETA

MOMENTS		QUANTILES(DEF=4)				EXTREMES	
N	50	100% MAX	8.37182	99%	8.37182	HIGHEST	8.37182
MEAN	-1.33395	75% Q3	0.816498	95%	6.3743	LOWEST	-27.7503
STD DEV	6.04505	50% MED	-0.0537566	90%	4.51754		-21.1306
SKEWNESS	-2.41091	25% Q1	-2.06319	10%	-6.10101		-11.1111
USS	1879.56	0% MIN	-27.7503	5%	-15.6199		-9.76784
CV	-453.168	RANGE	36.1221	1%	-27.7503		-6.169
T:MEAN=0	-1.56036	Q3-Q1	2.87969				
SGN RANK	-118	MODE	0				
NUM ^= 0	47						

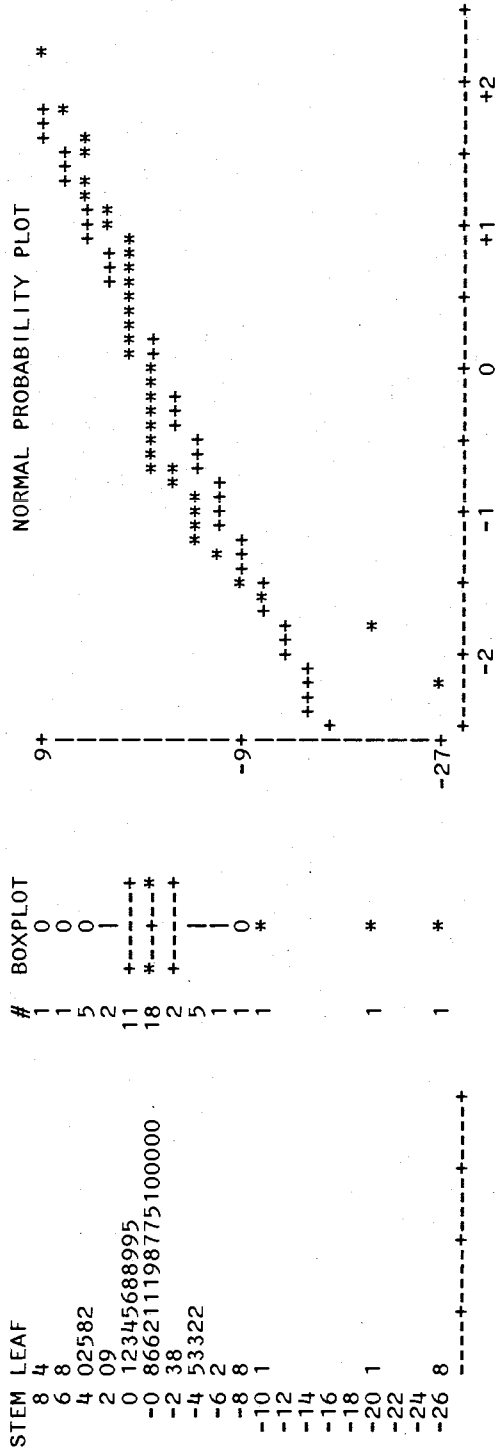


Figure 3. SAS Univariate summary of distribution of percent difference for β (PCBETA) from Elec-HO sample: RPRISM vs. PRISM

VARIABLE=PCNAC

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	50	8.42912	99%	8.42912	HIGHEST
MEAN	-0.138382	0.330604	95%	2.12148	1.53022
STD DEV	1.82203	0.140715	90%	1.50557	1.65187
SKENNESS	1.56312	-0.873389	10%	-1.9762	1.9099
USS	163.628	-5.52771	5%	-2.87329	2.38008
CV	-1316.67	13.9568	1%	-5.52771	8.42912
T:MEAN=0	-0.537043	1.20399			
SGN RANK	-110				
NUM	47				

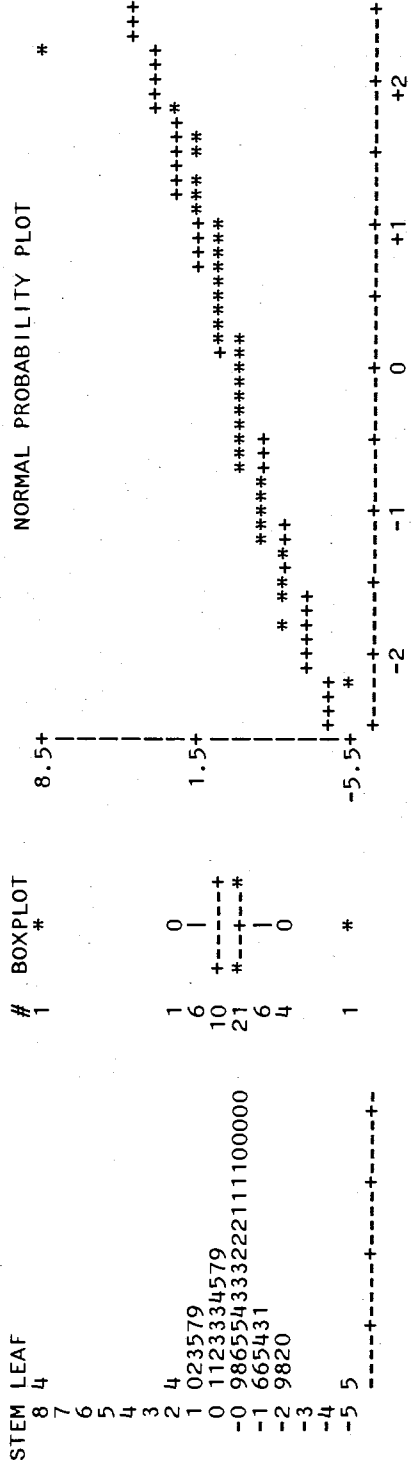


Figure 4. SAS Univariate summary of distribution of percent difference for NAC (PCNAC) from Elec-HO sample: RPRISM vs. PRISM

VARIABLE=PCBHO

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	50	SUM	70.463	LOWEST	3.87564
MEAN	1.28554	SUM	0.908801	HIGHEST	4.78354
STD DEV	12.7592	VARIANCE	-0.0549775		14.6172
SKEWNESS	4.21224	KURTOSIS	-1.64653		35.4004
USS	7327.08	CSS	-21.5682		70.463
CV	945.84	STD MEAN	92.0311		
T:MEAN=0	0.747597	PROB> T	2.55533		
SGN RANK	-68	PROB> S	0		
NUM	47				

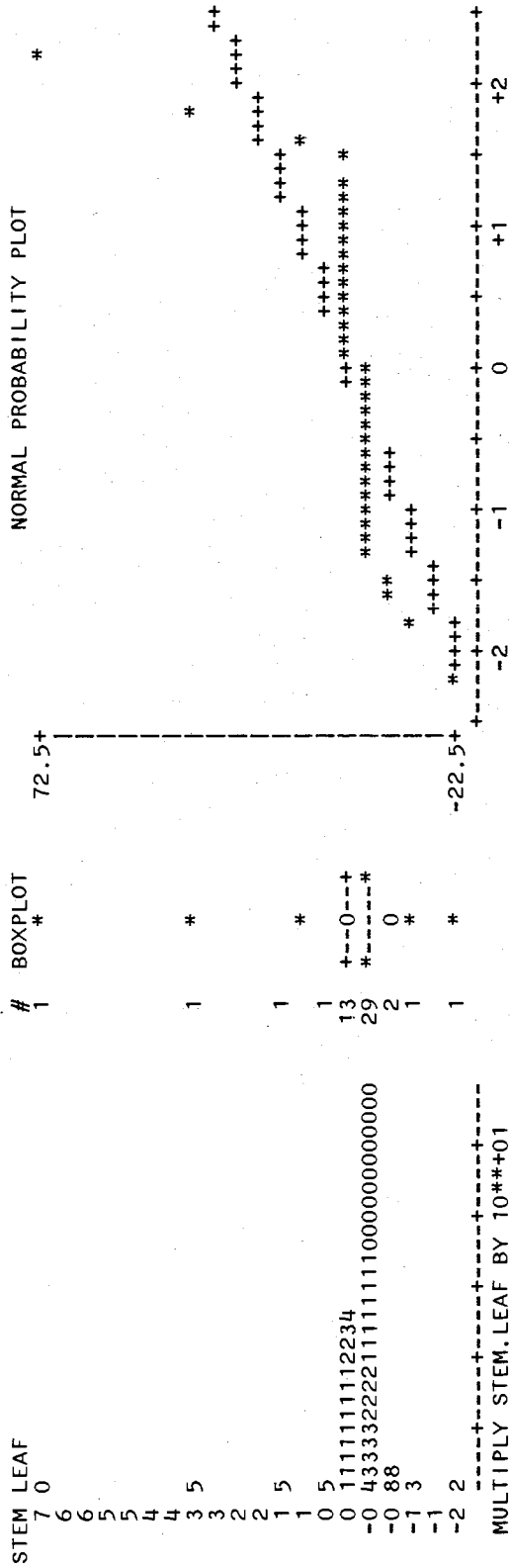


Figure 5. SAS Univariate summary of distribution of percent difference for β_{H_0} (PCBHO) from Elec-HO sample: RPRISM vs. PRISM

PERCENT DIFFERENCES FOR ELEC-HO

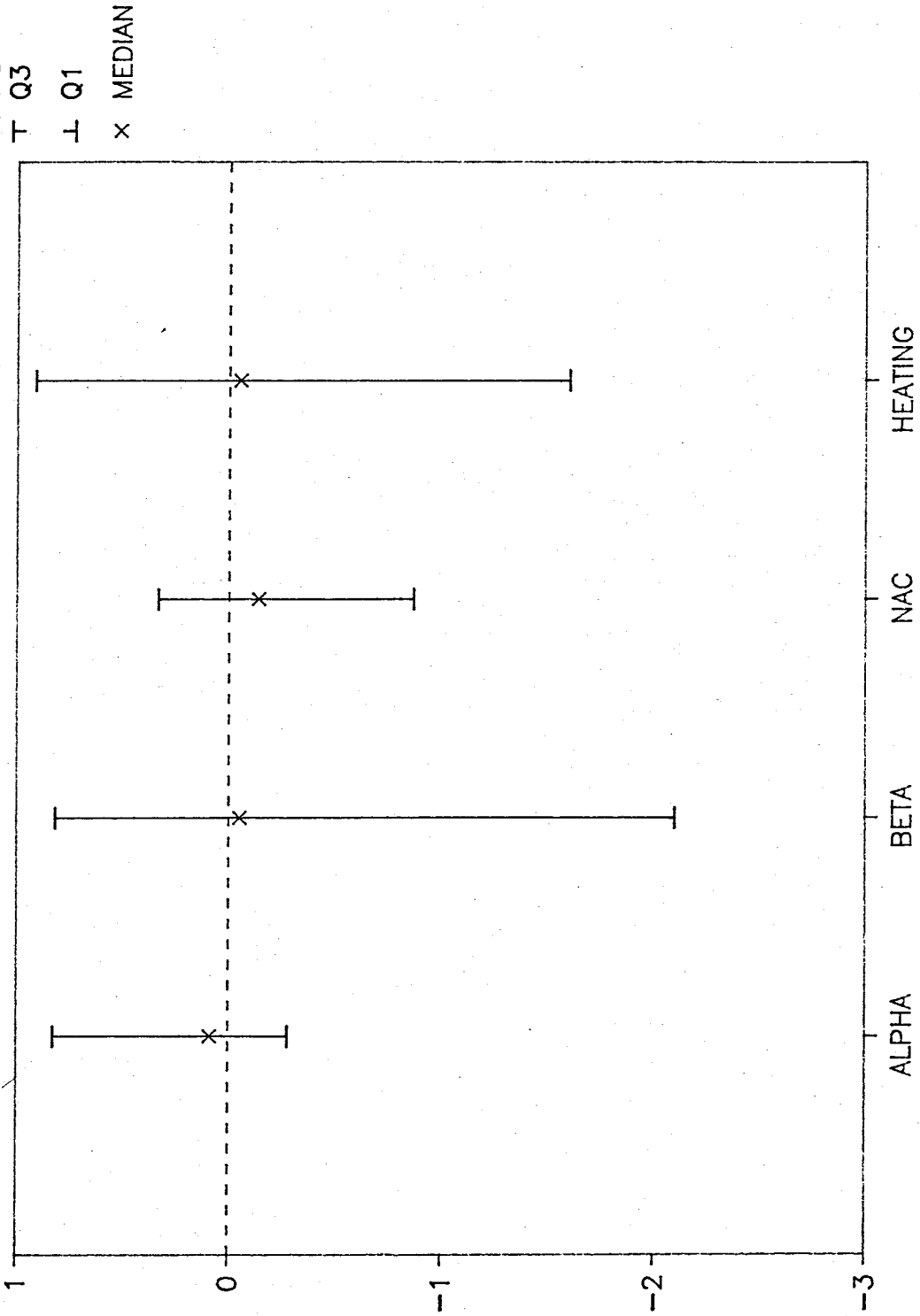


Figure 6. Plot of medians and quartiles of percent differences of PRISM vs. RPRISM parameters for Elec-HO sample.

VARIABLE=CVRBHO

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	50	100% MAX	7.56411	7.56411	HIGHEST
MEAN	1.44749	75% Q3	1.32531	4.08634	0.879089
STD DEV	1.13296	50% MED	1.12908	2.20057	0.918631
SKWENESS	4.13786	25% Q1	0.984768	0.927465	0.923393
USS	167.658	0% MIN	0.879089	0.92125	0.925549
CV	78.2703	RANGE	6.68502	0.879089	0.92736
T: MEAN=0	9.03417	Q3-Q1	0.34054		
SGN RANK	637.5	MODE	0.879089		
NUM ^= 0	50				

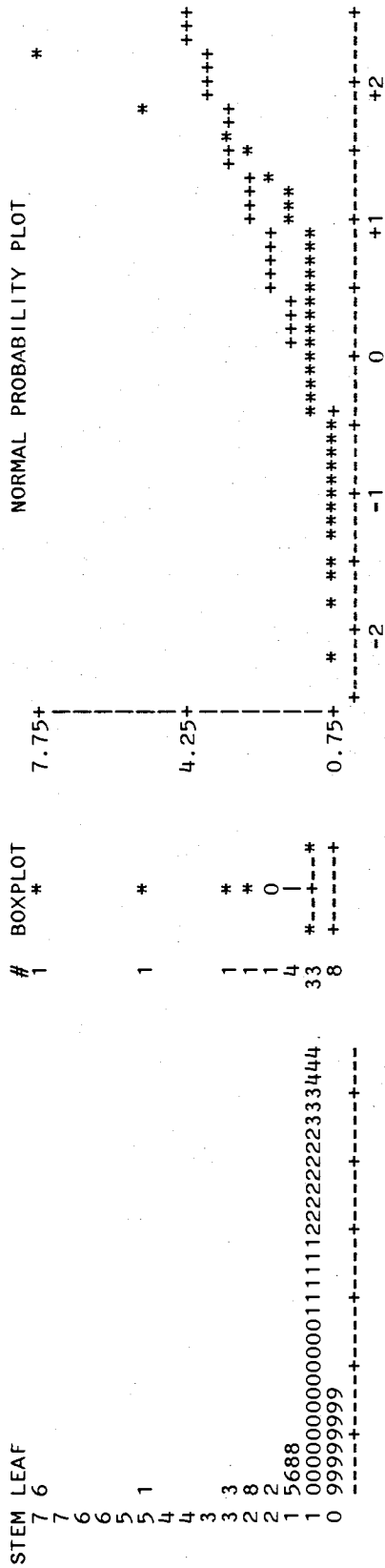


Figure 10. SAS Univariate summary of distribution of CVRs for β_{H_0} (CVRBHO) from Elec-HO sample.

CVR SUMMARIES FOR ELEC-HO

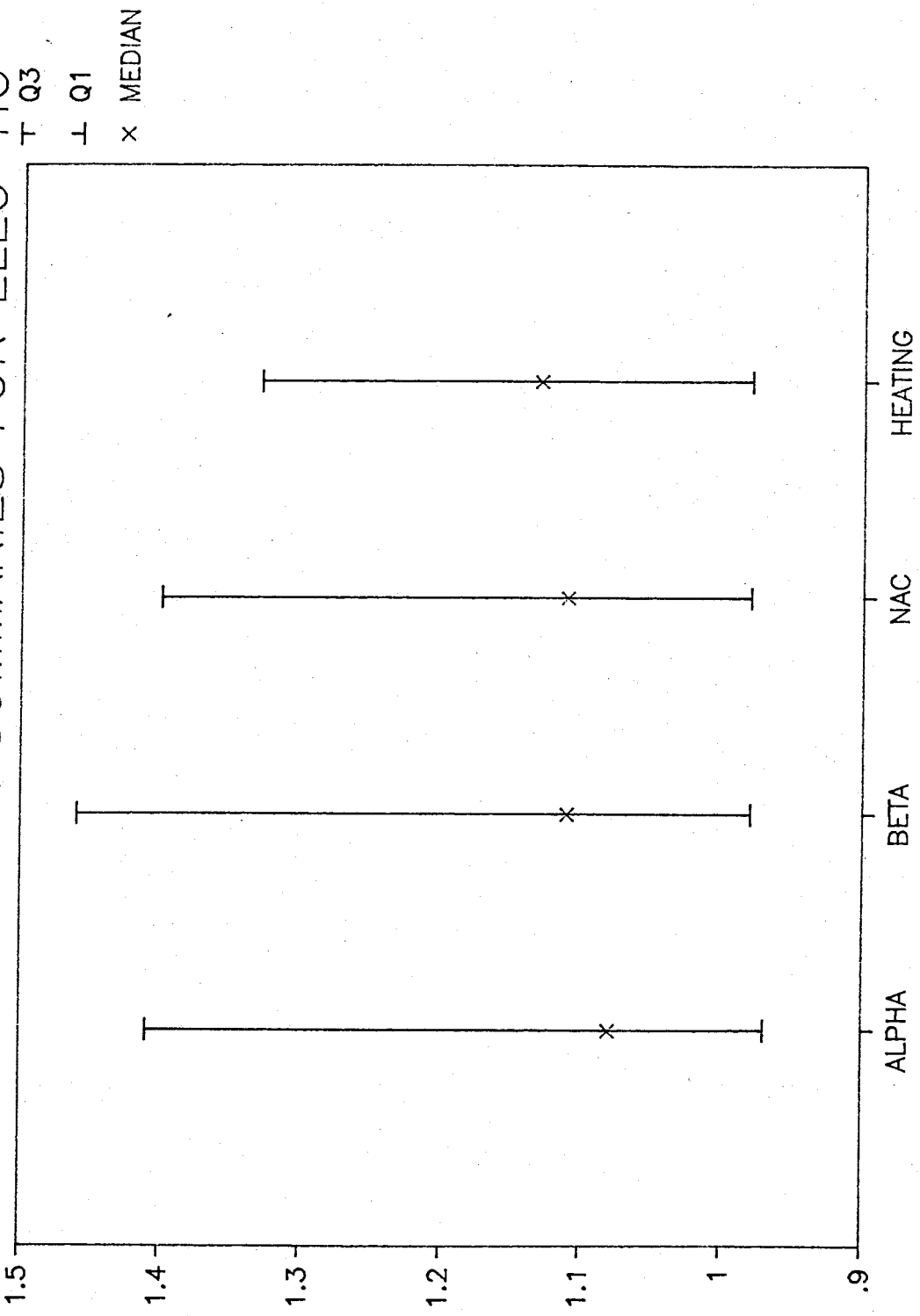


Figure 11. Plot of medians and quartiles of CVRs of PRISM vs. RPRISM parameters for Elec-HO sample.

CONS-HDD FOR J19, PRISM

House:J19 ,alpha= 19.79,beta= 5.31,R2= 0.9699

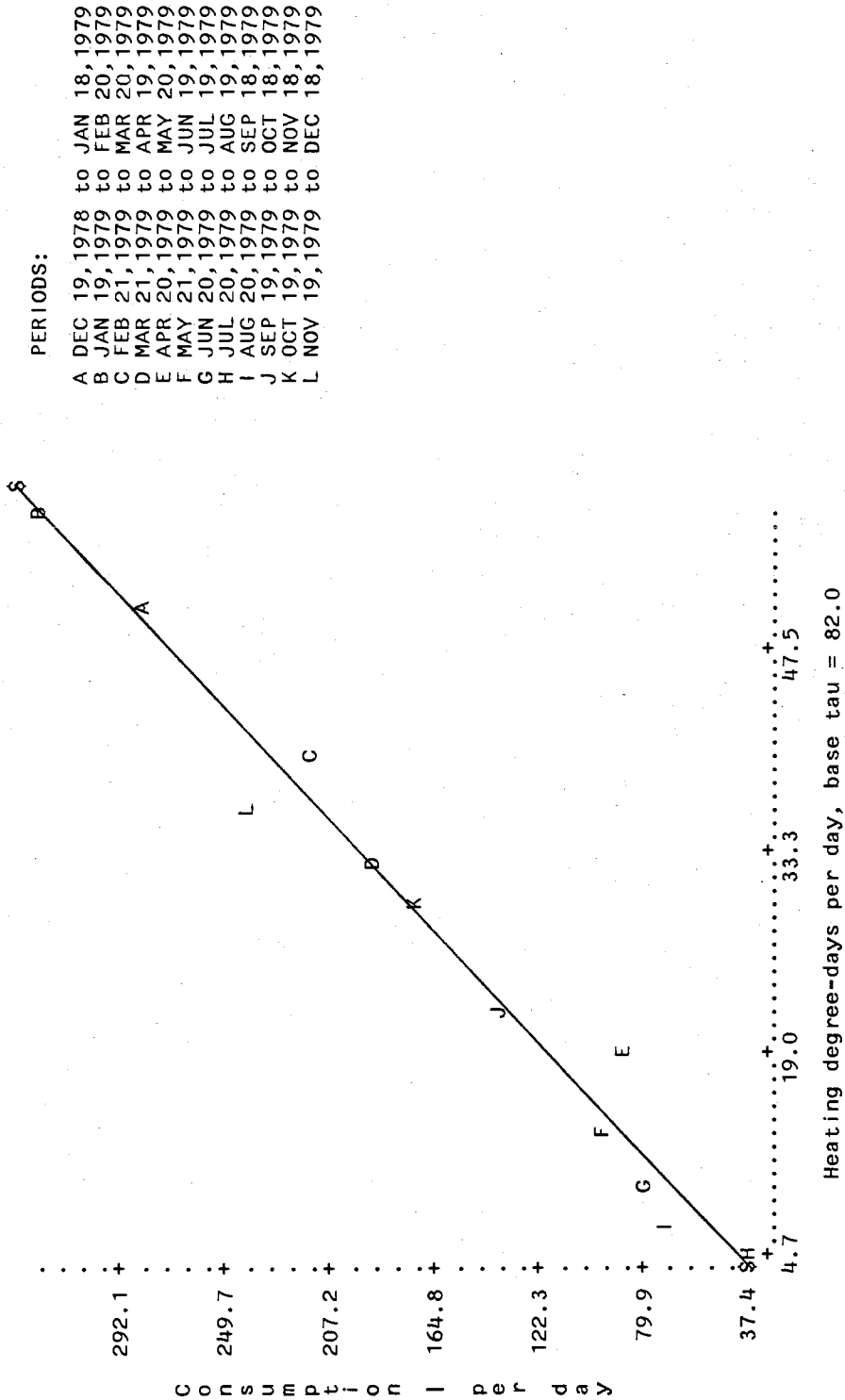


Figure 12. PRISM plot of consumption vs. heating-degree days for House J19 from Elec-HO sample.

RESIDS-HDD FOR J19, PRISM

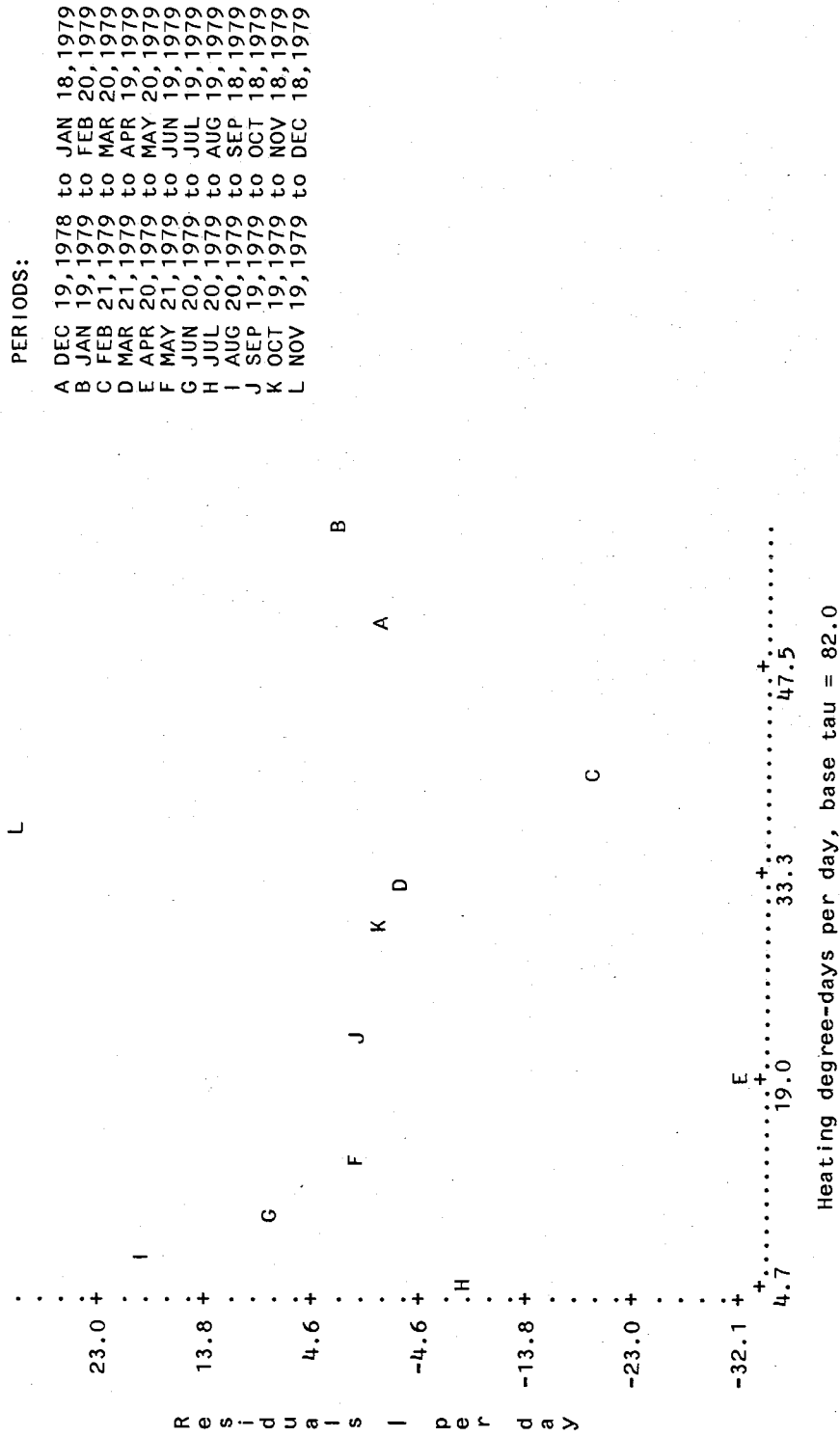


Figure 13. PRISM plot of residuals vs. heating degree-days for House J19 from Elec-H0 sample.

CONS-HDD FOR J19, RPRISM

House: J19 , alpha= 53.68, beta= 5.35, R2= 0.9920

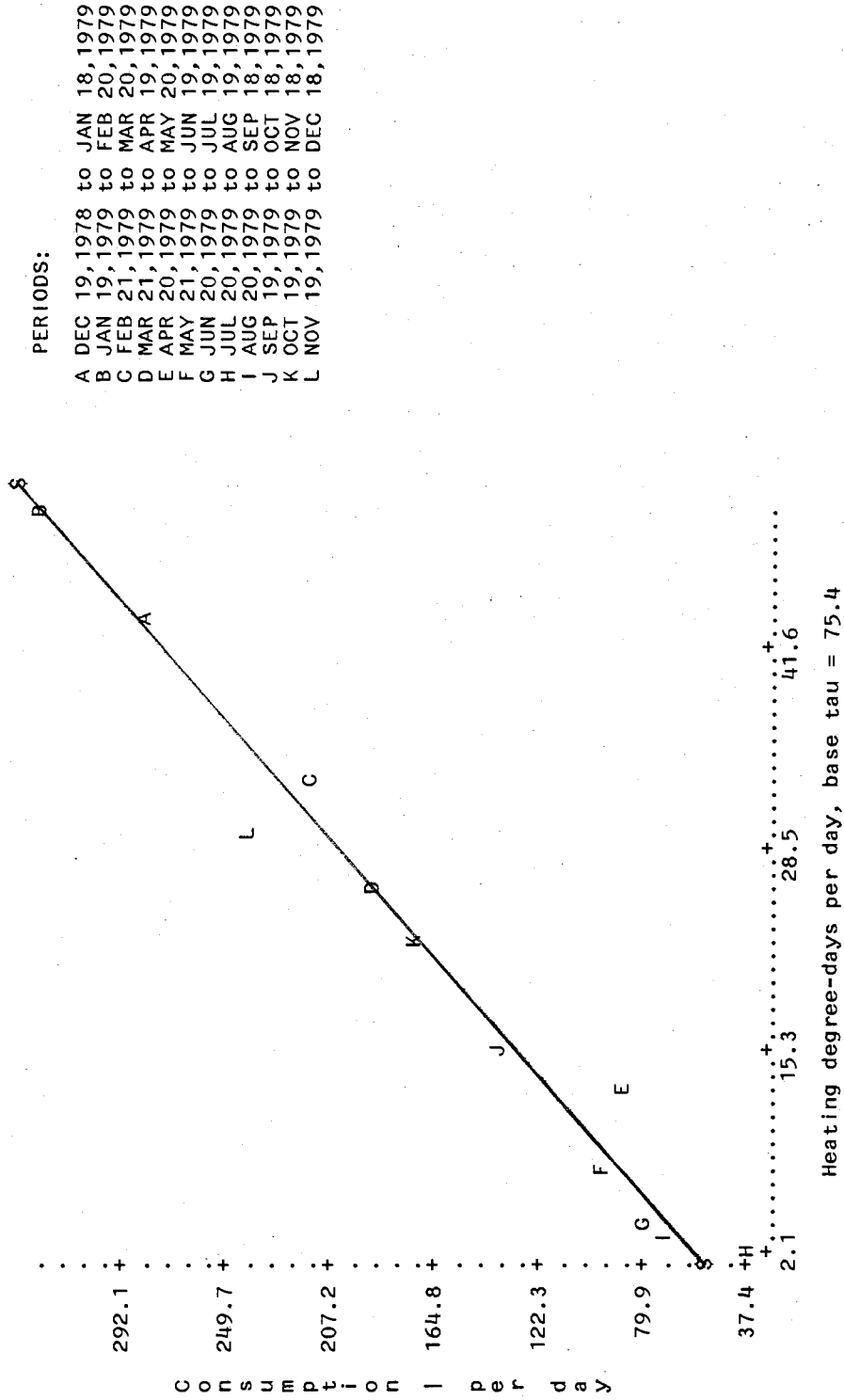


Figure 14. RPRISM plot of consumption vs. heating degree-days for House J19 from Elec-HO sample.

RESIDS-HDD FOR J19, RPRISM

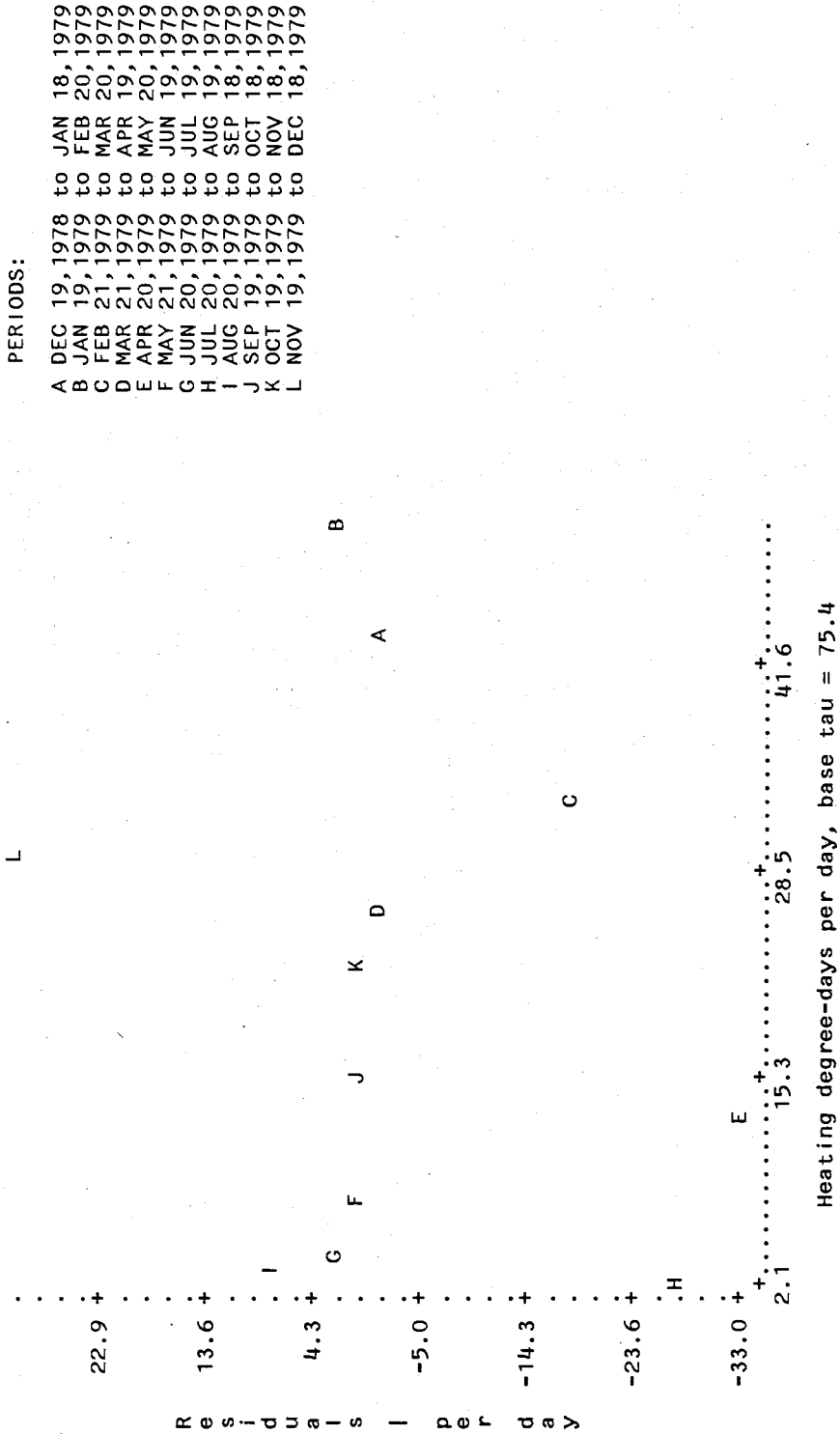


Figure 15. RPRISM plot of residuals vs. heating degree-days for House J19 from Elec-HO sample.

CONS-HDD FOR J43, PRISM

House: J43, alpha= 35.94, beta= 7.08, R2= 0.9153

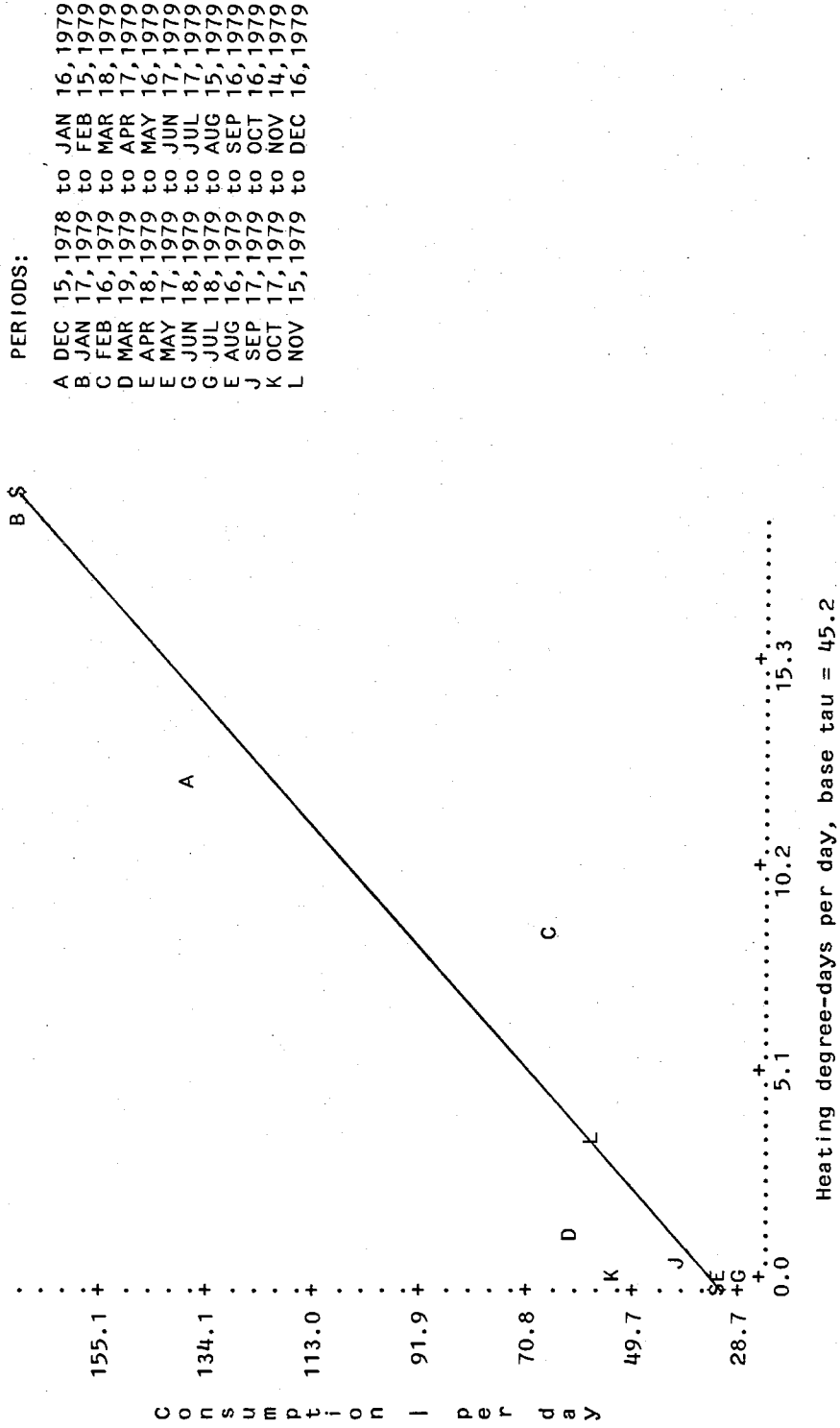


Figure 16. PRISM plot of consumption vs. heating-degree days for House J43 from Elec-HO sample.

RESIDS-HDD FOR J43, PRISM

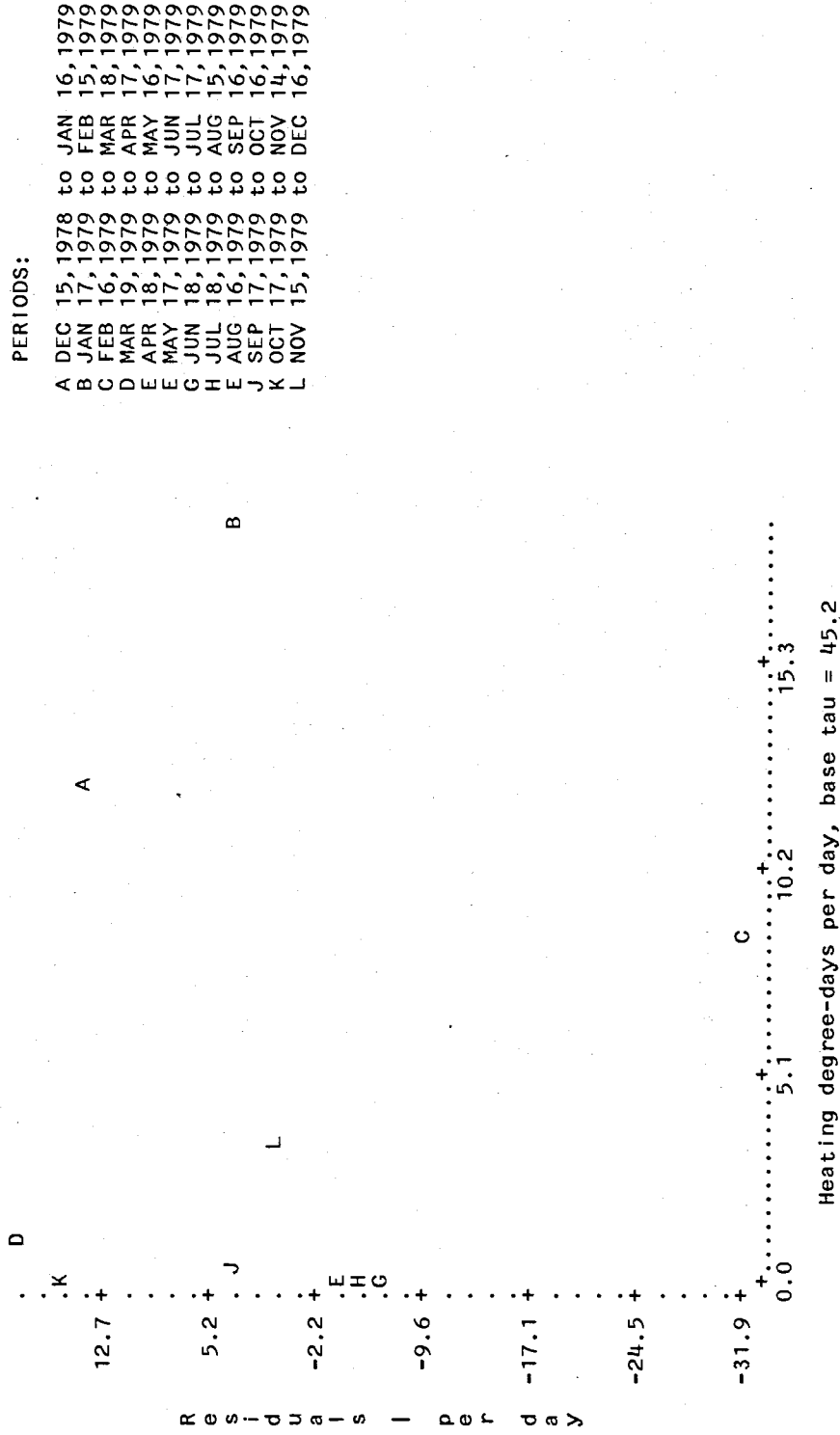


Figure 17. PRISM plot of residuals vs. heating degree-days for House J43 from Elec-HO sample.

CONS-HDD FOR J43, RPRISM

House: J43 , alpha= 31.75, beta= 5.12, R2= 0.9843

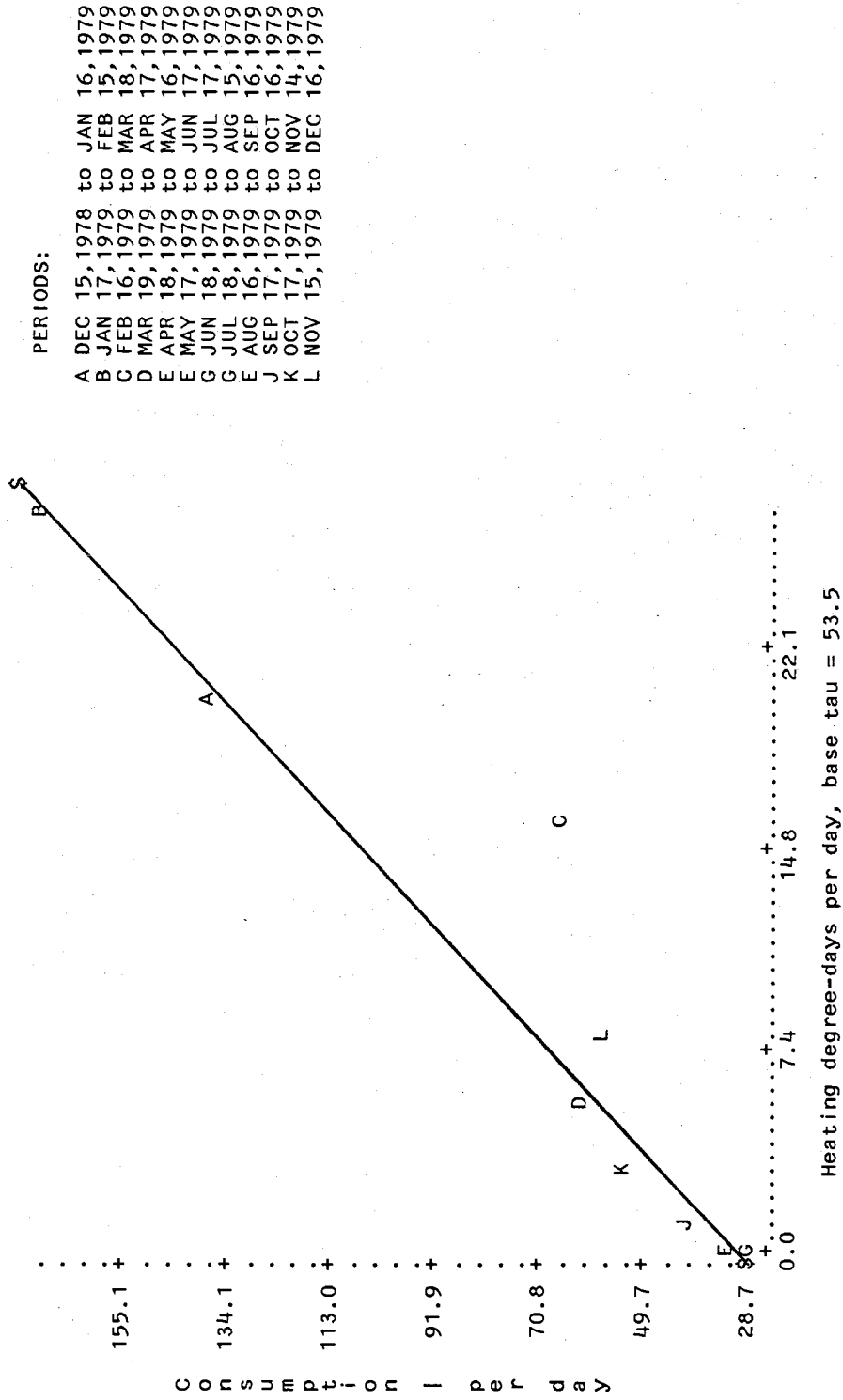
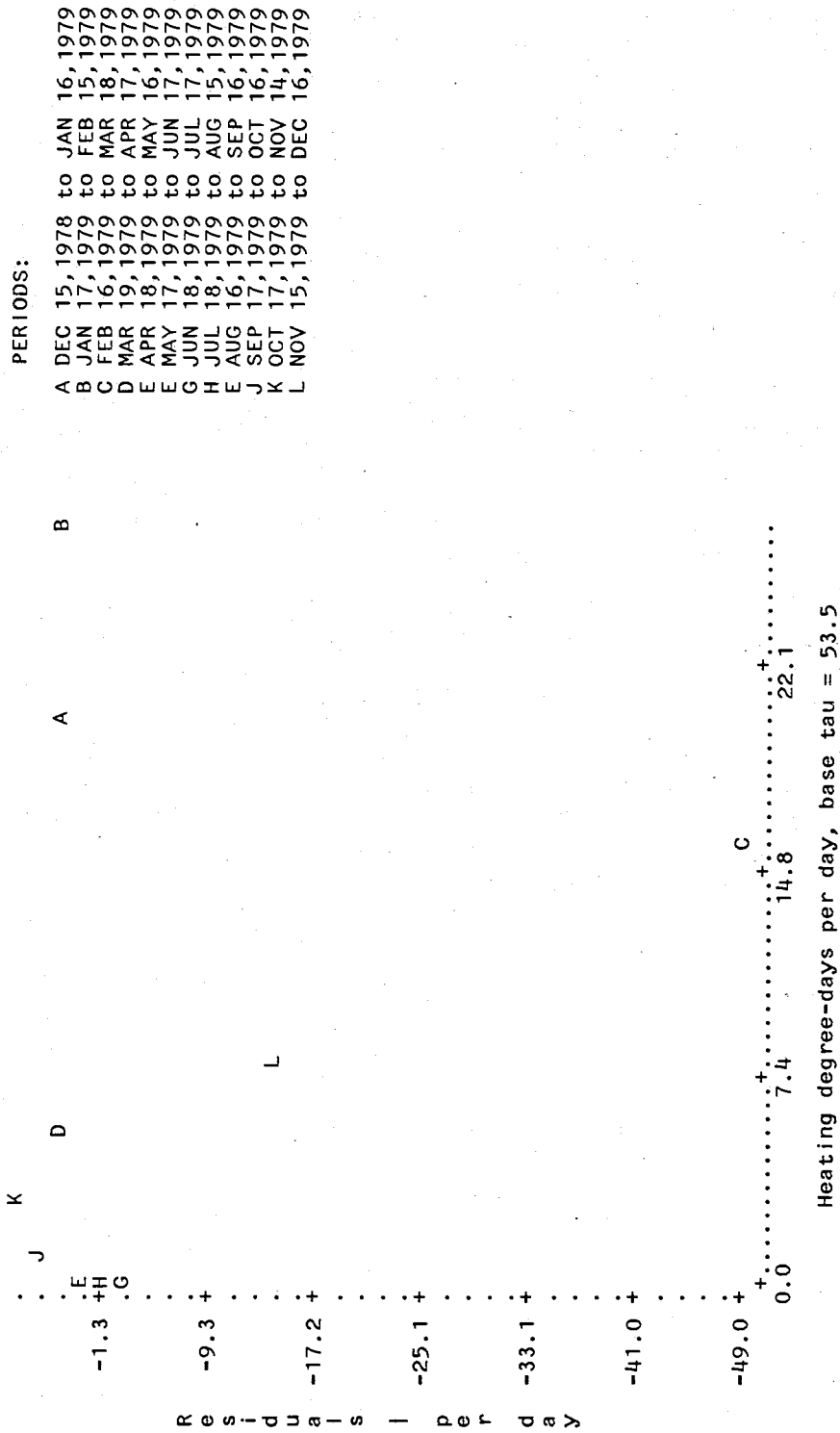


Figure 18. RPRISM plot of consumption vs. heating degree-days for House J43 from Elec-HO sample.

RESIDS-HDD FOR J43, RPRISM



PERIODS:

A DEC 15, 1978 to JAN 16, 1979
 B JAN 17, 1979 to FEB 15, 1979
 C FEB 16, 1979 to MAR 18, 1979
 D MAR 19, 1979 to APR 17, 1979
 E APR 18, 1979 to MAY 16, 1979
 F MAY 17, 1979 to JUN 17, 1979
 G JUN 18, 1979 to JUL 17, 1979
 H JUL 18, 1979 to AUG 15, 1979
 I AUG 16, 1979 to SEP 16, 1979
 J SEP 17, 1979 to OCT 16, 1979
 K OCT 17, 1979 to NOV 14, 1979
 L NOV 15, 1979 to DEC 16, 1979

Figure 19. RPRISM plot of residuals vs. heating degree-days for House J43 from Elec-HO sample.

CONS-HDD FOR J47, PRISM

House: J47, alpha= 24.98, beta= 2.43, R2= 0.8730

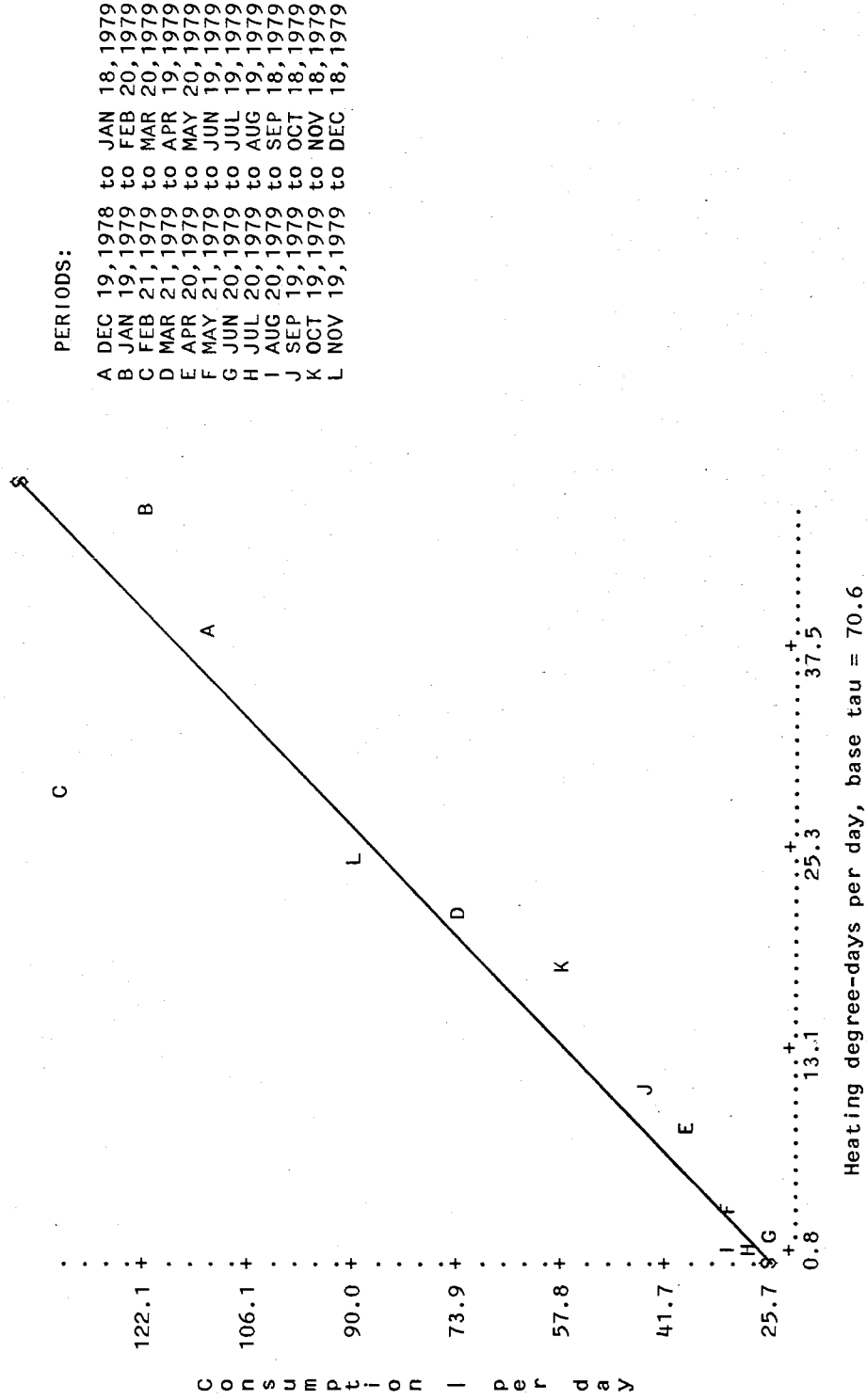


Figure 20. PRISM plot of consumption vs. heating-degree days for House J47 from Elec-HO sample.

RESIDS-HDD FOR J47, PRISM

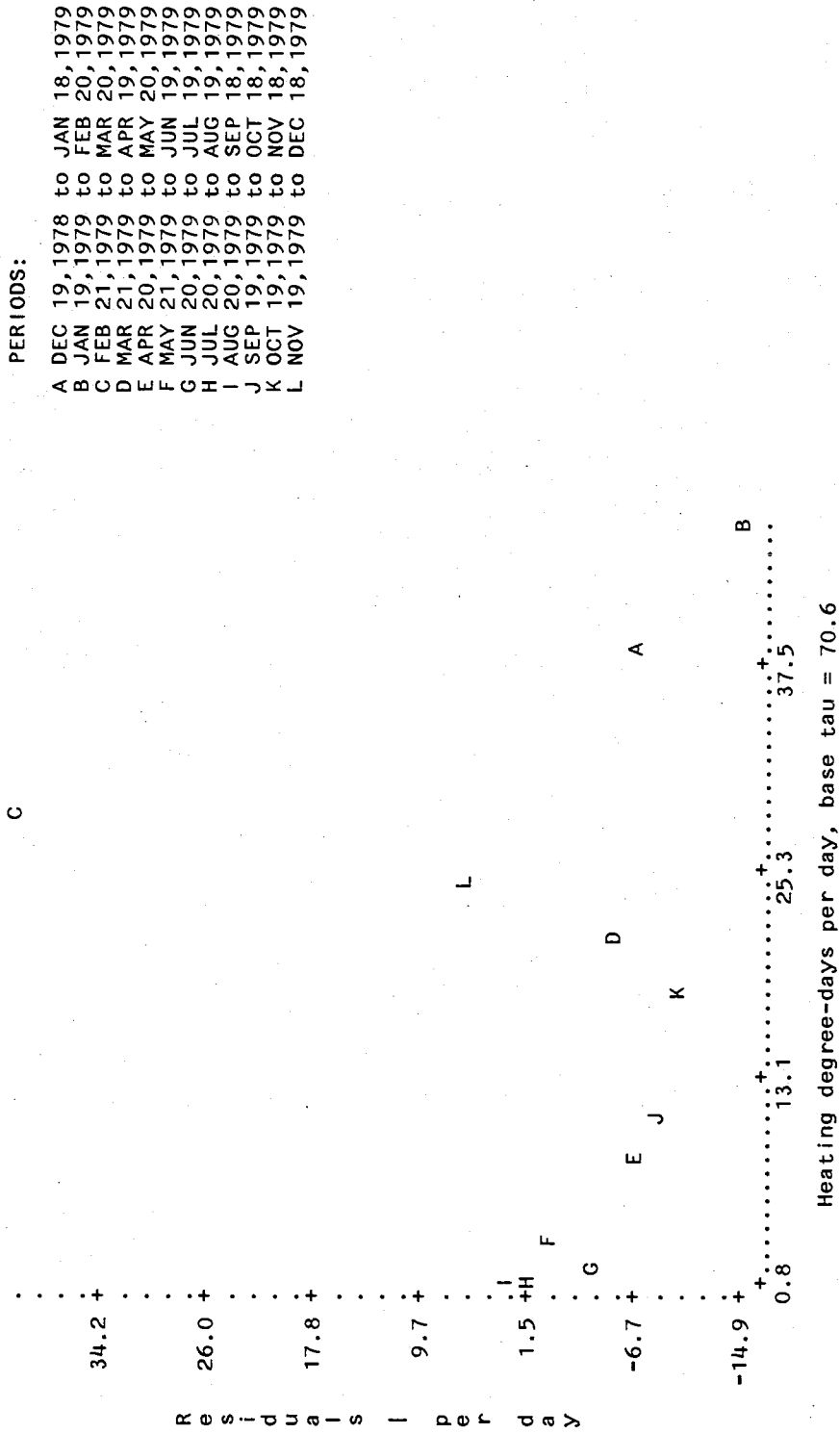


Figure 21. PRISM plot of residuals vs. heating degree-days for House J47 from Elec-HO sample.

CONS-HDD FOR J47, RPRISM

House: J47, alpha= 26.68, beta= 2.31, R2= 0.9586

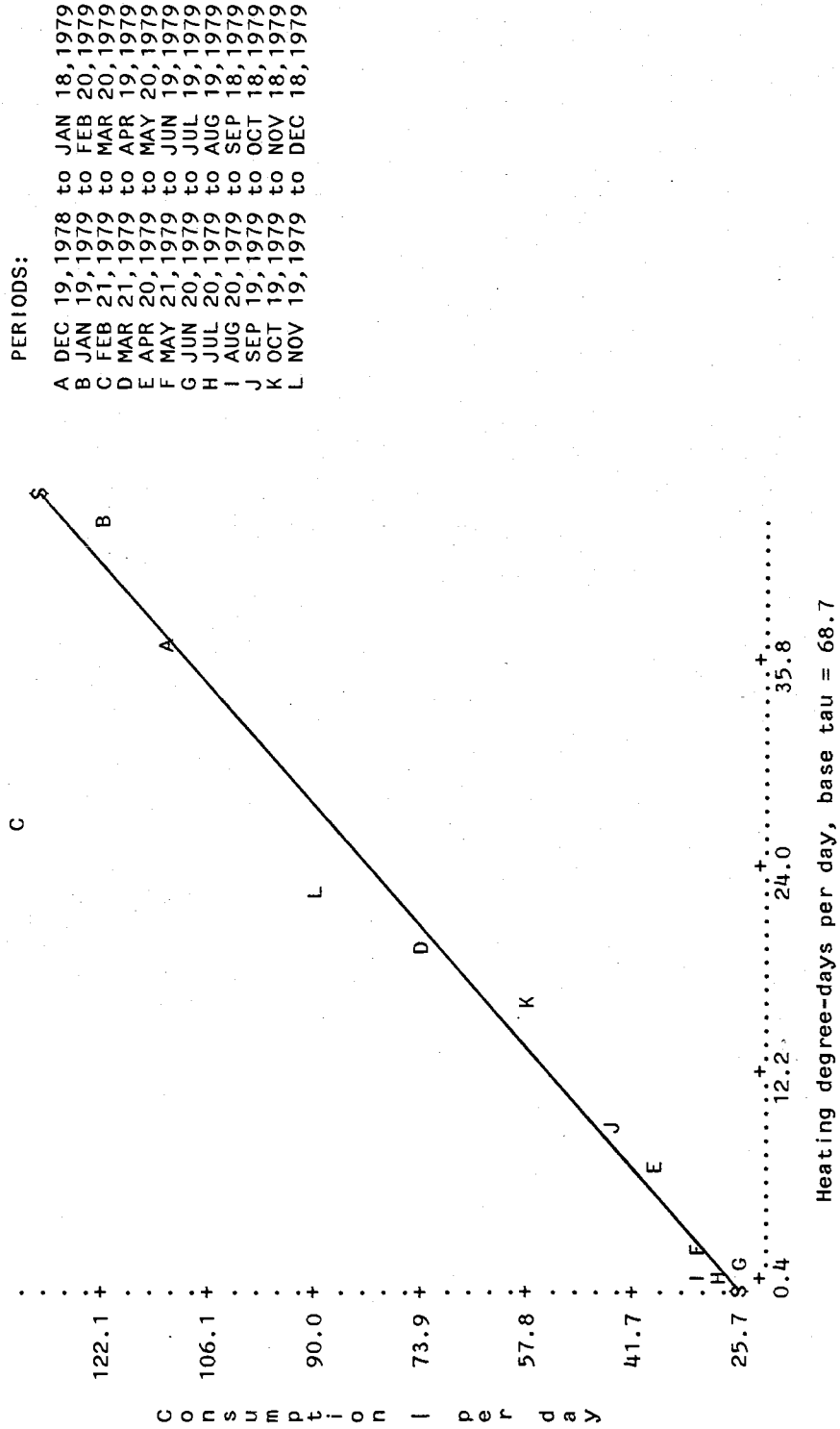
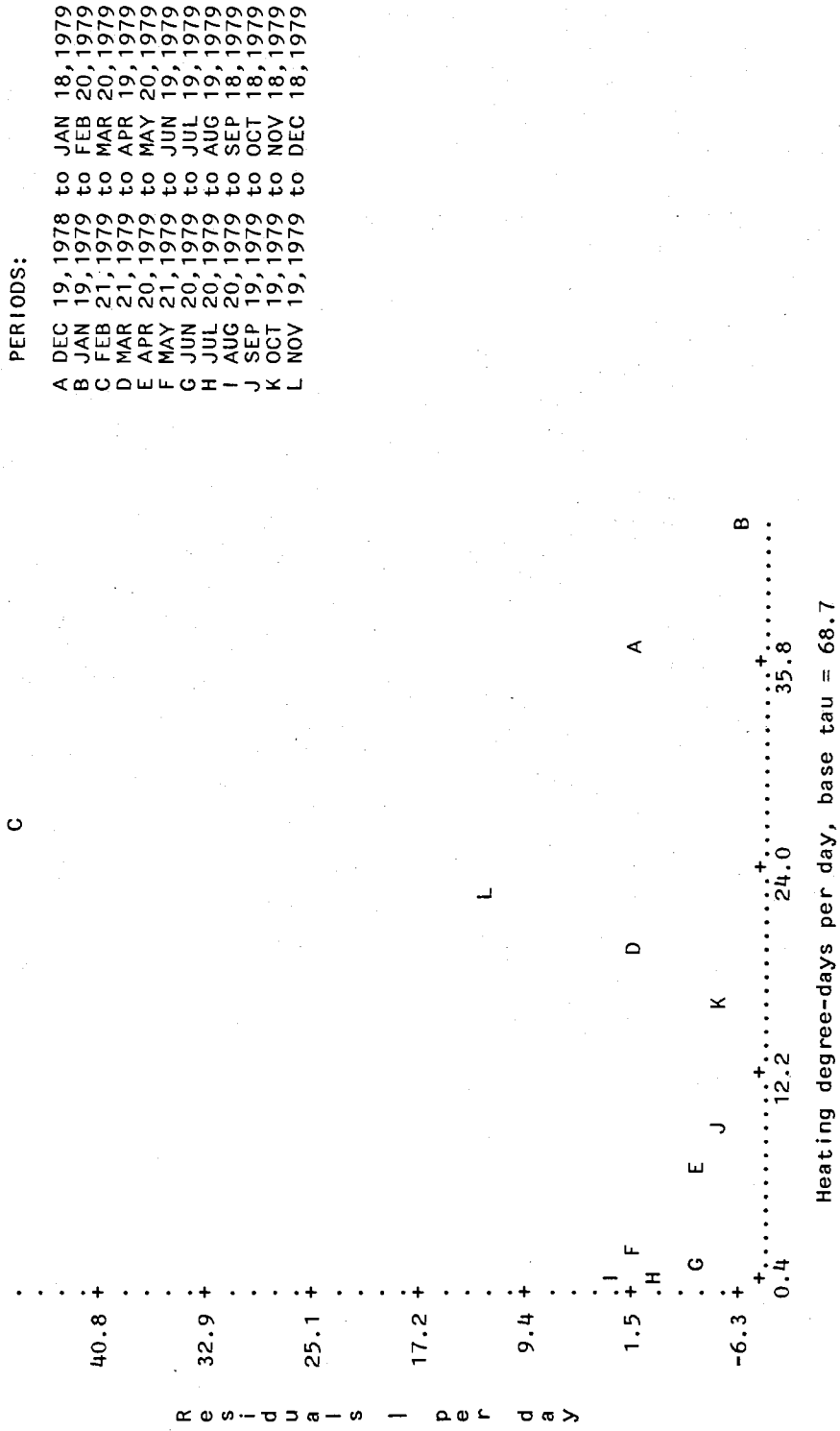


Figure 22. RPRISM plot of consumption vs. heating degree-days for House J47 from Elec-HO sample.

FIGURE 28: RESIDS-HDD FOR J47, RPRISM



PERIODS:

- A DEC 19, 1978 to JAN 18, 1979
- B JAN 19, 1979 to FEB 20, 1979
- C FEB 21, 1979 to MAR 20, 1979
- D MAR 21, 1979 to APR 19, 1979
- E APR 20, 1979 to MAY 20, 1979
- F MAY 21, 1979 to JUN 19, 1979
- G JUN 20, 1979 to JUL 19, 1979
- H JUL 20, 1979 to AUG 19, 1979
- I AUG 20, 1979 to SEP 18, 1979
- J SEP 19, 1979 to OCT 18, 1979
- K OCT 19, 1979 to NOV 18, 1979
- L NOV 19, 1979 to DEC 18, 1979

Figure 23. RPRISM plot of residuals vs. heating degree-days for House J47 from Elec-HO sample.

Robust vs. Ordinary R-Square ELEC-HO

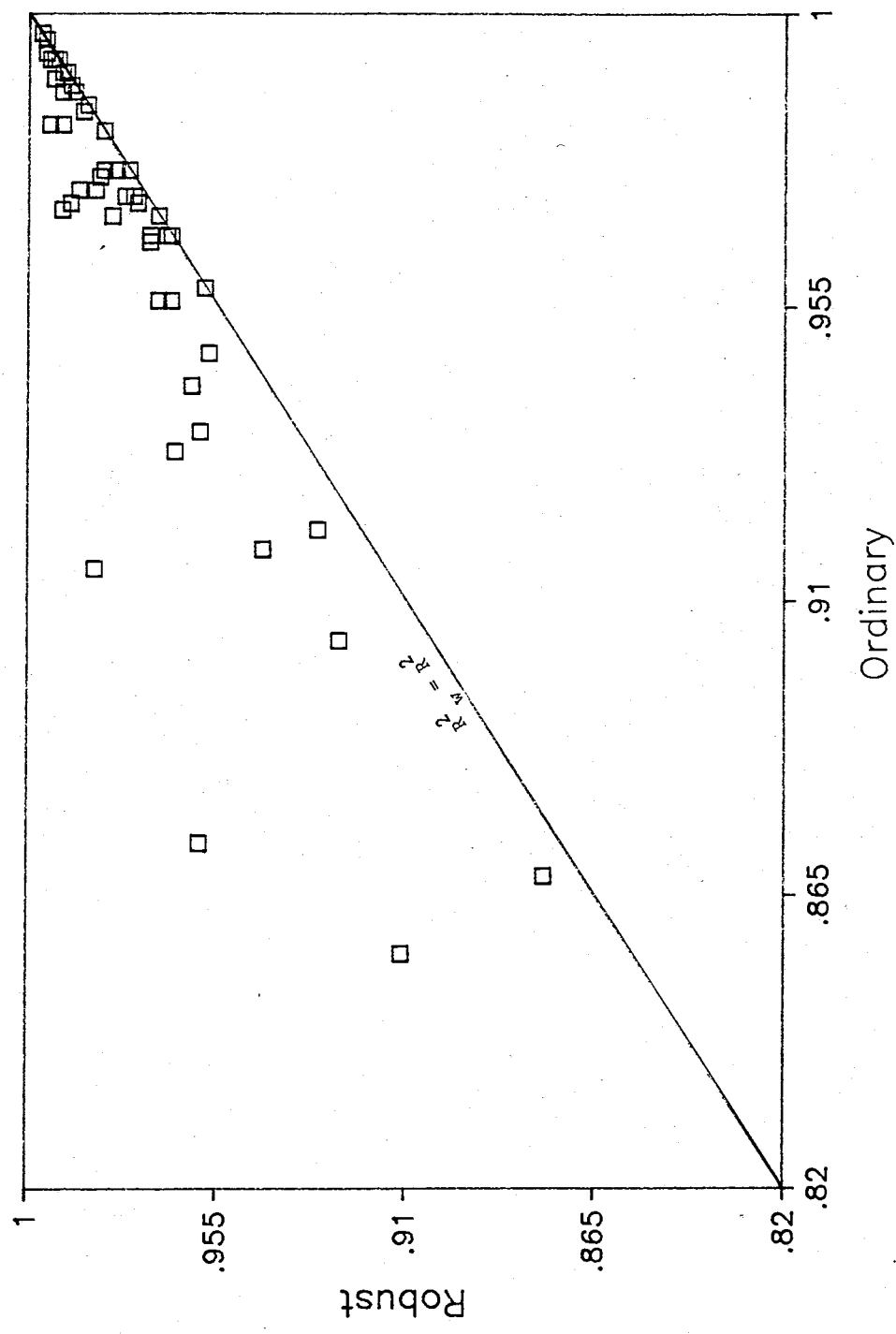


Figure 24. R² estimates for Robust (RPRISM) vs. Ordinary PRISM for Elec-HO sample.

VARIABLE=PCALPHA

MOMENTS			QUANTILES(DEF=4)			EXTREMES		
N	50	SUM WGT	2.03571	99%	2.03571	LOWEST	HIGHEST	
MEAN	-2.30721	SUM	0.724495	95%	1.53939	-12.9725	1.02985	
STD DEV	3.93168	VARIANCE	-0.573236	90%	1.02624	-12.4166	1.08165	
SKEWNESS	-1.3744	KURTOSIS	-3.94541	10%	-9.98623	-10.8894	1.50194	
USS	1023.61	CSS	-12.9725	5%	-11.5767	-10.7162	1.58516	
CV	-170.408	STD MEAN	15.0082	1%	-12.9725	-9.98775	2.03571	
T:MEAN=0	-4.14949	PROB> T	4.6699					
SGN RANK	-338.5	PROB> S	-12.9725					
NUM	49							

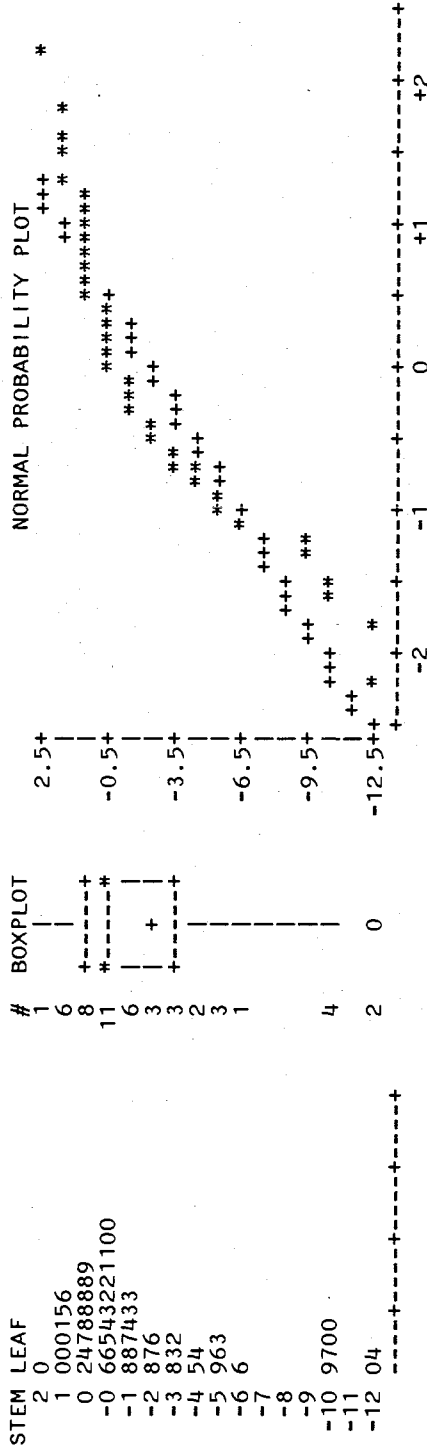


Figure 25. SAS Univariate summary of distribution of percent difference for α (PCALPHA) from Elec-AC sample: RPRISM vs. PRISM

VARIABLE=PCNAC

MOMENTS		QUANTILES(DEF=4)				EXTREMES	
N	50	4.05185	99%	4.05185	LOWEST	HIGHEST	
MEAN	-0.512275	0.438869	95%	1.44689	-6.68634	0.958104	
STD DEV	1.62296	0.462711	90%	0.9536	-4.26543	0.98488	
VARIANCE	-1.04635	-1.11233	10%	-2.37263	-3.73355	1.04106	
SKWENESS	142.188	-6.68634	5%	-3.9729	-2.75795	1.94292	
USS	-316.815	10.7382	1%	-6.68634	-2.42425	4.05185	
CV	-2.23193						
T-MEAN=0	-232.5						
SGN RANK	49						
NUM	0						

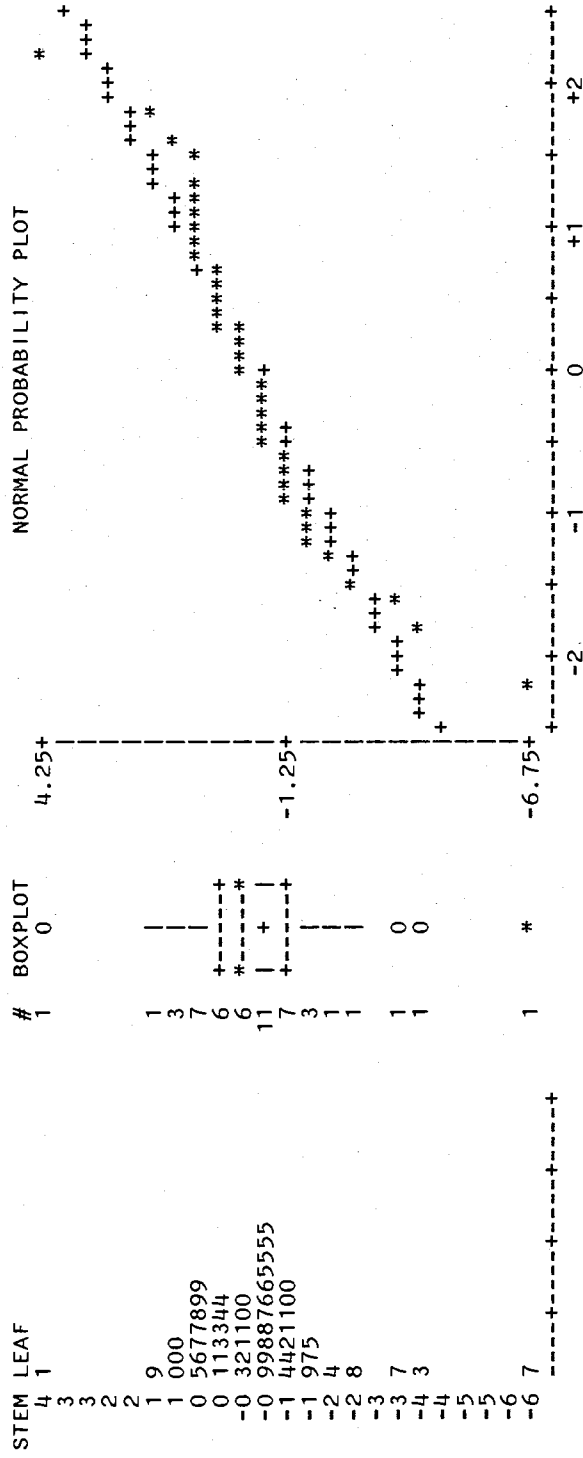


Figure 27. SAS Univariate summary of distribution of percent difference for NAC (PCNAC) from Elec-AC sample: RPRISM vs. PRISM

VARIABLE=PCBHO

MOMENTS		QUANTILES(DEF=4)				EXTREMES	
N	50	18.0015	18.0015	18.0015	18.0015	HIGHEST	
MEAN	1.44984	2.30829	2.30829	2.30829	15.1733	4.89031	
STD DEV	4.6915	0.86952	0.86952	0.86952	4.80344	7.51556	
VARIANCE	1.69969	0.75012	0.75012	0.75012	-2.25195	13.194	
SKEWNESS	1183.6	1078.5	1078.5	1078.5	-5.67565	17.5926	
USS	323.587	0.663479	0.663479	0.663479	-9.42339	18.0015	
CV	2.18521	0.0336836	0.0336836	0.0336836			
T:MEAN=0	268.5	0.00767882	0.00767882	0.00767882			
SGN RANK	49						
NUM							

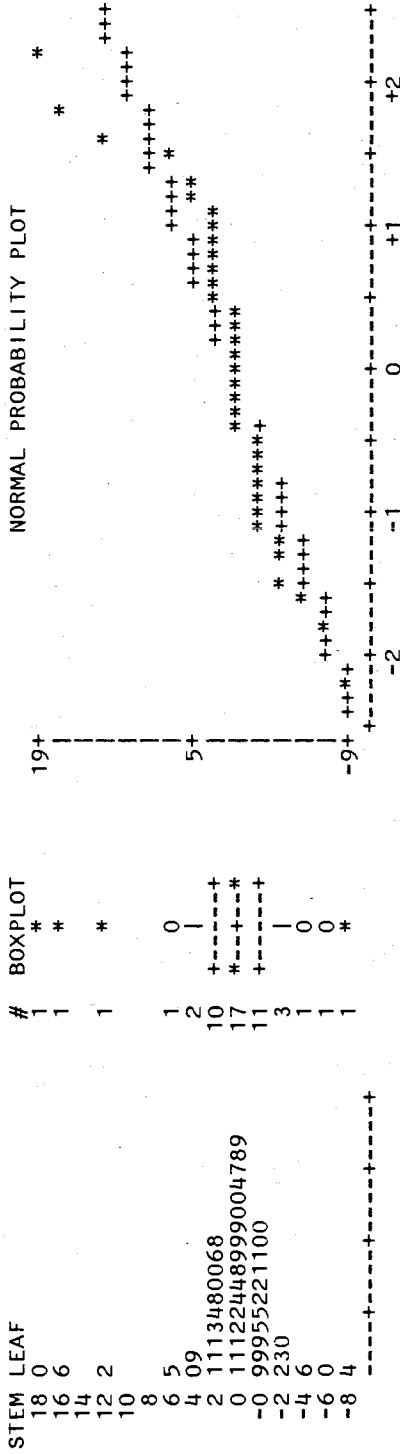


Figure 28. SAS Univariate summary of distribution of percent difference for βH_0 (PCBHO) from Elec-AC sample: RPRISM vs. PRISM

PERCENT DIFFERENCES FOR ELEC-AC

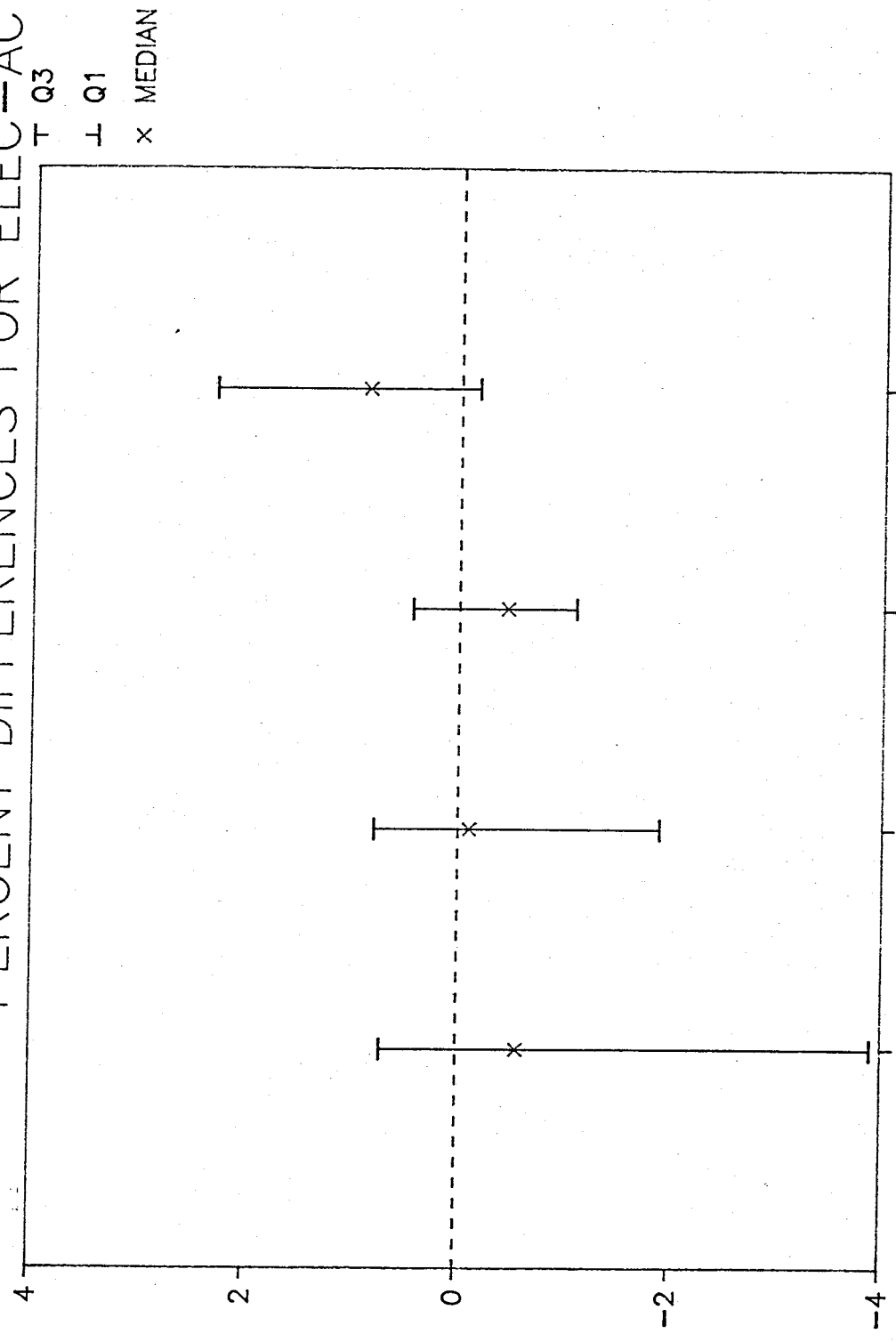


Figure 29. Plot of medians and quartiles of percent differences of PRISM vs. RPRISM parameters for Elec-AC sample.

VARIABLE=CVRALPHA

MOMENTS

N 50
 MEAN 1.14854
 STD DEV 0.275786
 SKEWNESS 1.36573
 USS 69.6837
 CV 24.012
 T:MEAN=0 29.4481
 SCN RANK 637.5
 NUM ^= 0 50

SUM WGTs
 SUM 1.14854
 VARIANCE 0.275786
 KURTOSIS 1.36573
 CSS 69.6837
 STD MEAN 24.012
 PROB>|T| 29.4481
 PROB>|S| 637.5

50 100% MAX 2.0941
 75% Q3 1.29692
 50% MED 1.07846
 25% Q1 0.934605
 0% MIN 0.761248
 RANGE .133285
 Q3-Q1 0.362314
 MODE 0.761248

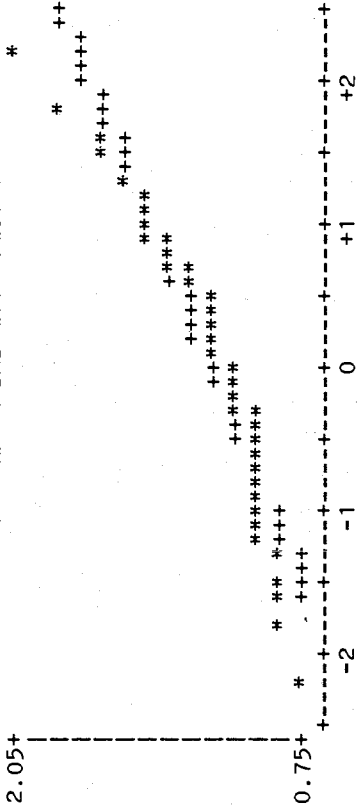
QUANTILES(DEF=4)
 99% 2.0941
 95% 1.75446
 90% 1.53312
 10% 0.892262
 5% 0.844246
 1% 0.761248

EXTREMES

LOWEST 0.761248
 HIGHEST 1.53914
 1.62985
 1.68528
 1.83901
 2.0941

STEM LEAF # BOXPLOT
 20 9 1
 19 4 1
 18 4 1
 17 4 2
 16 39 1
 15 4 4
 14 2448 3
 13 159 4
 12 0259 4
 11 33345667 8
 10 00023488 8
 9 003333446788 13
 8 4599 4
 7 6 1

NORMAL PROBABILITY PLOT



MULTIPLY STEM, LEAF BY 10** -01

Figure 30. SAS Univariate summary of distribution of CVRs for α (CVRALPHA) from Elec-AC sample.

VARIABLE=CVRBETA

MOMENTS		QUANTILES(DEF=4)				EXTREMES	
N	50	100% MAX	2.49047	2.49047	HIGHEST	2.49047	
MEAN	1.21077	75% Q3	1.35675	2.28764	LOWEST	0.748206	
STD DEV	0.38262	50% MED	1.05956	1.56867		0.826666	
SKWNESS	1.84822	25% Q1	0.968688	0.916948		0.831043	
USS	80.4711	0% MIN	0.748206	0.829073		0.899257	
CV	31.6015	RANGE	1.74226	0.748206		0.9158	
T:MEAN=0	22.3757	Q3-Q1	0.388065				
SGN RANK	637.5	MODE	0.748206				
NUM ^= 0	50						

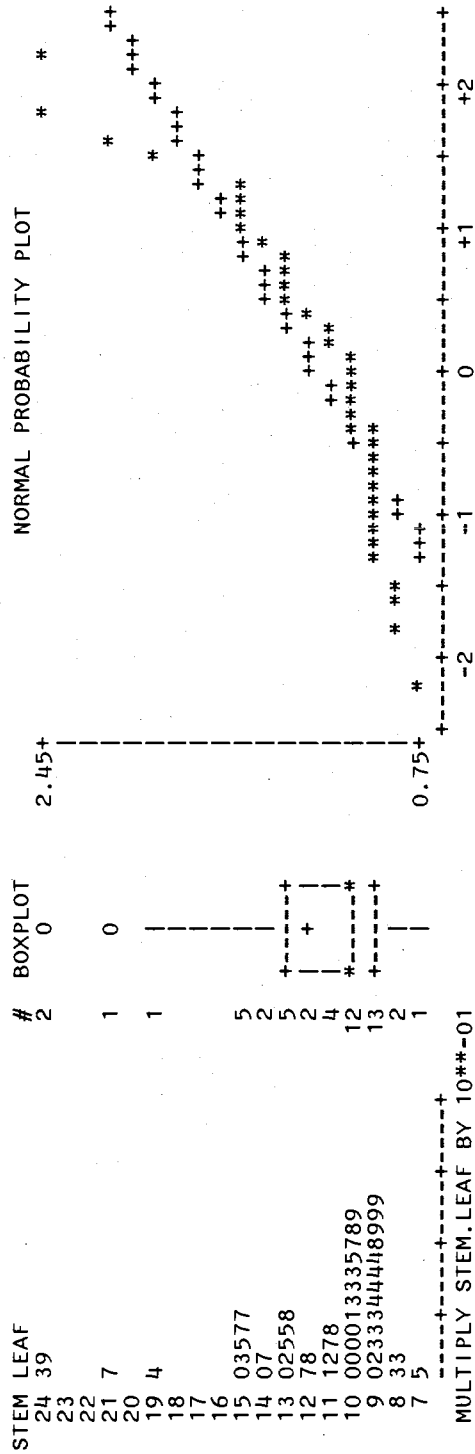


Figure 31. SAS Univariate summary of distribution of CVRs for β (CVRBETA) from Elec-AC sample.

VARIABLE=CVRNAC

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	50	2.29004	99%	2.29004	HIGHEST
MEAN	1.18269	1.3337	95%	1.97893	1.57713
STD DEV	0.320822	1.08303	90%	1.57521	1.6888
SKWNESS	1.56515	0.939813	10%	0.926884	1.89823
USS	74.9812	0.757609	5%	0.83783	2.07757
CV	27.1265		1%	0.757609	2.29004
T:MEAN=0	26.067	1.53243			
SGN RANK	637.5	0.393883			
NUM = 0	50	0.757609			

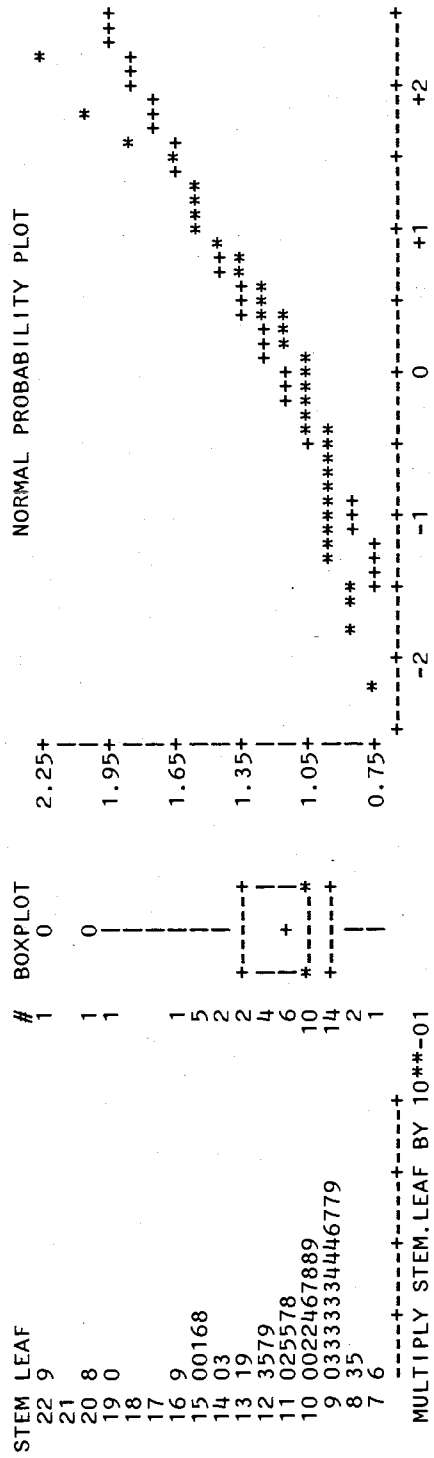


Figure 32. SAS Univariate summary of distribution of CVRs for NAC (CVRNAC) from Elec-AC sample.

VARIABLE=CVRBHO

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	50	2.66135	99%	2.66134	HIGHEST
MEAN	1.20309	1.32039	95%	0.750756	LOWEST
STD DEV	0.365876	1.07567	90%	0.819553	
VARIANCE	2.01373	0.946623	10%	0.842051	
SKWENESS	78.9301	0.750756	5%	0.900559	
USS	30.4115	1.91059	1%	0.918009	
CV	23.2513	0.37377		0.750756	
T:MEAN=0	637.5	0.750756			
SGN RANK					
NUM	= 0				

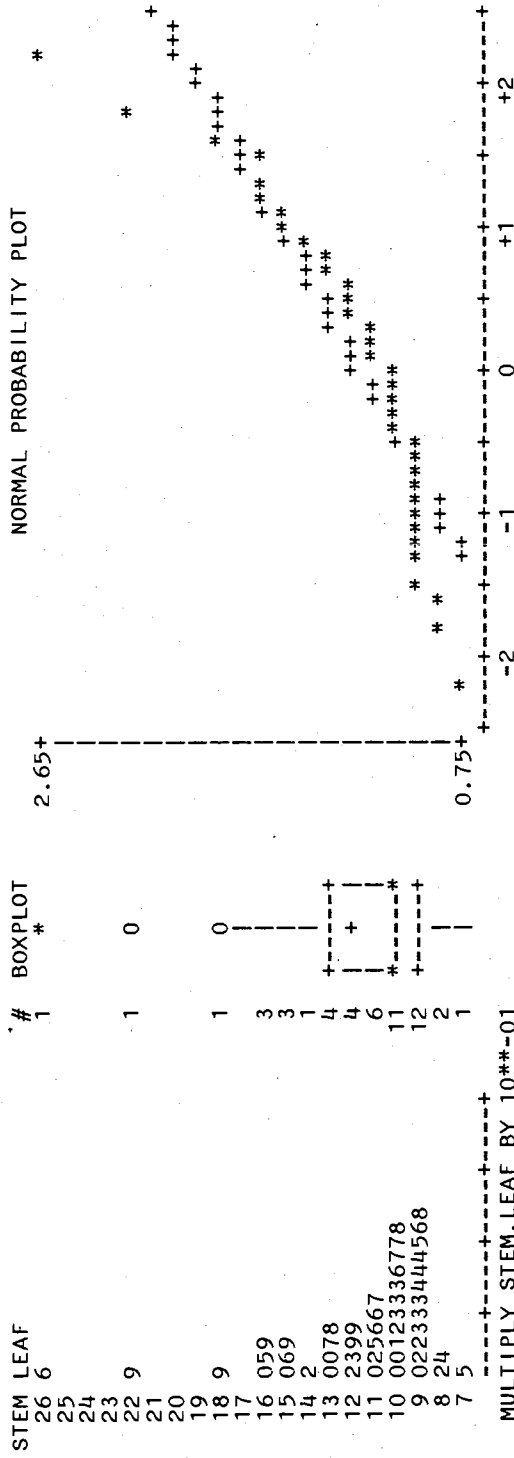


Figure 33. SAS Univariate summary of distributions of CVRs for βH_0 (CVRBHO) from Elec-AC sample.

CVR SUMMARIES FOR ELEC AC

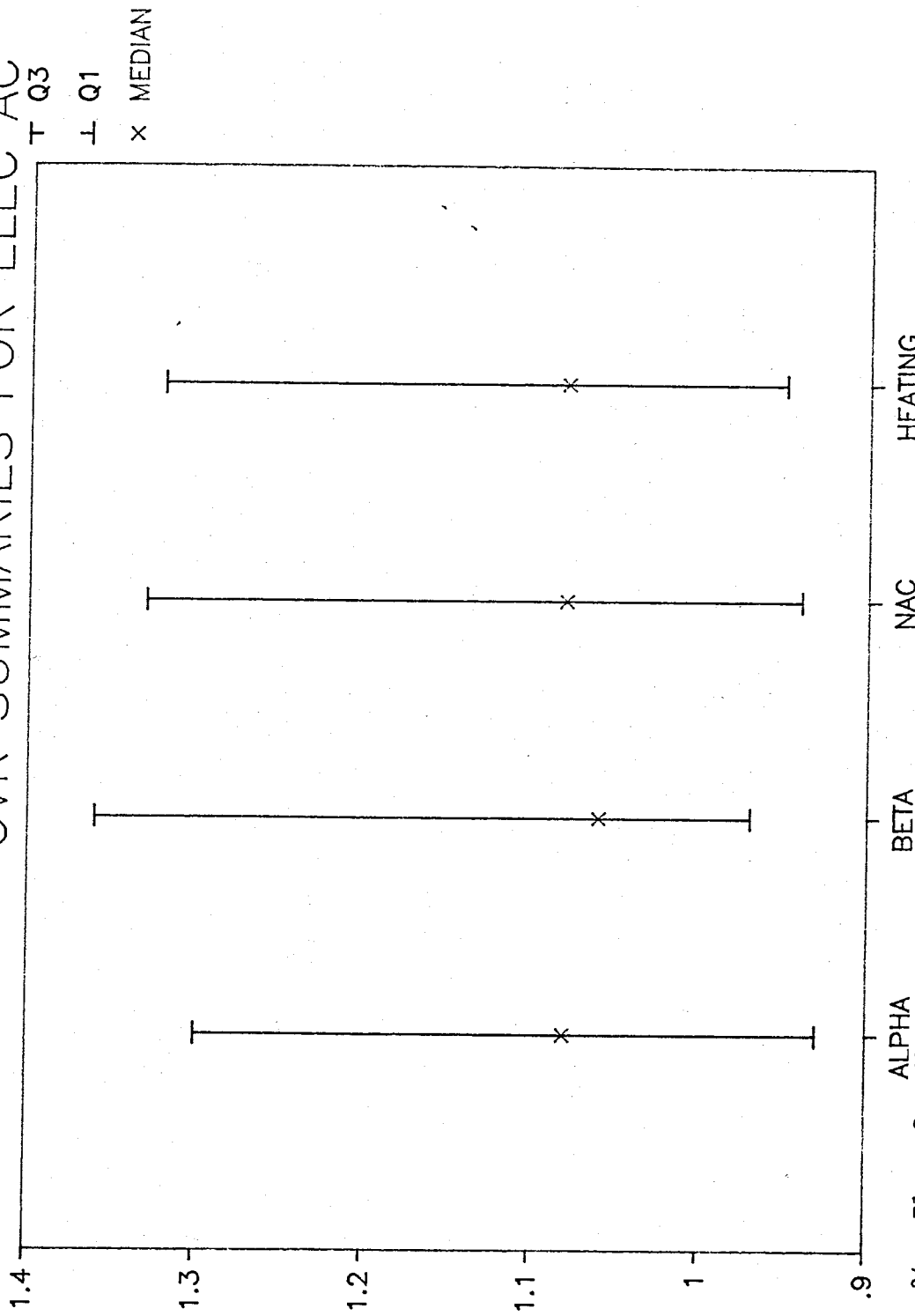


Figure 34. Plot of medians and quartiles of CVRs of PRISM vs. RPRISM parameters for Elec-AC sample.

Robust vs. Ordinary R-Square
ELEC-AC

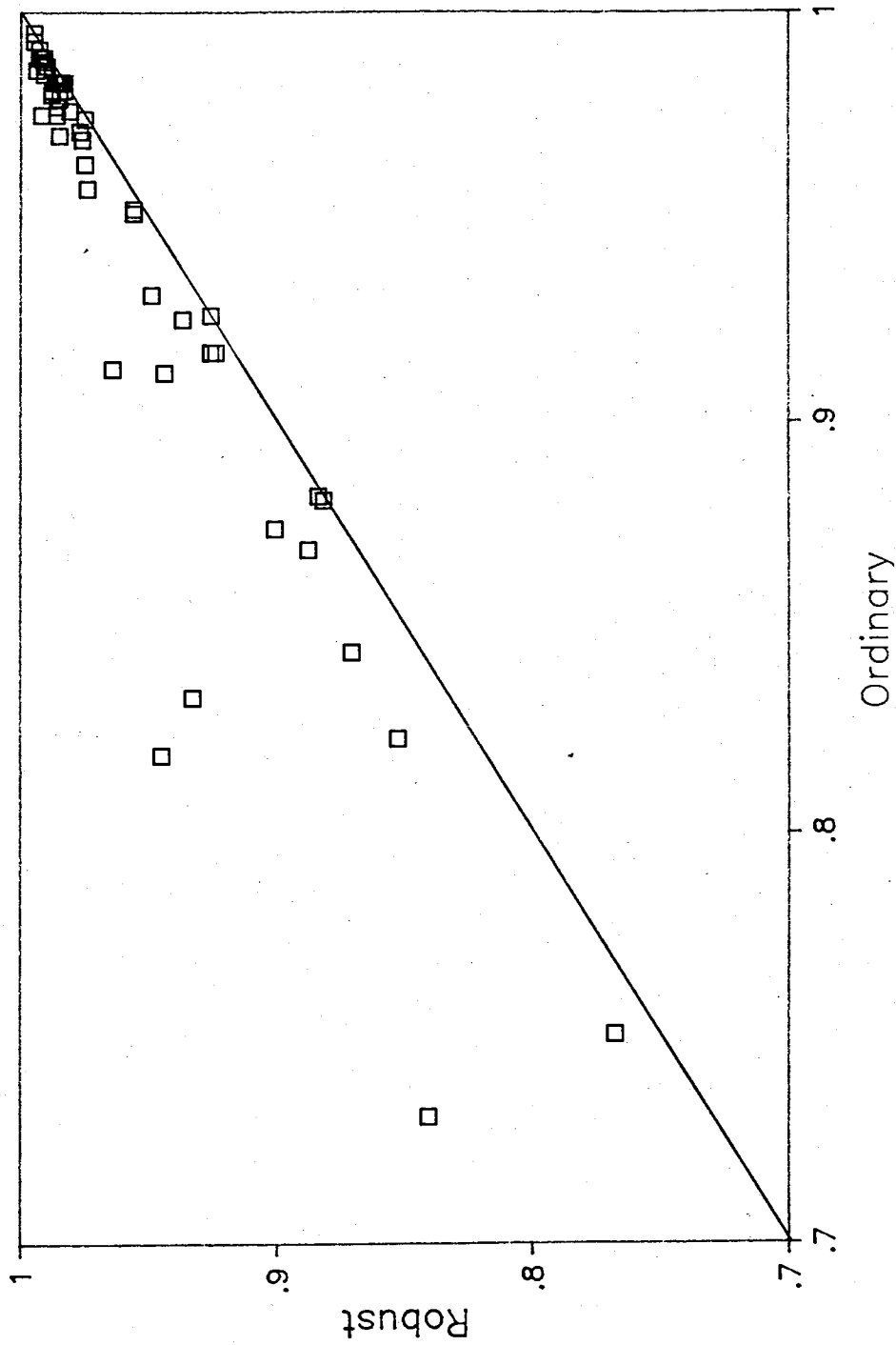


Figure 35. R^2 estimates for Robust (RPRISM) vs. Ordinary PRISM for Elec-AC sample.

CONS-PERIOD FOR J2832

House: J2832

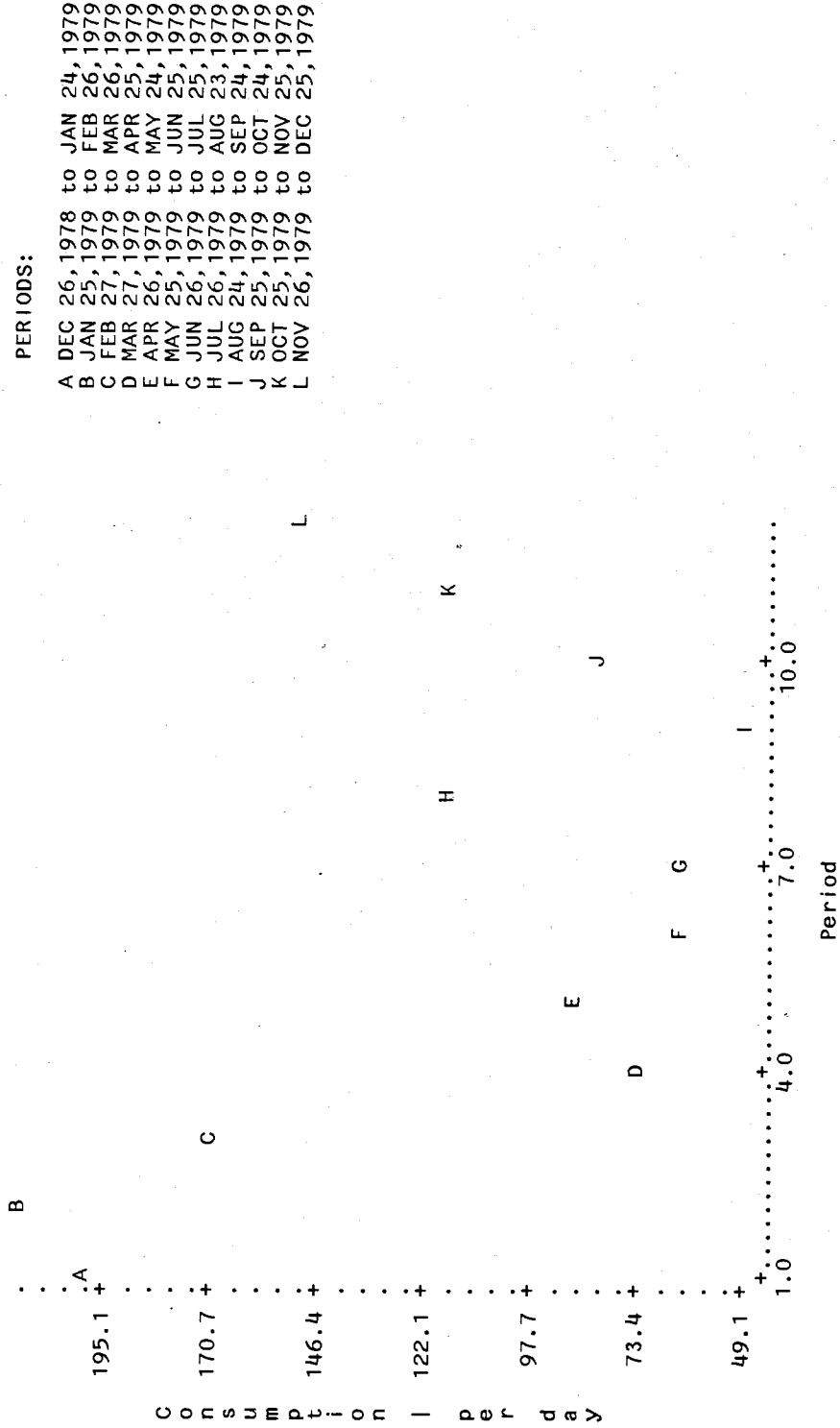


Figure 36. Plot of consumption vs. period for House J2832 from Elec-AC sample.

CONS-HDD FOR J2832, PRISM

House: J2832 , alpha= 74.08, beta= 4.40, R2= 0.8332

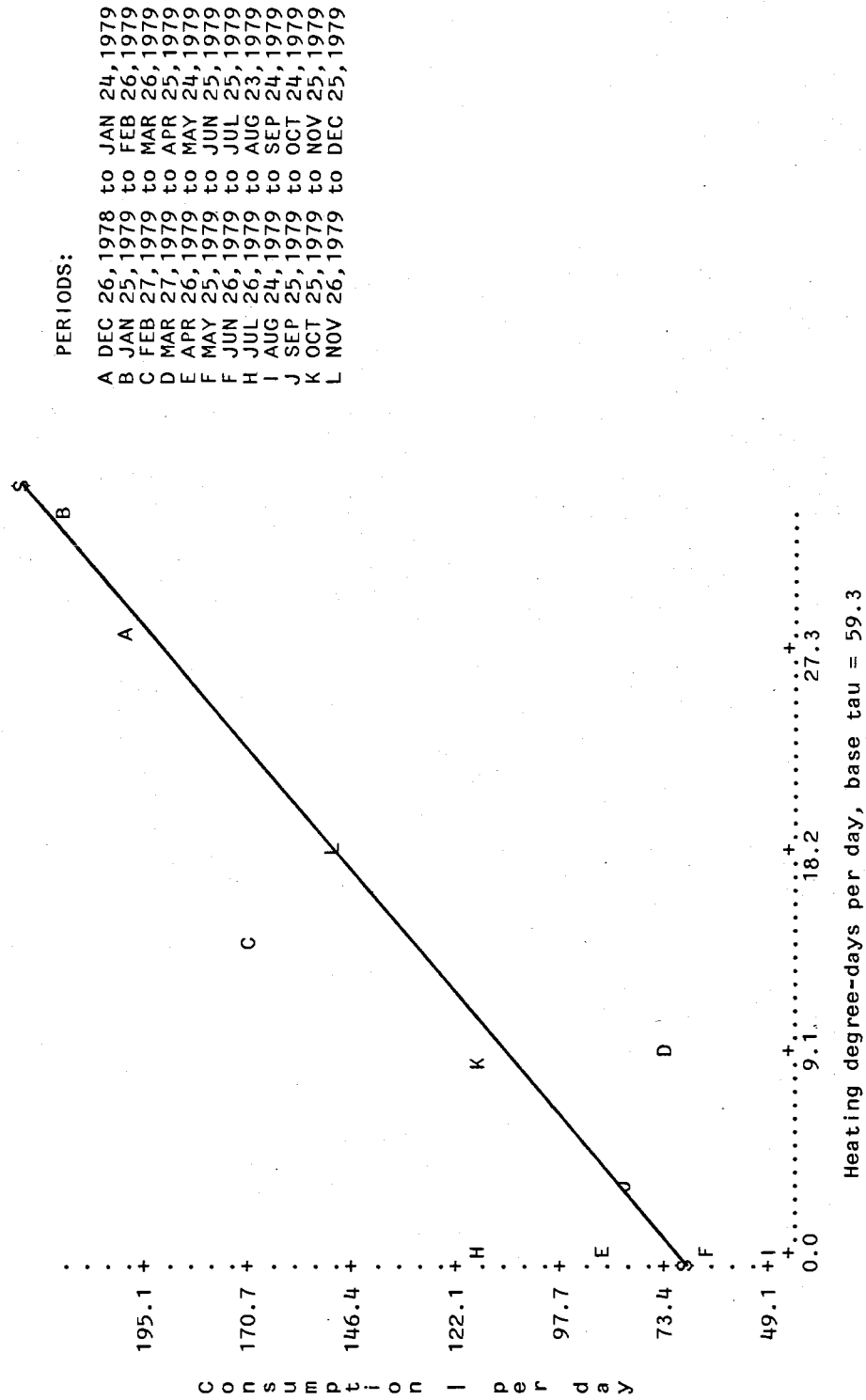


Figure 37. PRISM plot of consumption vs. heating degree-days for House J2832 from Elec-AC sample.

RESIDS-HDD FOR J2832, PRISM

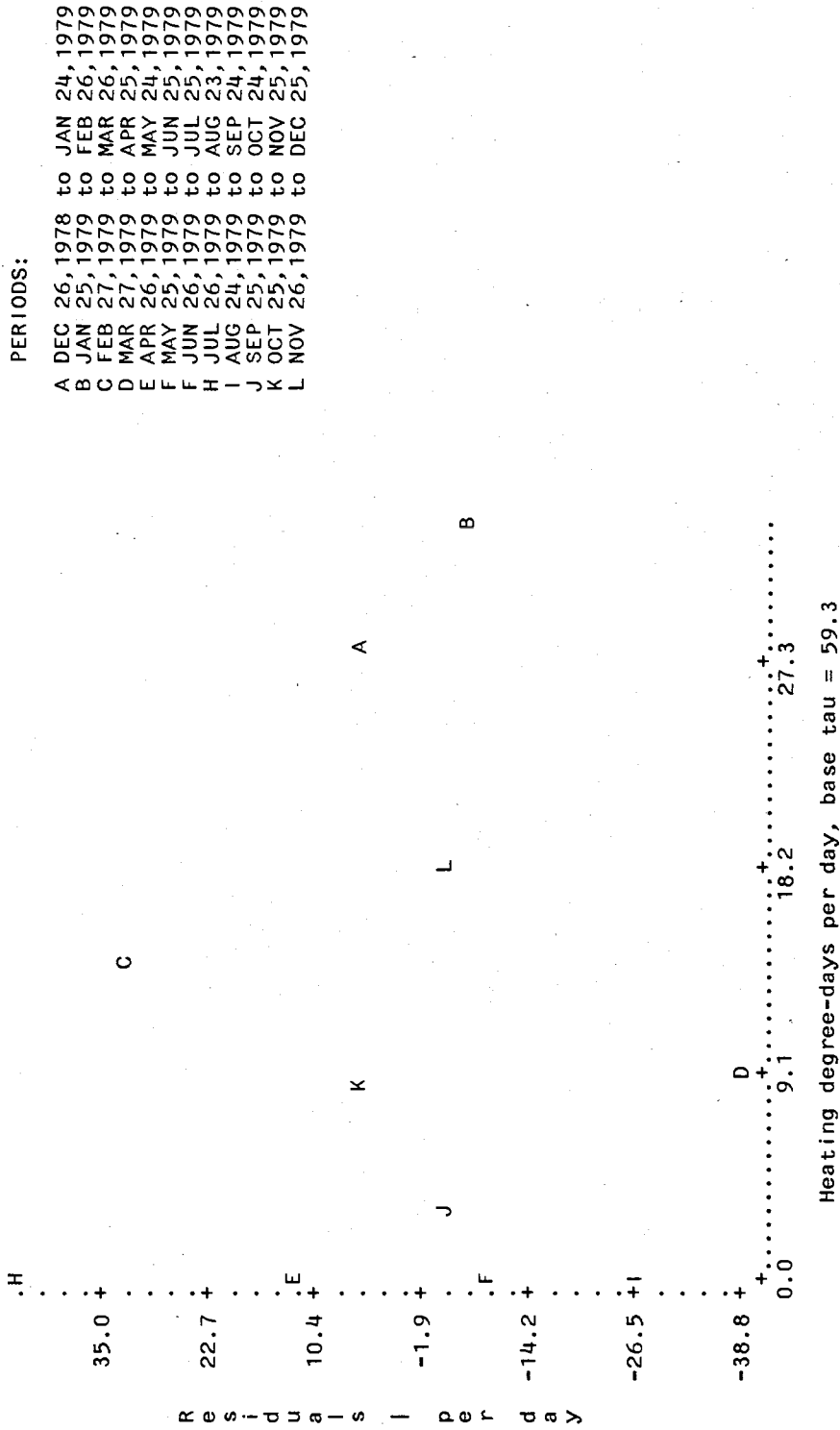


Figure 38. PRISM plot of residuals vs. heating degree-days for House J2832 from Elec-AC sample.

CONS-HDD FOR J2832, RPRISM

House: J2832, alpha= 64.47, beta= 3.95, R2= 0.9330

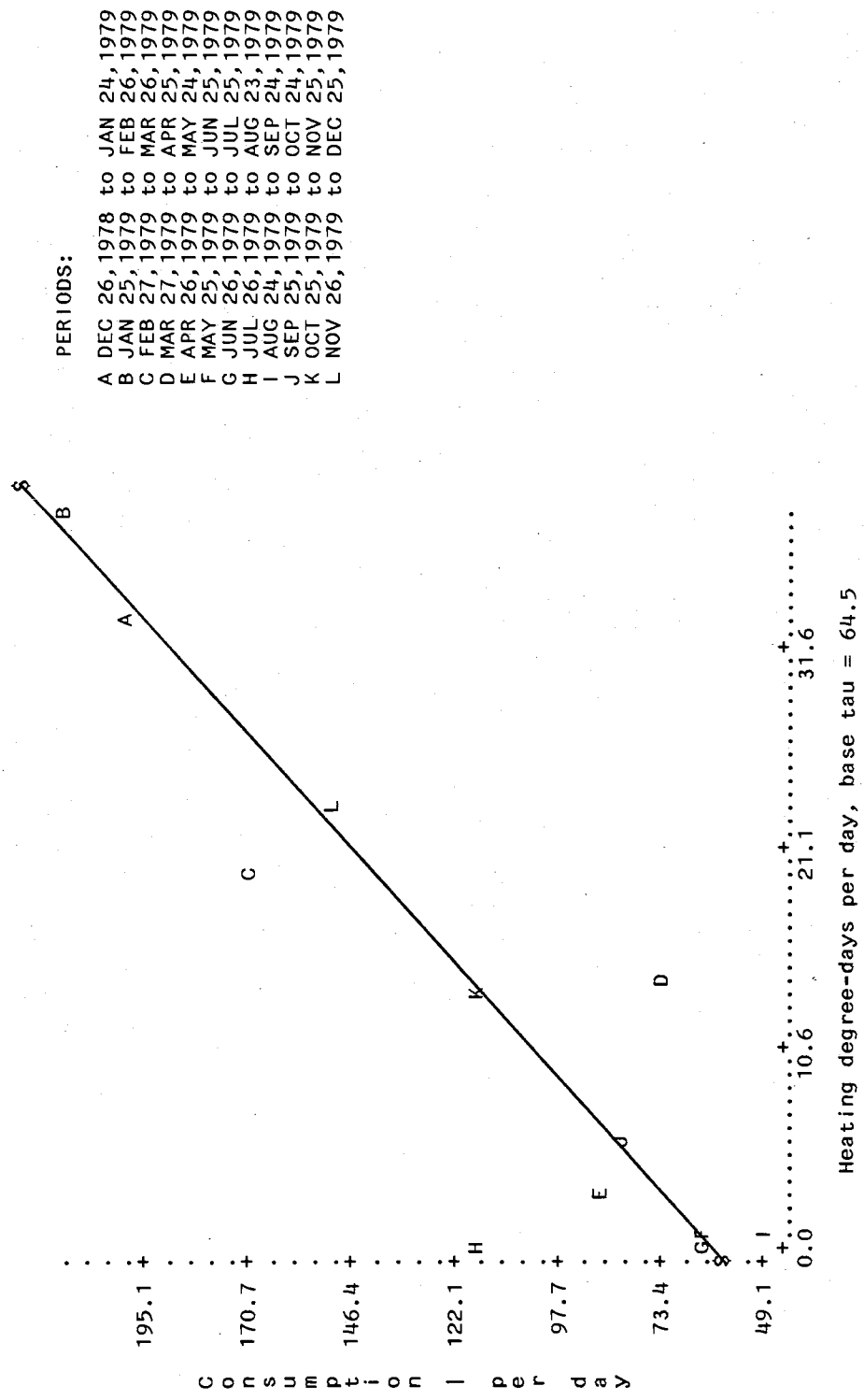


Figure 39. RPRISM plot of consumption vs. heating degree-days for House J2832 from Elec-AC sample.

RESIDS-HDD FOR J2832, RPRISM

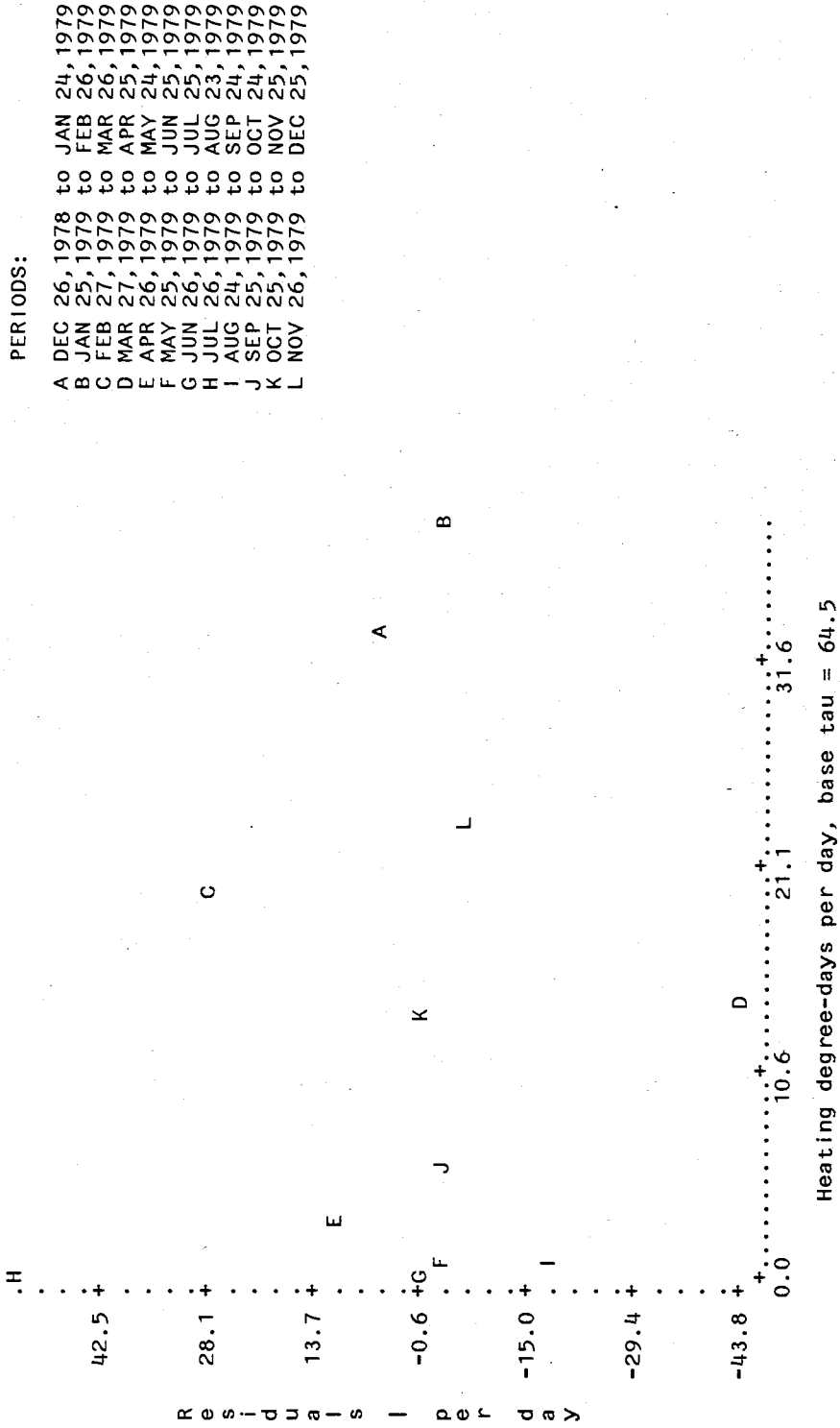


Figure 40. RPRISM plot of residuals vs. heating degree-days for House J2832 from Elec-AC sample.

CONS-PERIOD FOR J3075

House: J3075

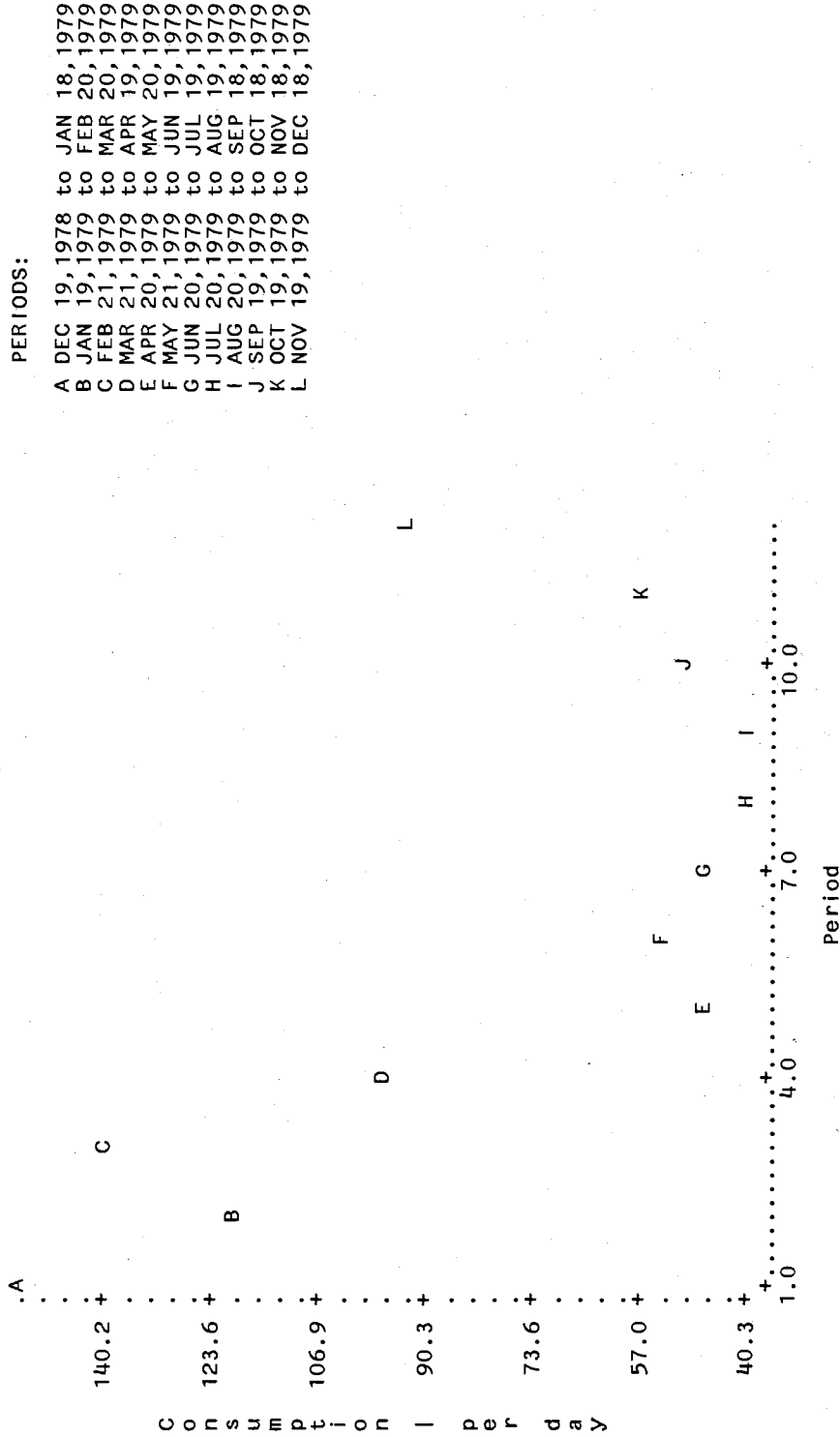


Figure 41. Plot of consumption vs. period for House J3075 from Elec-AC sample.

CONS-HDD FOR J3075, PRISM

House: J3075, alpha= 41.28, beta= 2.61, R2= 0.8233

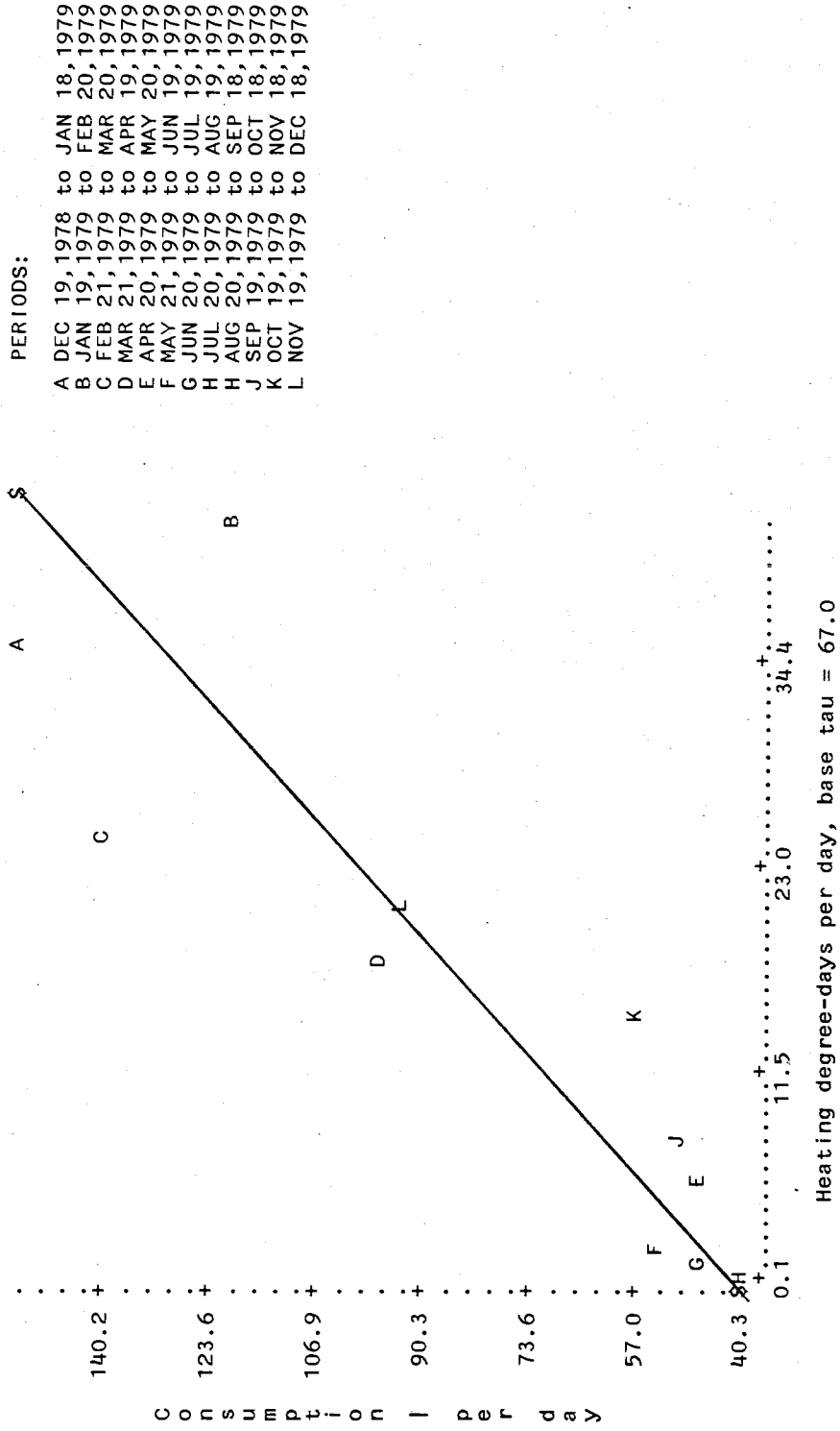


Figure 42. PRISM plot of consumption vs. heating-degree days for House J3075 from Elec-AC sample.

CONS-HDD FOR J3075, RPRISM

House: J3075, alpha= 41.90, beta= 2.90, R2= 0.8531

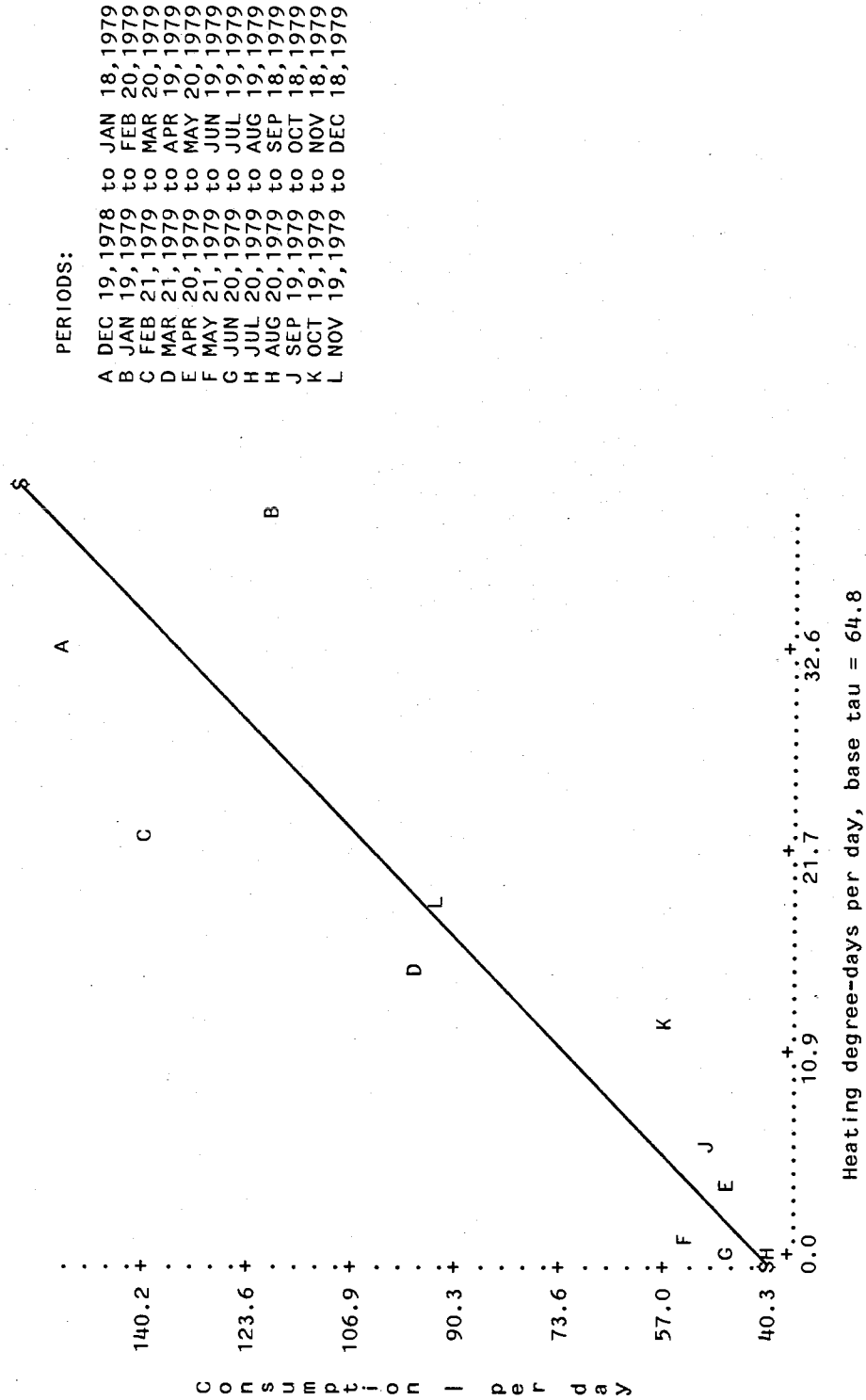


Figure 43. RPRISM plot of consumption vs. heating degree-days for House J3075 from Elec-AC sample.

CONS-PERIOD FOR J3076

House: J3076

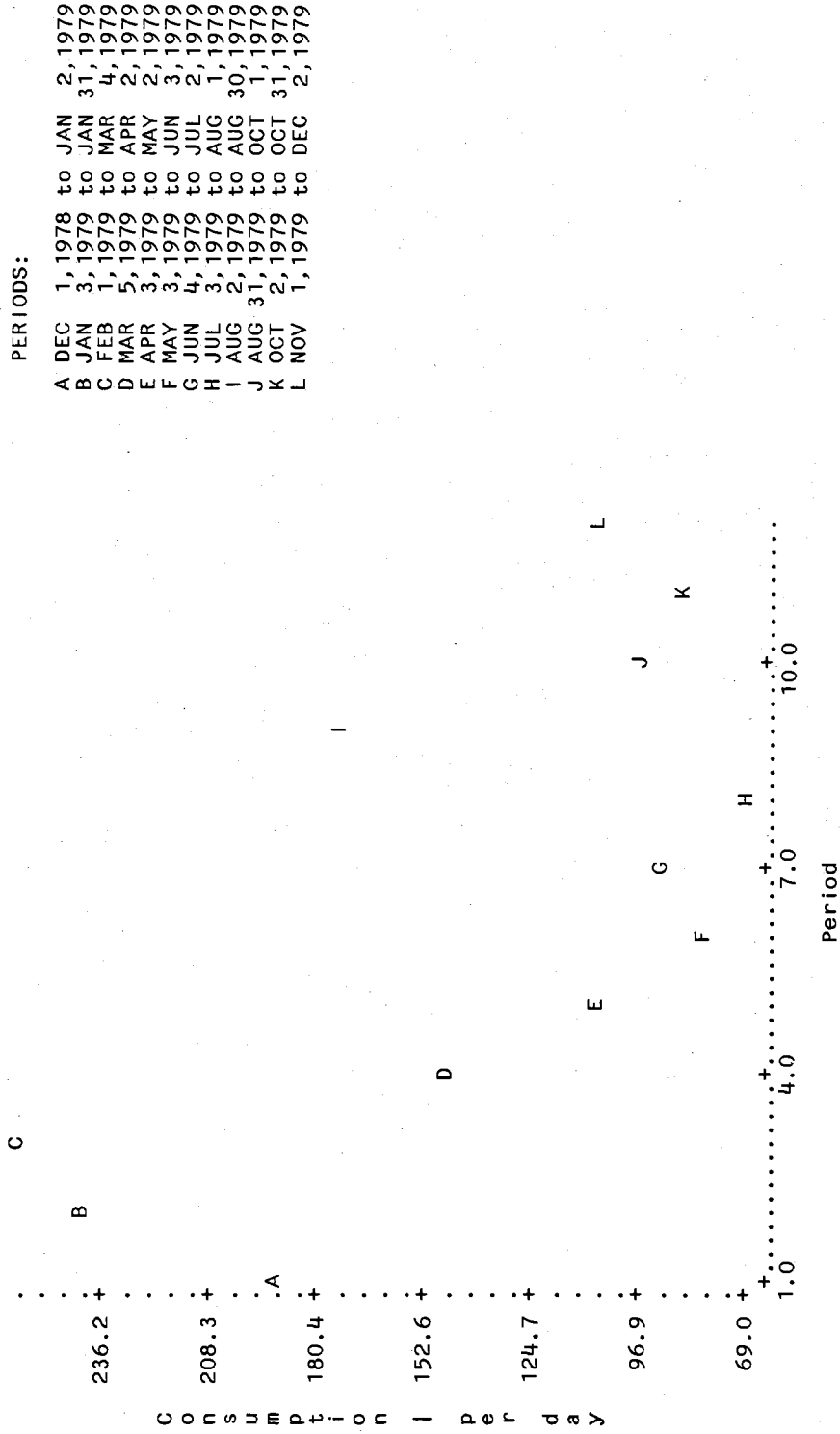


Figure 44. Plot of consumption vs. period for House J3076 from Elec-AC sample.

CONS-HDD FOR J3076, PRISM

House: J3076, alpha = 98.90, beta = 7.17, R2 = 0.8192

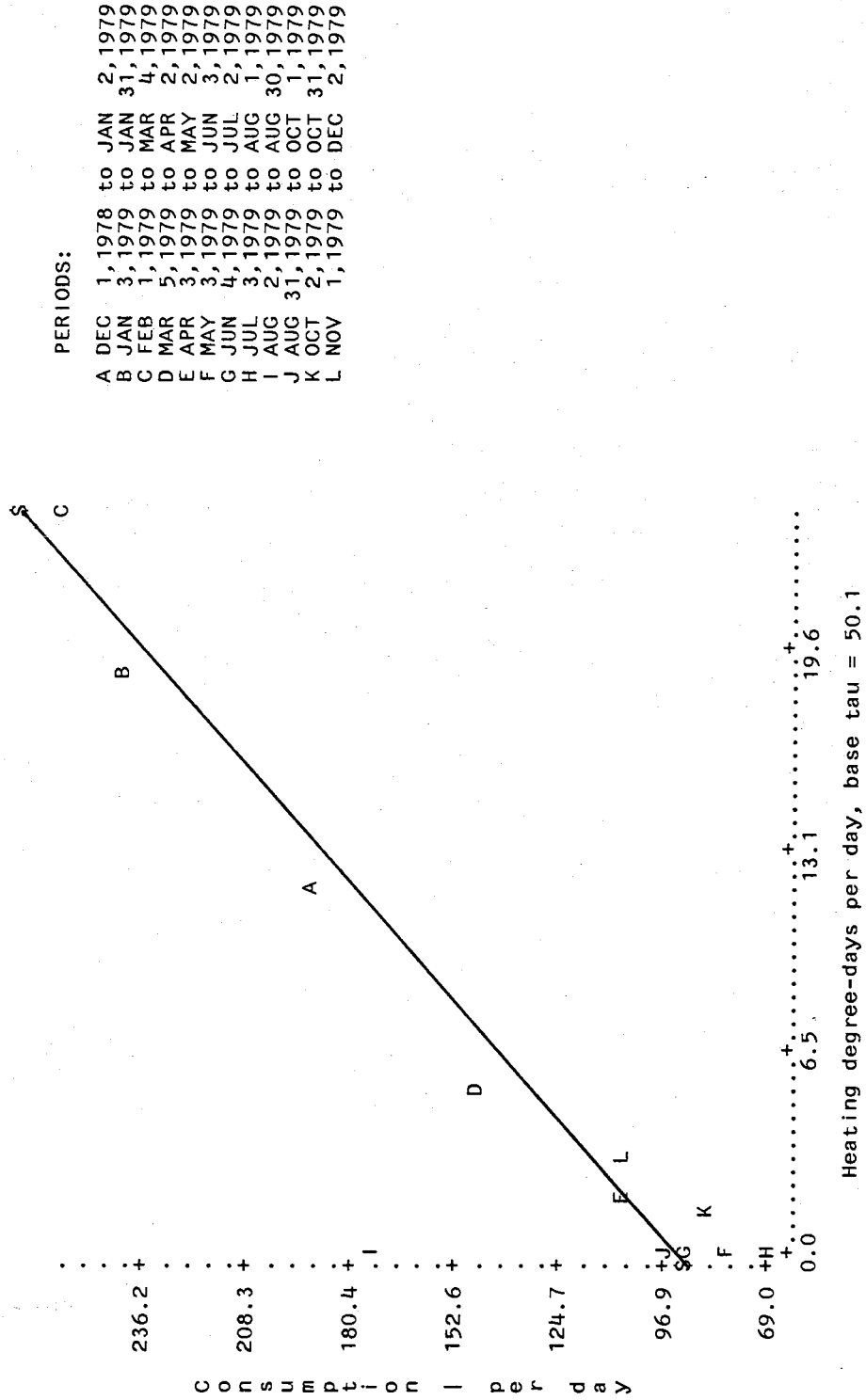
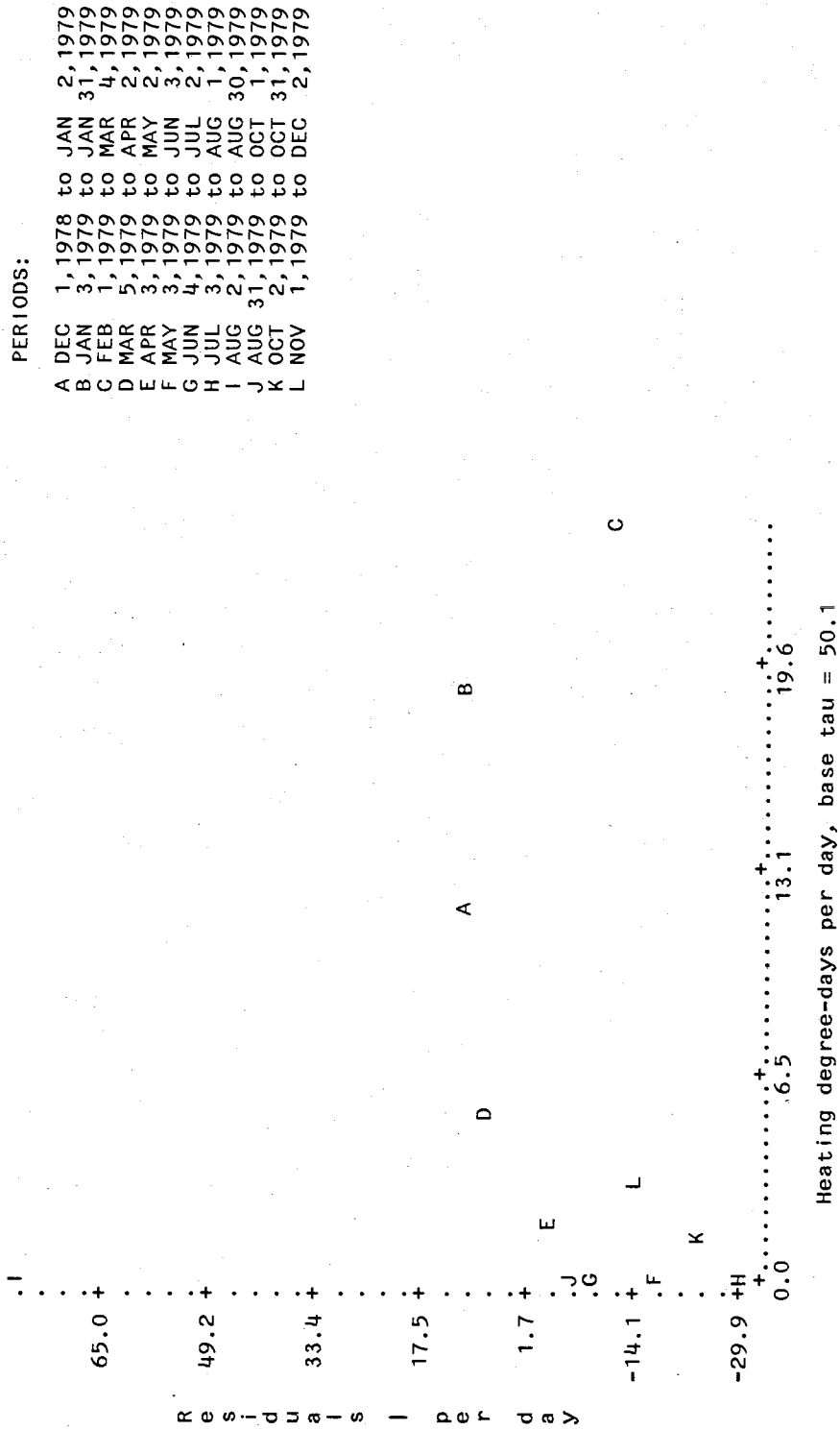


Figure 45. PRISM plot of consumption vs. heating degree-days for House J3076 from Elec-AC sample.

RESIDS-HDD FOR J3076, PRISM



PERIODS:

A	DEC	1, 1978	to	JAN	2, 1979
B	JAN	3, 1979	to	JAN	31, 1979
C	FEB	1, 1979	to	MAR	4, 1979
D	MAR	5, 1979	to	APR	2, 1979
E	APR	3, 1979	to	MAY	2, 1979
F	MAY	3, 1979	to	JUN	3, 1979
G	JUN	4, 1979	to	JUL	2, 1979
H	JUL	3, 1979	to	AUG	1, 1979
I	AUG	2, 1979	to	AUG	30, 1979
J	AUG	31, 1979	to	OCT	1, 1979
K	OCT	2, 1979	to	OCT	31, 1979
L	NOV	1, 1979	to	DEC	2, 1979

Figure 46. PRISM plot of residuals vs. heating degree-days for House J3076 from Elec-AC sample.

CONS-HDD FOR J3076, RPRISM

House: J3076 , alpha= 86.62, beta= 6.71, R2= 0.9453

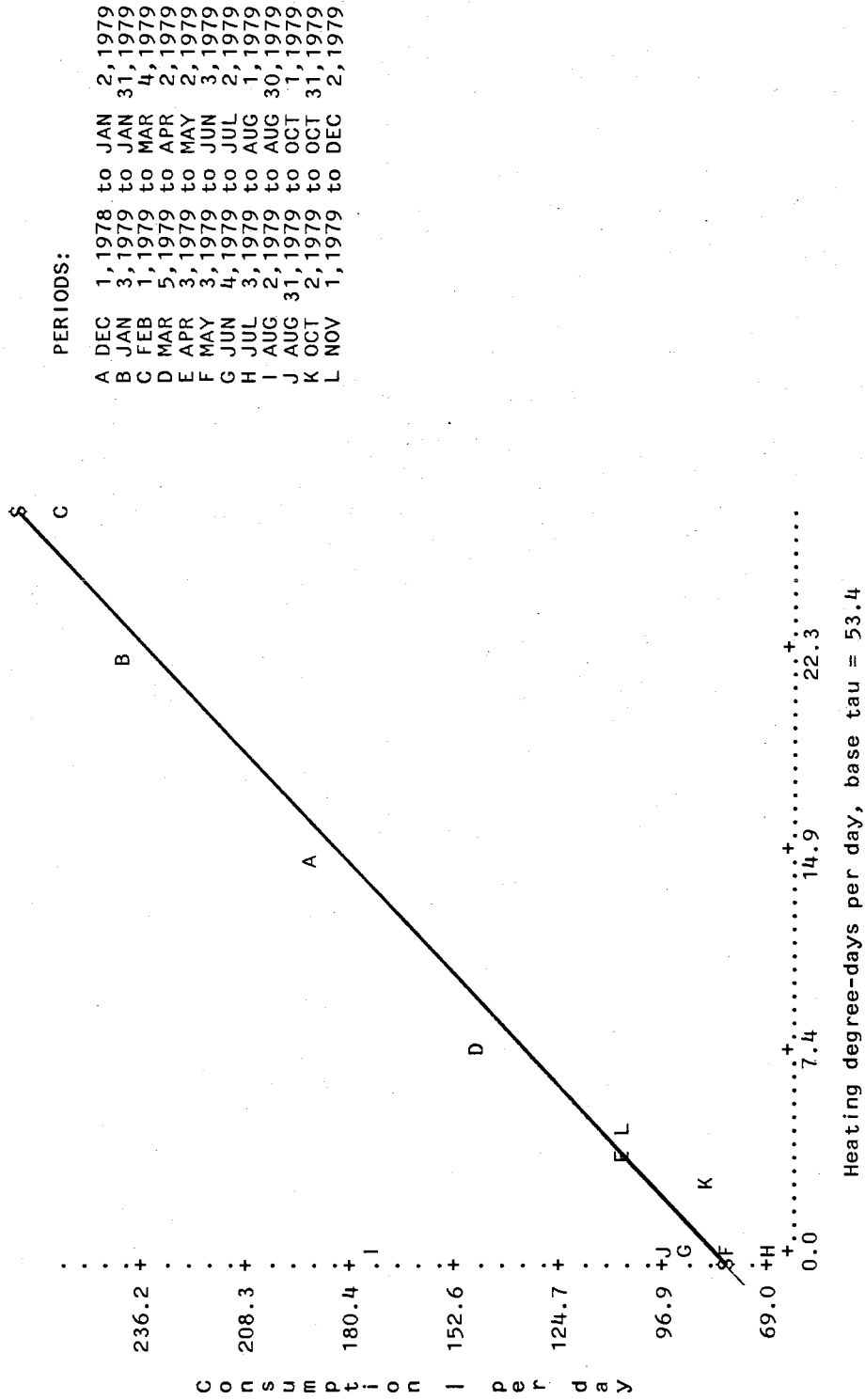
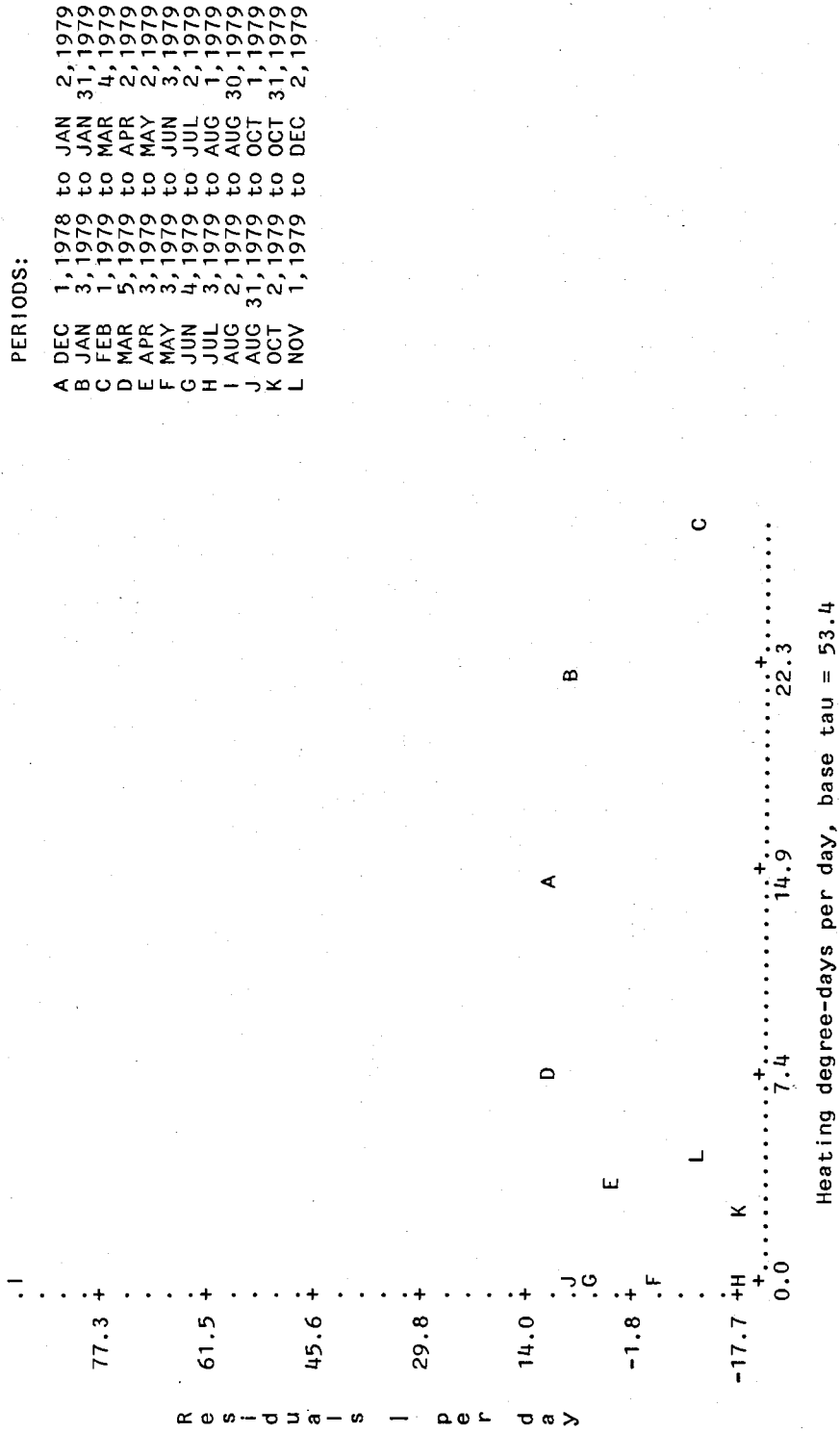


Figure 47. RPRISM plot of consumption vs. heating degree-days for House J3076 from Elec-AC sample.

RESIDS-HDD FOR J3076, RPRISM



PERIODS:
 A DEC 1, 1978 to JAN 2, 1979
 B JAN 3, 1979 to JAN 31, 1979
 C FEB 1, 1979 to MAR 4, 1979
 D MAR 5, 1979 to APR 2, 1979
 E APR 3, 1979 to MAY 2, 1979
 F MAY 3, 1979 to JUN 3, 1979
 G JUN 4, 1979 to JUL 2, 1979
 H JUL 3, 1979 to AUG 1, 1979
 I AUG 2, 1979 to AUG 30, 1979
 J AUG 31, 1979 to OCT 1, 1979
 K OCT 2, 1979 to OCT 31, 1979
 L NOV 1, 1979 to DEC 2, 1979

Figure 48. RPRISM plot of residuals vs. heating degree-days for House J3076 from Elec-AC sample.

Schematic for OUTWTS

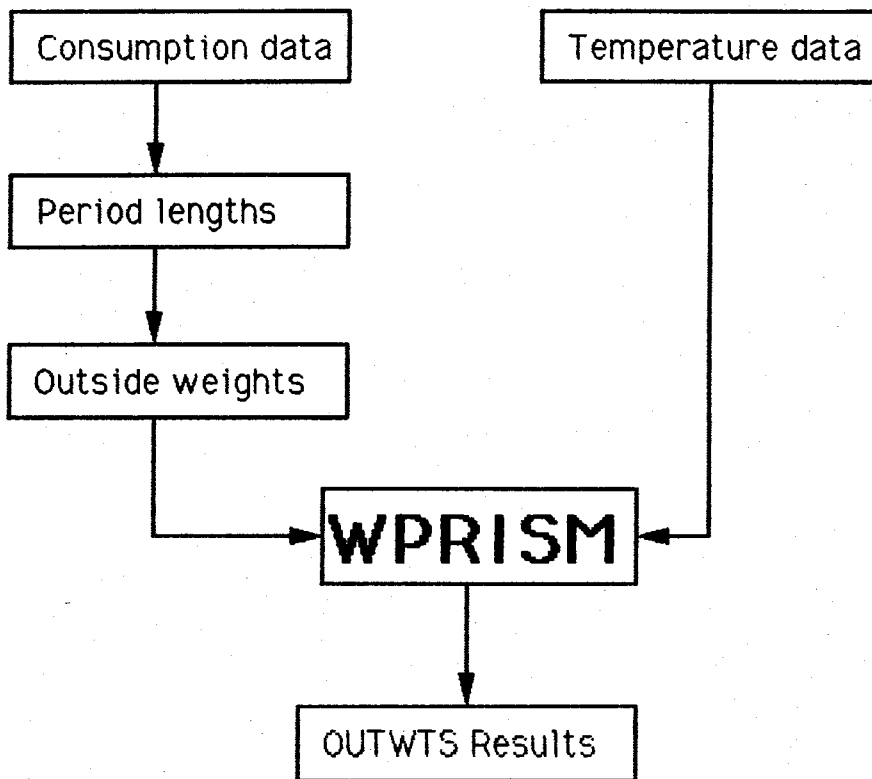


Figure 49. Schematic of weighted PRISM (OUTWTS) algorithm.

VARIABLE=PCBETA

MOMENTS		QUANTILES(DEF=4)				EXTREMES	
N	69	100% MAX	10.5023	99%	10.5023	HIGHEST	
MEAN	-1.8966	75% Q3	2.69058	95%	7.22295	LOWEST	
STD DEV	11.2099	50% MED	0.416667	90%	5.10947		
SKWNESS	-3.33988	25% Q1	-2.32646	10%	-4.93273		
USS	8793.13	0% MIN	-51.2821	5%	-40.7873		
CV	-591.051	RANGE	61.7843	1%	-51.282		
T:MEAN=0	-1.4054	Q3-Q1	5.01704				
SGN RANK	75	MODE	0				
NUM	67						

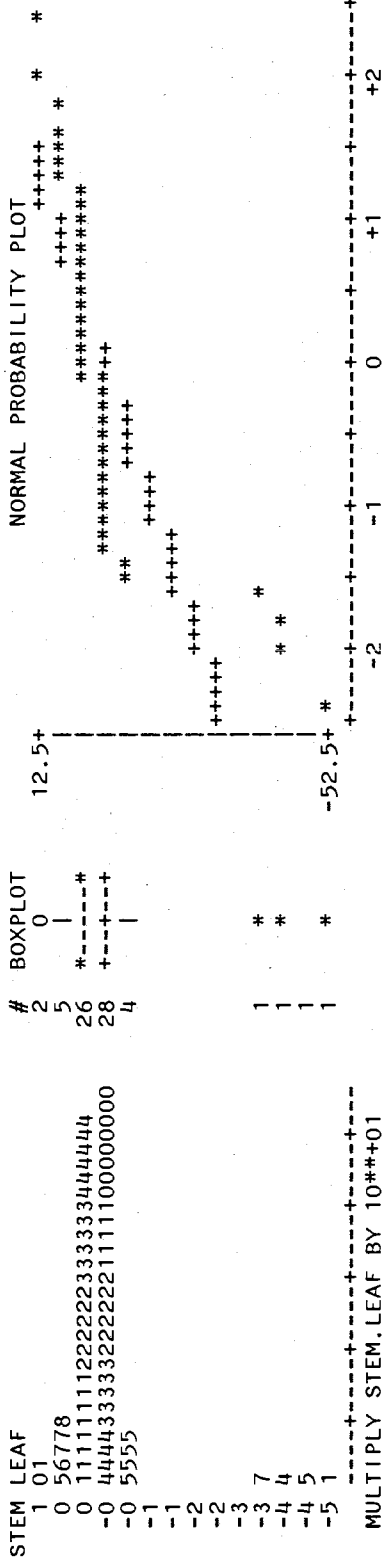


Figure 51. SAS Univariate summary of distribution of percent difference for β (PCBETA) from OIL sample: OUTWTS vs. PRISM

VARIABLE=PCNAC

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	69	0.876062	0.876062	0.876062	
MEAN	-0.928853	-0.02277	0.573579	-21.3673	HIGHEST
STD DEV	2.89981	8.40891	0.337211	-10.7316	0.474273
SKENNESS	-5.88844	38.6405	-1.51826	-4.06362	0.491111
USS	631.337	571.806	-3.51873	-2.97384	0.656052
CV	-312.193	0.349096	-21.3673	-2.51574	0.686807
T:MEAN=0	-2.66073	0.00971847	22.2433		0.876062
SGN RANK	-829.5	0.0001	0.740469		
NUM = 0	69		-21.3673		

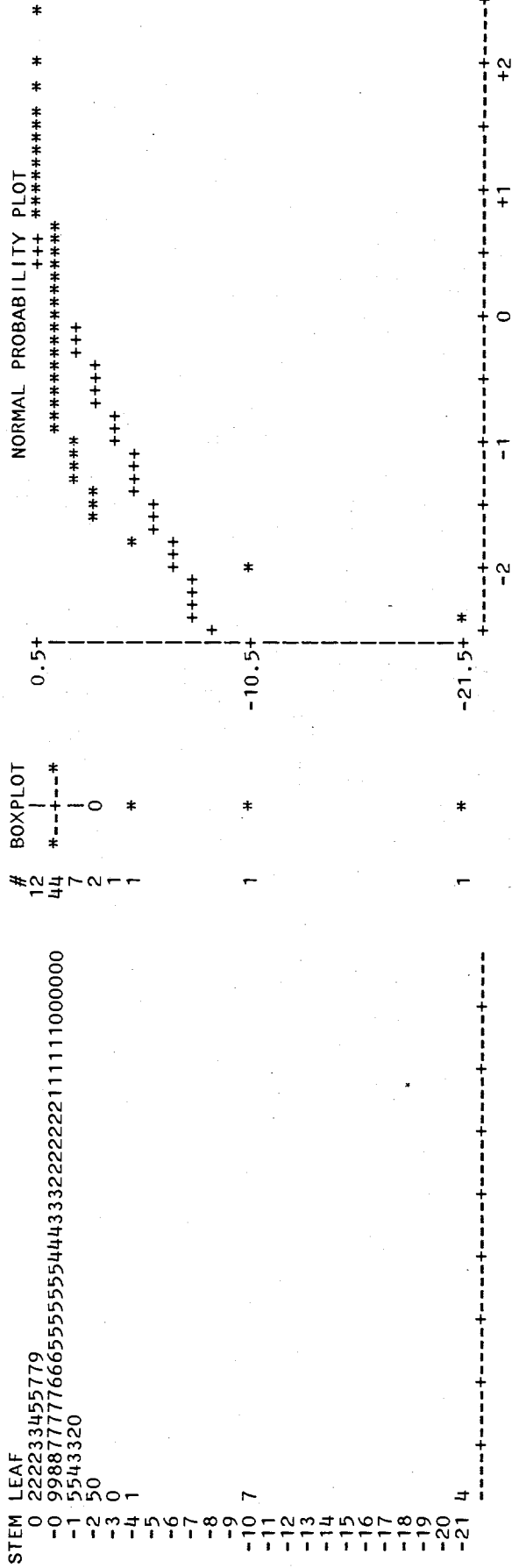


Figure 52. SAS Univariate summary of distribution of percent difference for NAC (PCNAC) from OIL sample: OUTWTS vs. PRISM

VARIABLE=PCBHO

MOMENTS		QUANTILES(DEF=4)			EXTREMES		
N	69	69	680.306	680.306	680.306	HIGHEST	32.4906
MEAN	11.731	809.437	2.99092	49.4463	21.0807	LOWEST	-21.0807
STD DEV	82.7649	6850.03	0.35504	8.41985	13.5802		40.1319
VARIANCE	7.98624	65.2666	0.12603	-6.70711	8.78207		58.7613
SKEWNESS	475297	465802	0.77335	-21.0807	-8.25549		68.4446
USS	705.524	9.96372	0.00000	701.387	-8.03919		680.306
CV	1.17737	0.243153	0.00000	6.76427			
T: MEAN=0	-56.5	0.73776		-21.0807			
SGN RANK							
NUM	69						

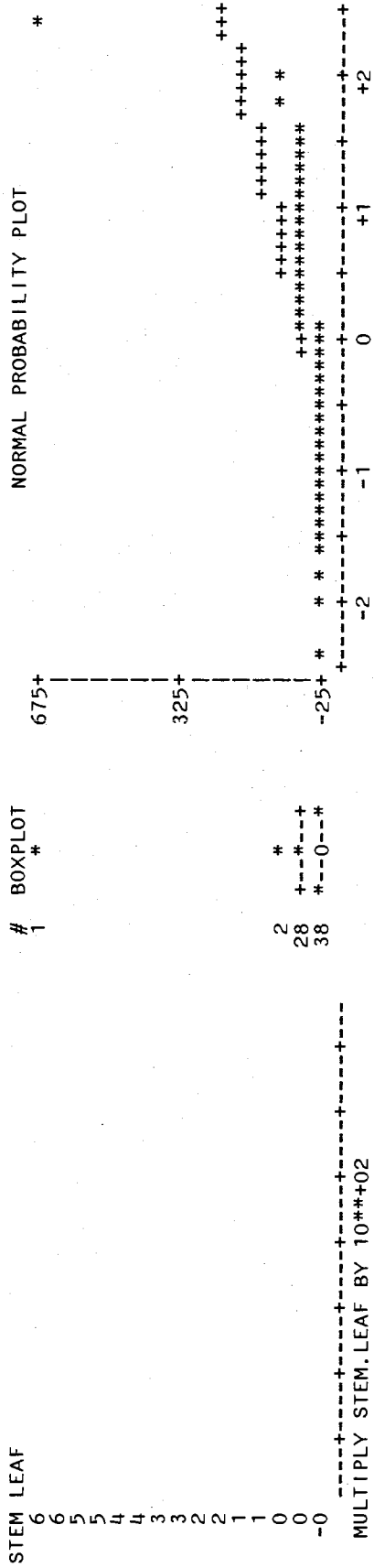


Figure 53. SAS Univariate summary of distribution of percent difference for β_{H_0} (PCBHO) from OIL sample: OUTWTS vs. PRISM

PERCENT DIFFERENCES FOR OIL

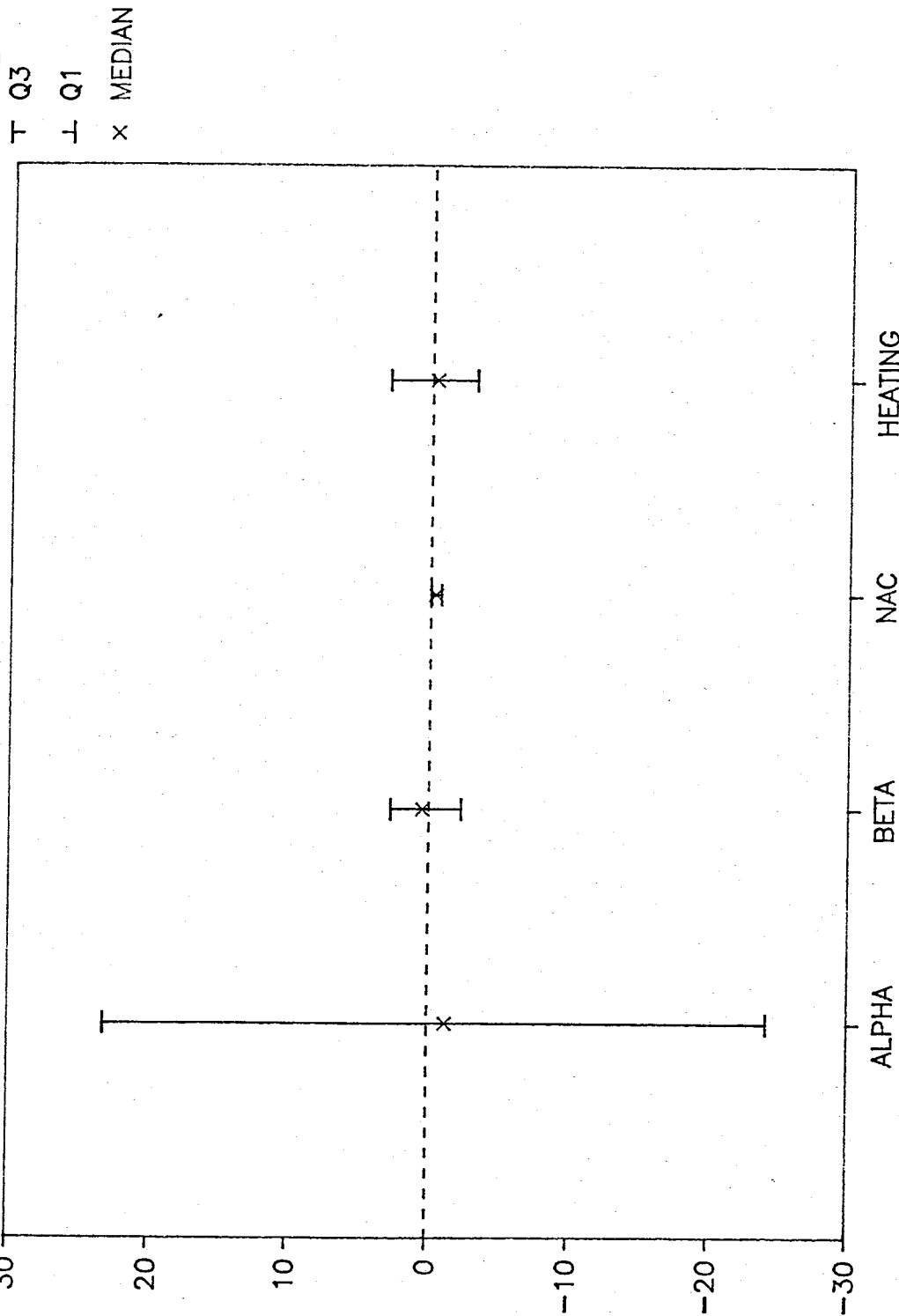


Figure 54. Plot of medians and quartiles of percent differences of PRISM vs. OUTWTS parameters for OIL sample.

VARIABLE=CVRNAC

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	69	2.21479	0.908318	LOWEST	HIGHEST
MEAN	1.60795	2.13763	0.908318	0.908318	2.10902
STD DEV	0.313581	2.05316	0.974827	0.974827	2.11321
VARIANCE	0.098333	1.23305	1.01604	1.01604	2.16205
SKEWNESS	-0.0966207	1.37872	1.13566	1.13566	2.18227
USS	185.087	0.908318			2.21479
CV	19.5019				
T: MEAN=0	42.594				
SGN RANK	1207.5				
NUM	69				

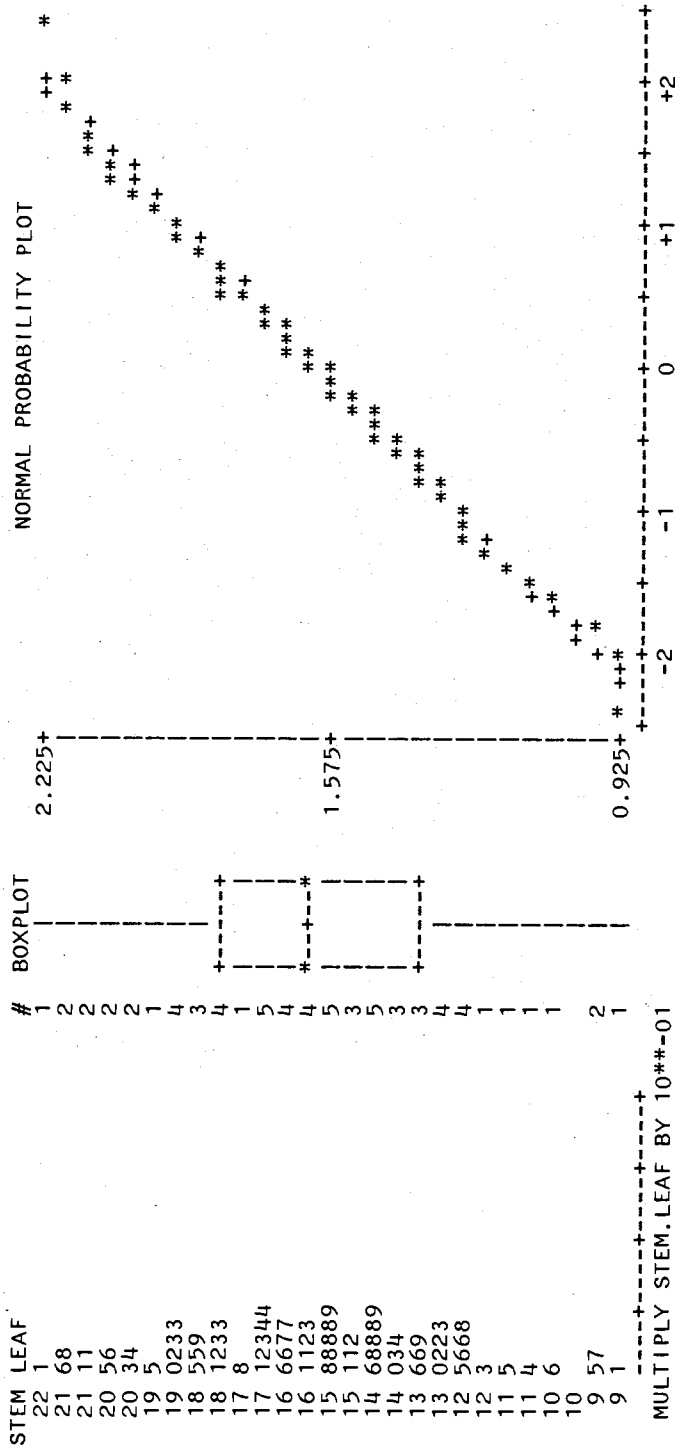


Figure 57. SAS Univariate summary of distribution of CVRs for NAC (CVRNAC) from OIL sample.

VARIABLE=CVRBHO

MOMENTS		QUANTILES(DEF=4)		EXTREMES	
N	64	3.3543	3.3543	LOWEST	HIGHEST
MEAN	1.46688	1.71508	2.10408	0.0254649	2.04338
STD DEV	0.46199	1.43504	2.00317	0.659767	2.06821
STD DEV	0.685592	1.13681	1.02434	0.894954	2.11604
US	151.158	0.0254649	0.899775	0.914239	2.33393
CV	31.4947		0.0254649	0.934666	3.3543
T:MEAN=0	25.4011				
SGN RANK	1040				
NUM ^= 0	64				

MISSING VALUE
COUNT 5
% COUNT/NOBS 7.25

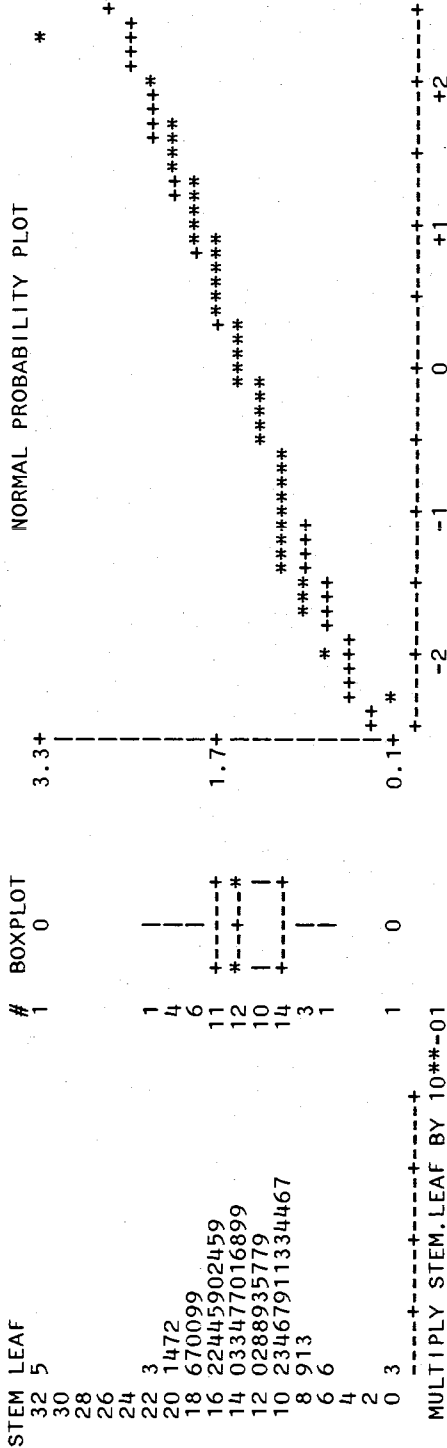


Figure 58. SAS Univariate summary of distribution of CVRs for βH_0 (CVRBHO) from OIL sample. Five homes were eliminated from the sample for this analysis because the standard error of τ was infinite.

CVR SUMMARIES FOR OIL

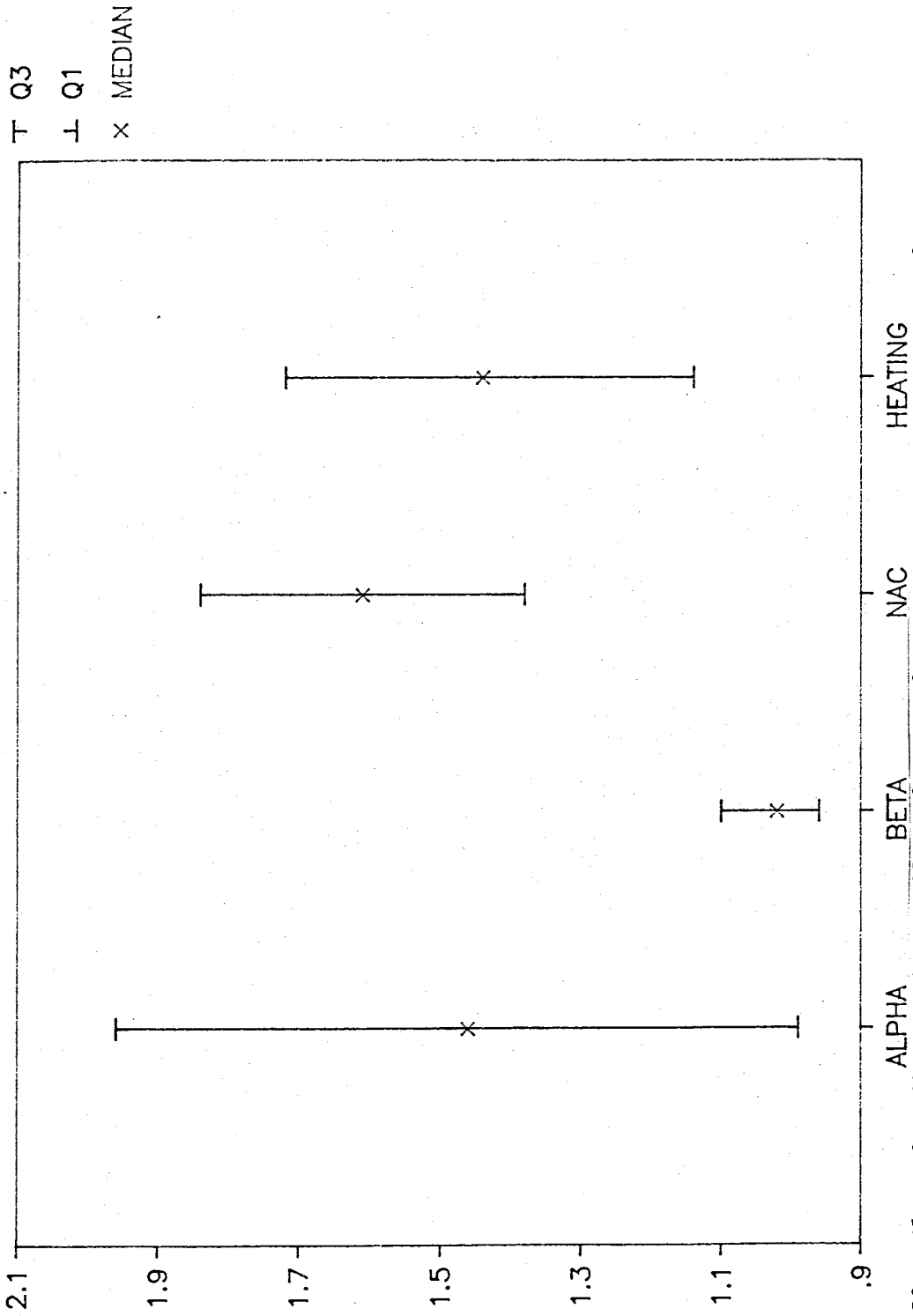


Figure 59. Plot of medians and quartiles of CVRs of PRISM vs. OUTWTS parameters for OIL sample. For CVR(α), only the 30 HW houses with positive α and finite $se(\alpha)$ for both PRISM and OUTWTS were included in the analysis.

Outwts vs. Ordinary R-square OIL

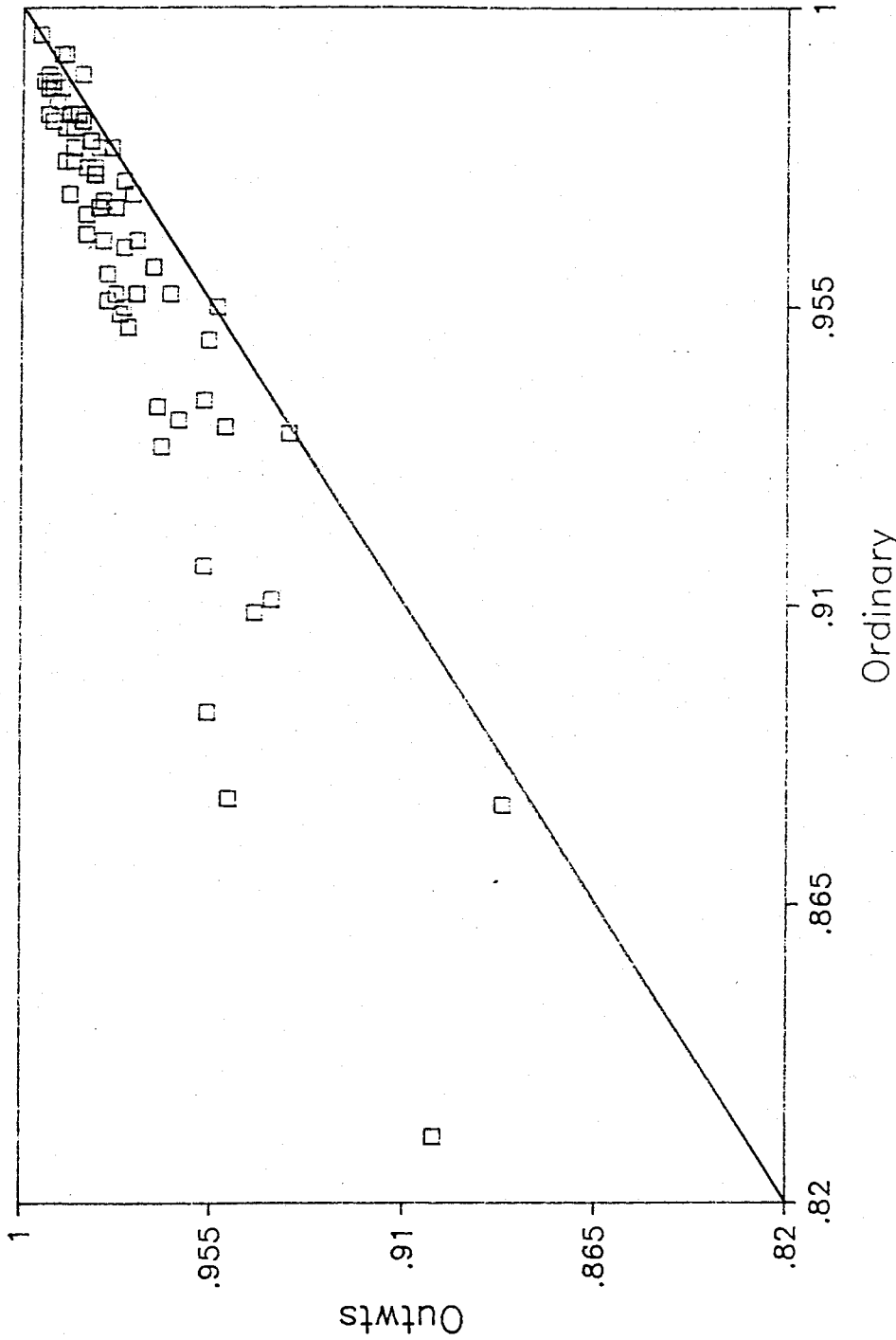


Figure 60. R² estimates for Weighted (OUTWTS) vs. Ordinary PRISM for OIL sample.

CONS-PERIOD FOR P76263

House: P76263

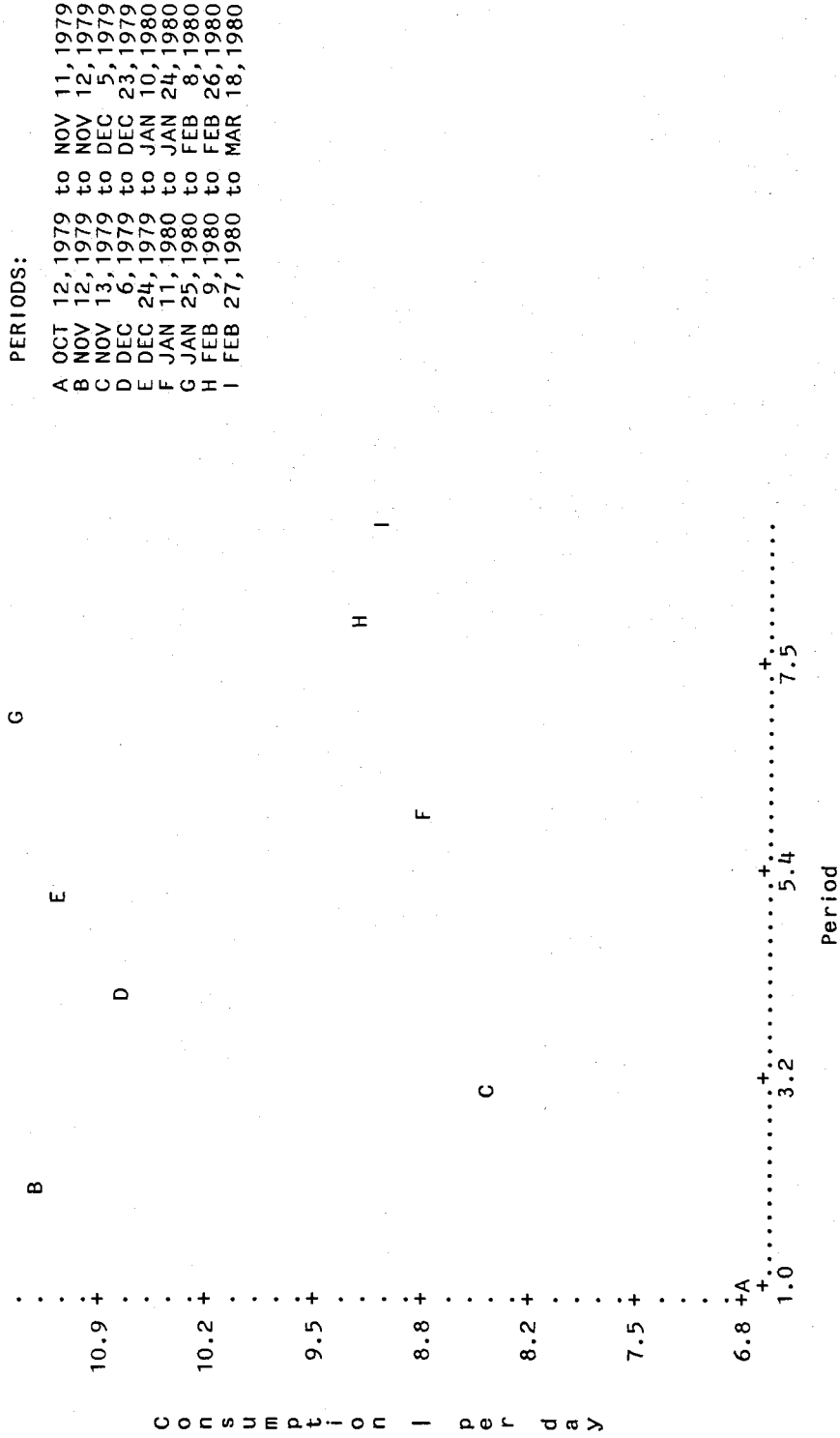


Figure 61. Plot of consumption vs. period for House P76263 from OIL sample.

CONS-HDD FOR P76263, PRISM

House: P76263, alpha= 8.98, beta= 0.22, R2= 0.2049

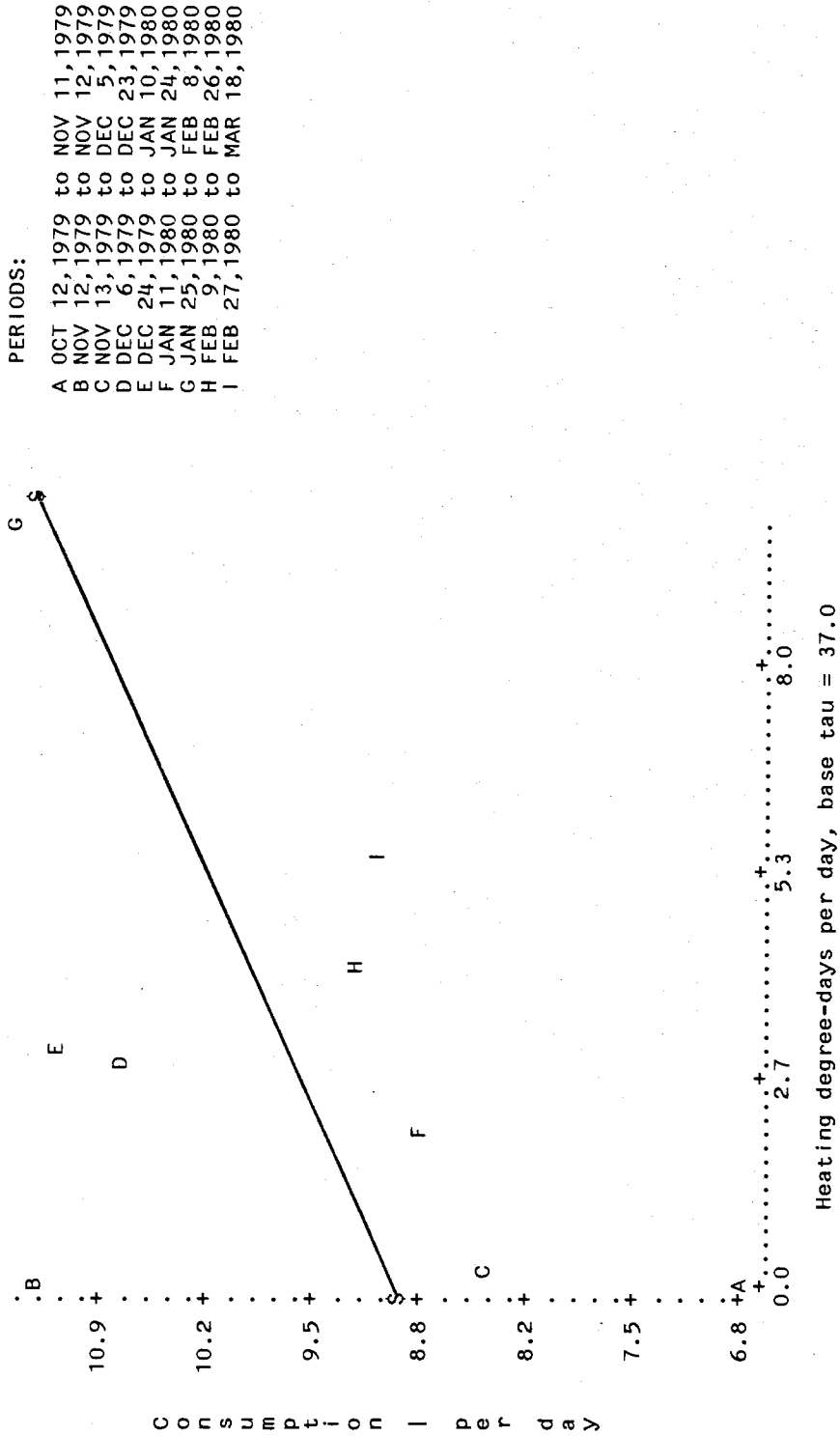


Figure 62. PRISM plot of consumption vs. heating degree-days for House P76263 from OIL sample.

CONS-HDD FOR P76263, OUTWTS
 House: P76263 , alpha= 4.43, beta= 0.14, R2= 0.6546

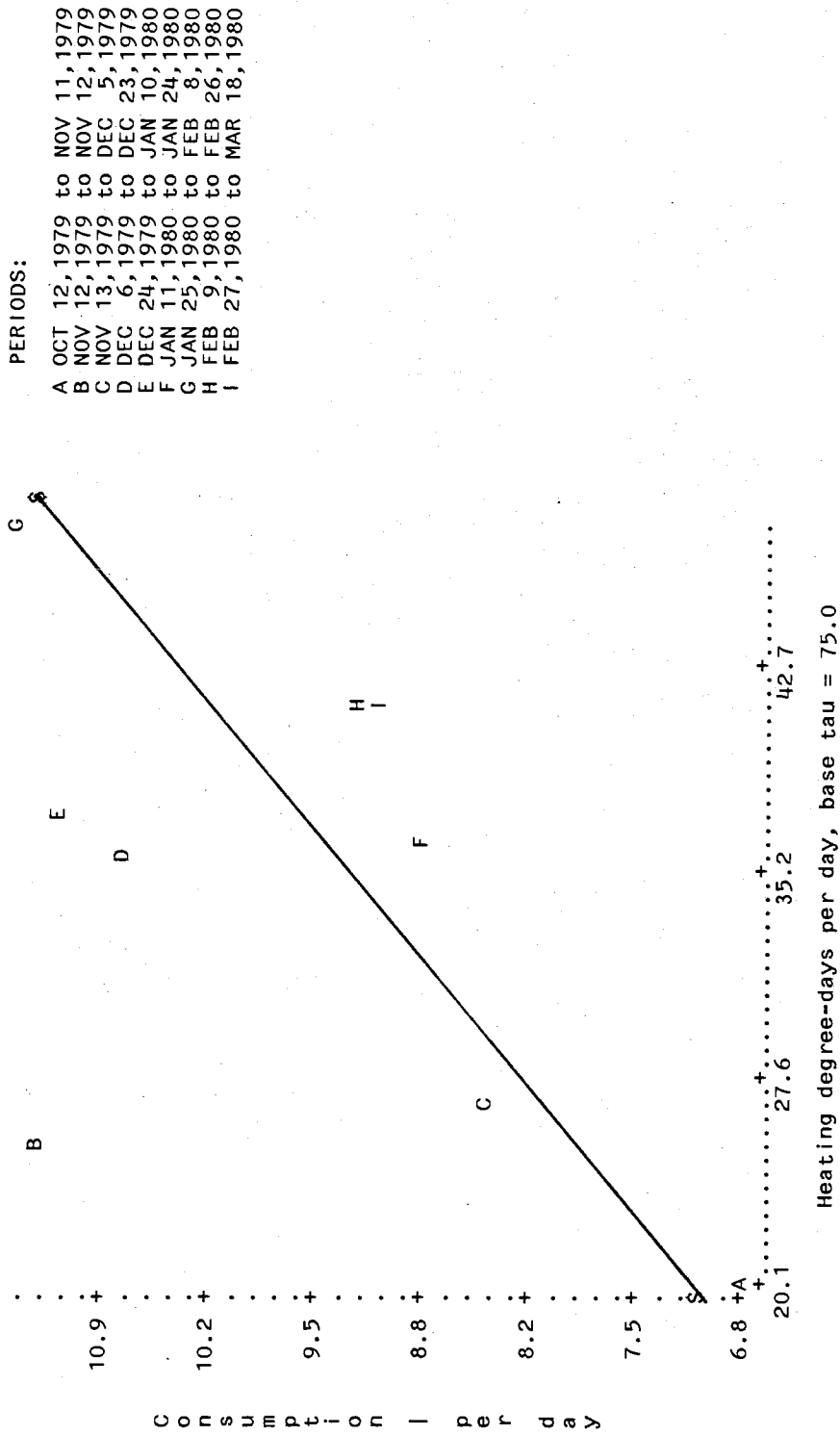
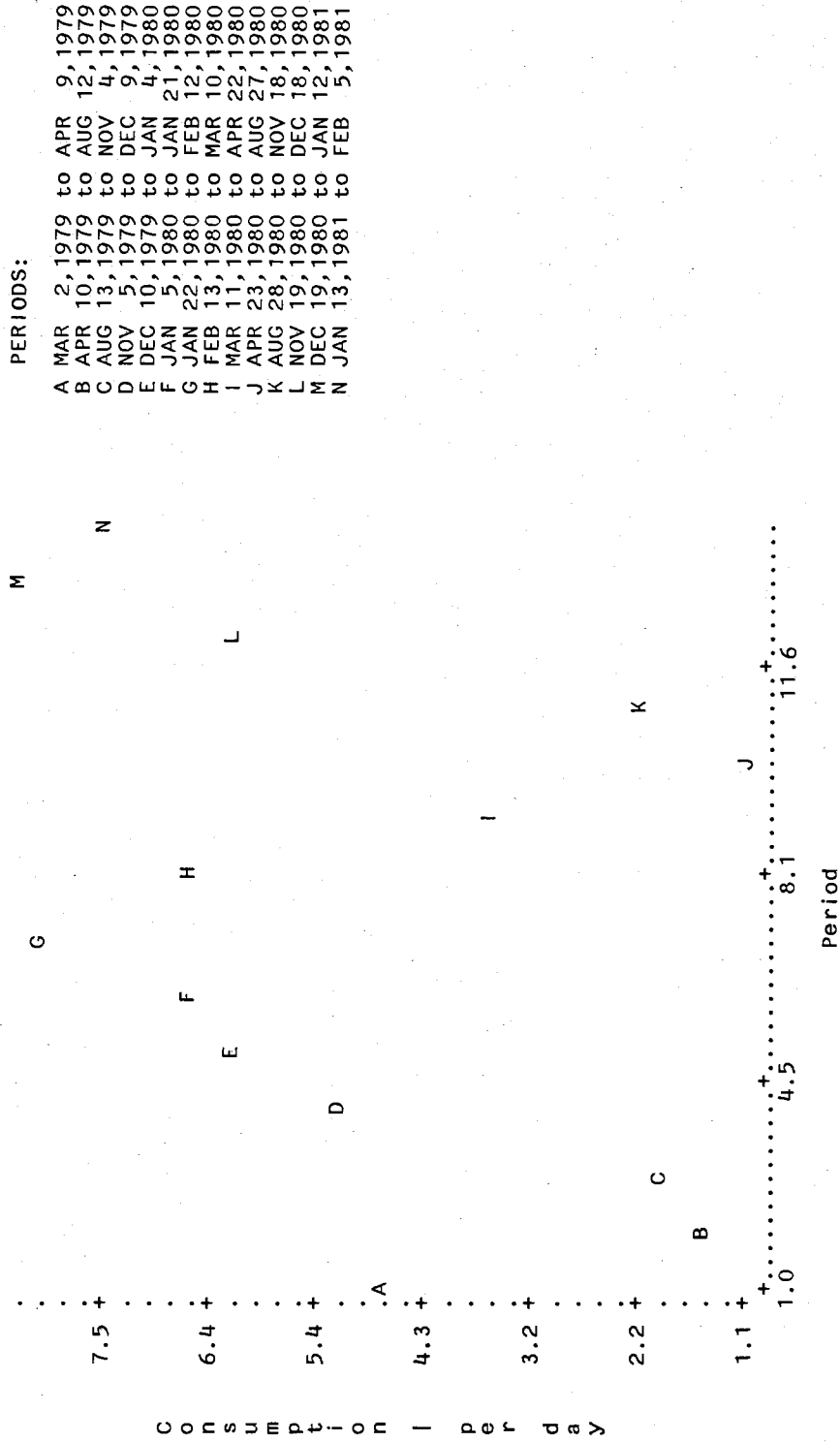


Figure 63. OUTWTS plot of consumption vs. heating degree-days for House P76263 from OIL sample.

CONS-PERIOD FOR P57490

House: P57490



PERIODS:
 A MAR 2, 1979 to APR 9, 1979
 B APR 10, 1979 to AUG 12, 1979
 C AUG 13, 1979 to NOV 4, 1979
 D NOV 5, 1979 to DEC 9, 1979
 E DEC 10, 1979 to JAN 4, 1980
 F JAN 5, 1980 to JAN 21, 1980
 G JAN 22, 1980 to FEB 12, 1980
 H FEB 13, 1980 to MAR 10, 1980
 I MAR 11, 1980 to APR 22, 1980
 J APR 23, 1980 to AUG 27, 1980
 K AUG 28, 1980 to NOV 18, 1980
 L NOV 19, 1980 to DEC 18, 1980
 M DEC 19, 1980 to JAN 12, 1981
 N JAN 13, 1981 to FEB 5, 1981

Figure 64. Plot of consumption vs. period for House P57490 from OIL sample.

CONS-HDD FOR P57490, PRISM

House: P57490 , alpha= 0.02, beta= 0.16, R2= 0.9654

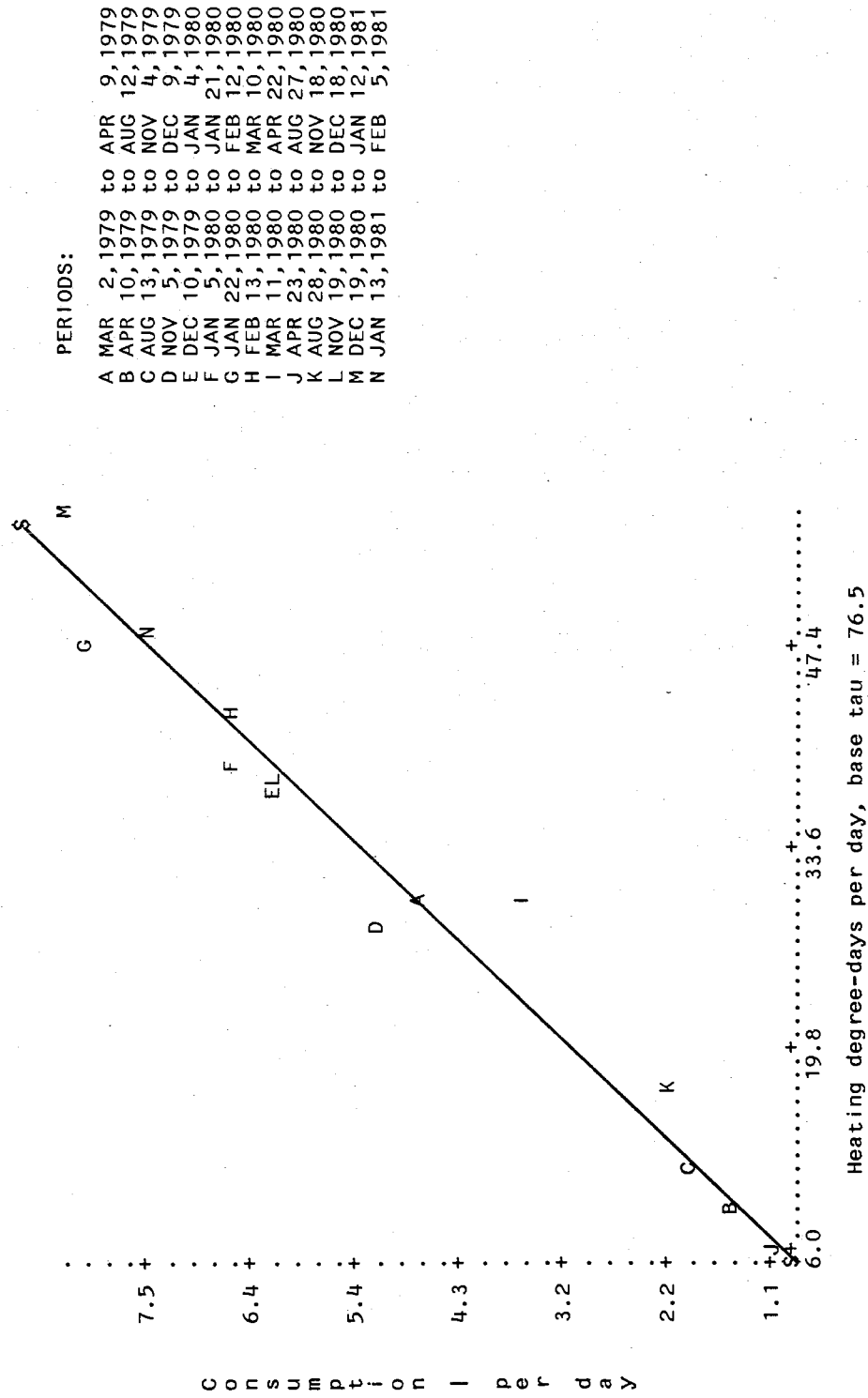
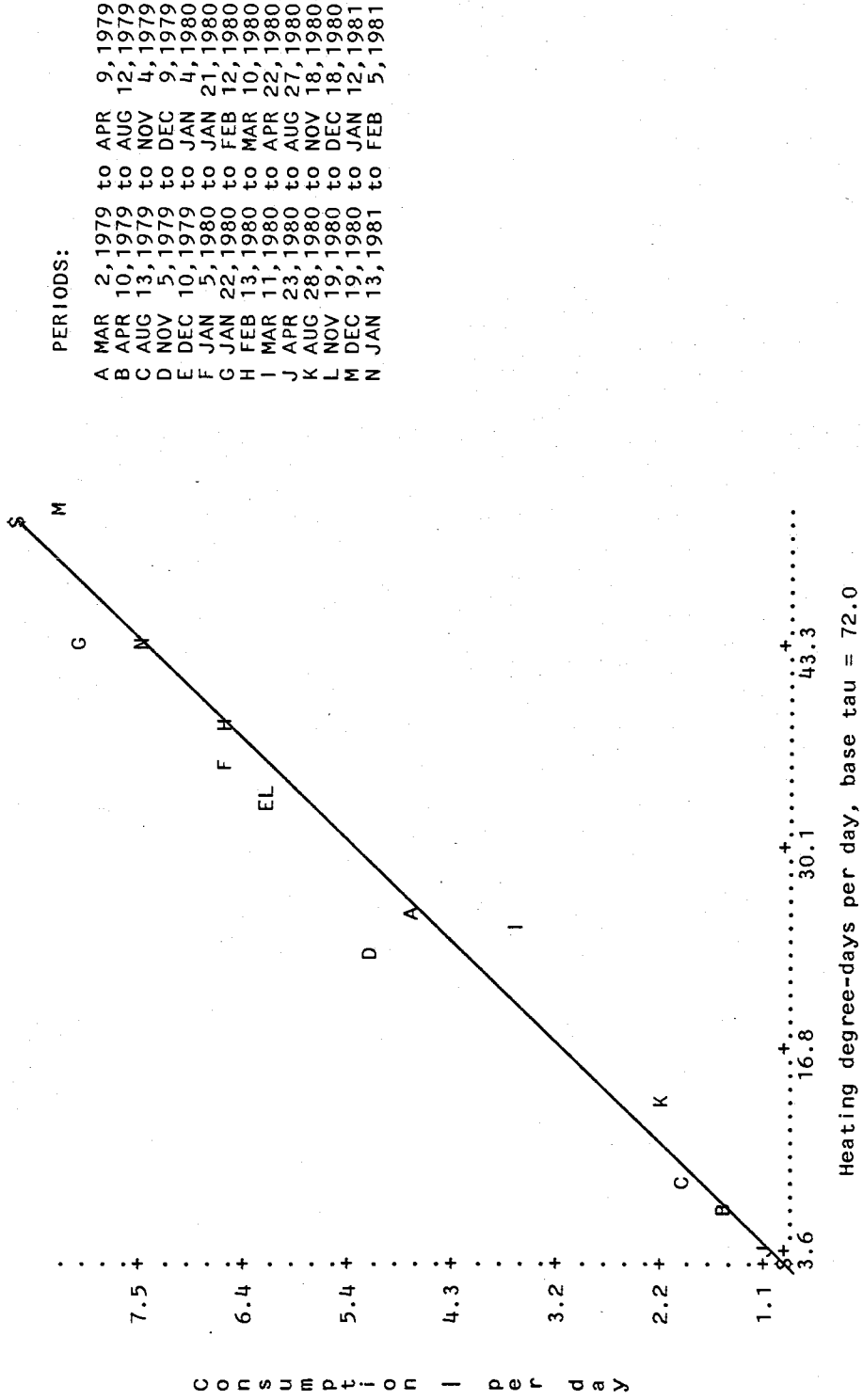


Figure 65. PRISM plot of consumption vs. heating degree-days for House P57490 from OIL sample.

CONS-HDD FOR P57490, OUTWTS

House: P57490, alpha= 0.45, beta= 0.16, R2= 0.9727



PERIODS:

- A MAR 2, 1979 to APR 9, 1979
- B APR 10, 1979 to AUG 12, 1979
- C AUG 13, 1979 to NOV 4, 1979
- D NOV 5, 1979 to DEC 9, 1979
- E DEC 10, 1979 to JAN 4, 1980
- F JAN 5, 1980 to JAN 21, 1980
- G JAN 22, 1980 to FEB 12, 1980
- H FEB 13, 1980 to MAR 10, 1980
- I MAR 11, 1980 to APR 22, 1980
- J APR 23, 1980 to AUG 27, 1980
- K AUG 28, 1980 to NOV 18, 1980
- L NOV 19, 1980 to DEC 18, 1980
- M DEC 19, 1980 to JAN 12, 1981
- N JAN 13, 1981 to FEB 5, 1981

Figure 66. OUTWTS plot of consumption vs. heating degree-days for House P57490 from OIL sample.

Robust vs. Ordinary CV(NAC)

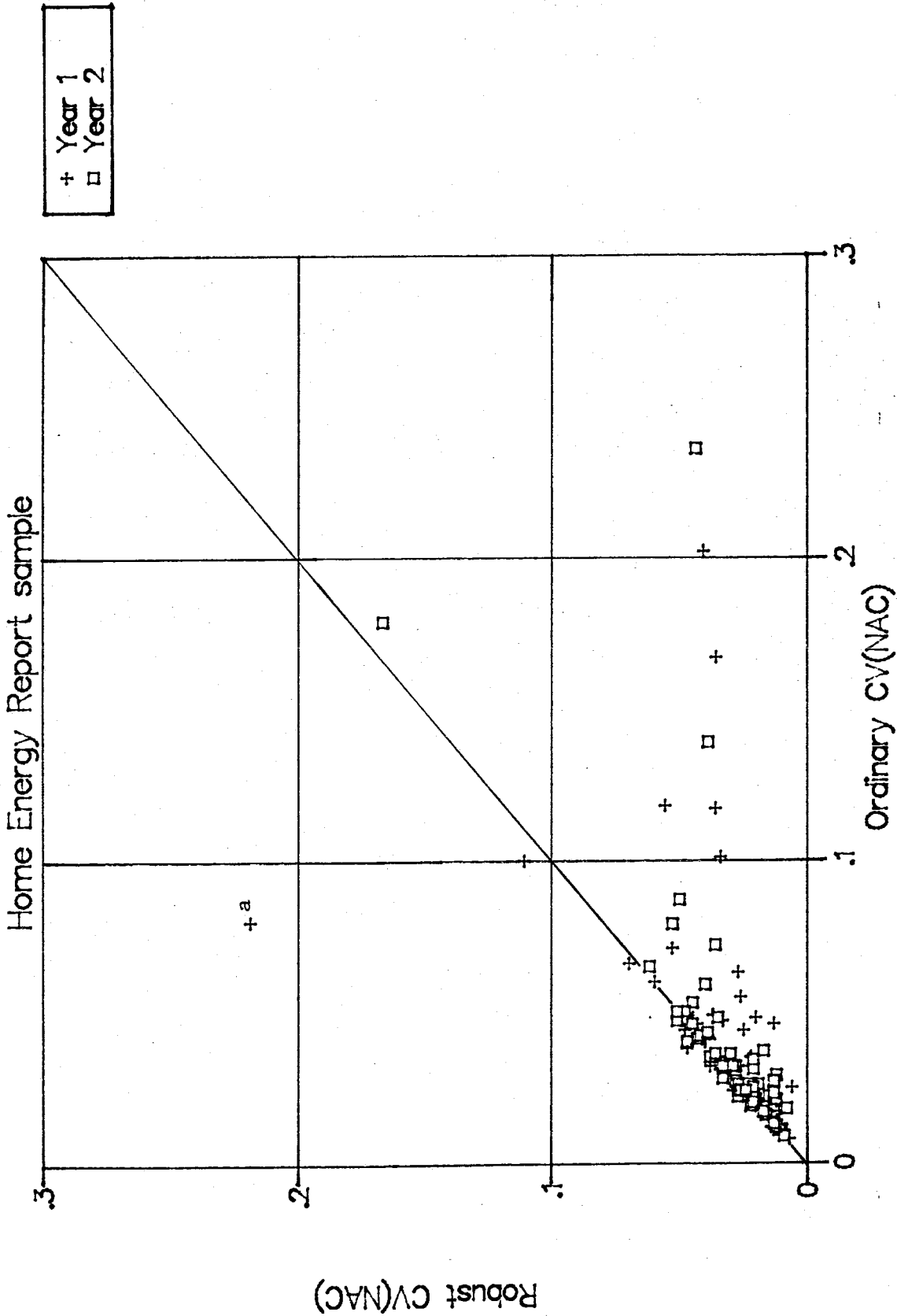


Figure 67. CV(NAC) for Robust (RPRISM) vs. Ordinary PRISM for Home Energy Report sample.

^a This case, showing a large increase in CV(NAC), is from the set of houses preselected for probable data anomalies. House was without electric heating, and had extremely low R^2 (<0.2) with and without using Robust PRISM.

Robust vs. Ordinary NAC

Home Energy Report sample

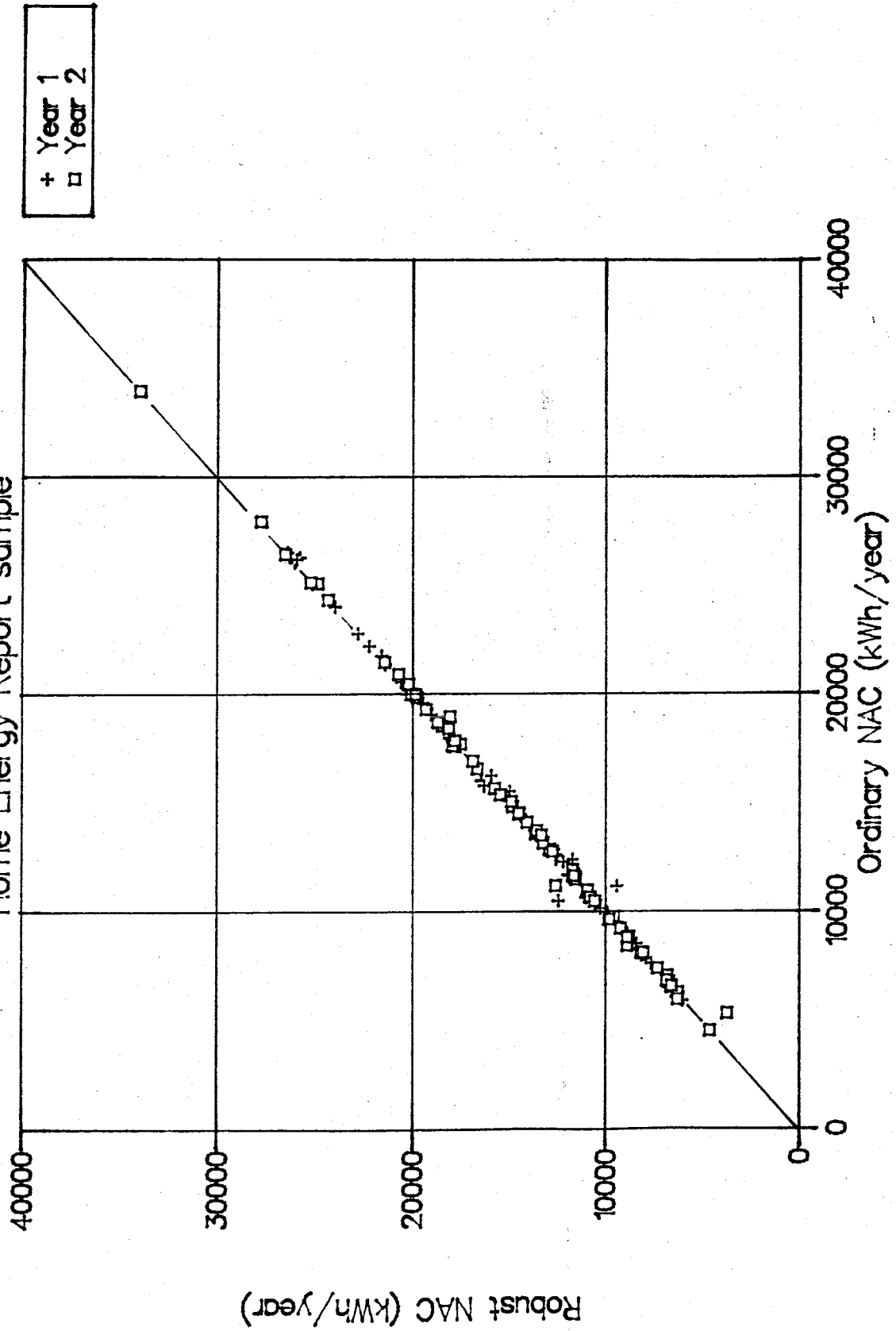


Figure 68. NAC estimates for Robust (RPRISM) vs. Ordinary PRISM for Home Energy Report sample.