

**A MODEL FOR SIMULATING DAILY
TEMPERATURE AND PRECIPITATION READINGS**

by

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Introduction:

The quantities which seem to best summarize a set of daily temperatures are the maximum and minimum temperatures for that day. These are the temperatures which express potential damage most accurately when compared with either the daily mean temperature or the temperature at some time of observation. Also these are the most common measurements taken for recording the daily temperatures. Therefore, when studying daily temperatures, one is usually lead to studying the daily maximum and minimum temperatures.

The ultimate objective of this study was a computer simulation of both precipitation and daily maximum and minimum temperatures. Ison [1] wrote a computer program which simulated both the length and amount of precipitation of a wet period. In this study Ison's work was used to simulate precipitation and the simulation of temperatures was added.

Casual observation suggested that daily maximum and minimum temperatures were influenced by precipitation conditions before and during the period of time when the temperature measurements were taken. The simulation model should reflect this partial dependence of temperature on precipitation.

Casual observation also suggested that daily temperatures are influenced by the previous temperatures, and by the time of year. The simulation model should also show the partial dependence of temperatures on these variables.

The data studied were from weather station 4972, in Manhattan, Kansas. The data are recorded on magnetic tape in the Kansas Agricultural Experiment Station Weather Data Library. The precipitation is recorded in inches and the temperatures are recorded in degrees Fahrenheit. The period of record for which all the parameters in the model were estimated was from March 1, 1900, to February 27, 1970. The climatological year beginning on March 1, of the year was used as is customary in climatological studies. Since the simulation program for precipitation did not simulate data for either February 28 or 29, it was decided to disregard both these dates when simulating temperatures.

Dependence of Temperatures on Precipitation:

Since precipitation readings are taken at 7 am and temperature readings are taken at 7 pm, recorded precipitation and temperatures for day t , ($t = 1, 2, \dots, 364$; $t = 1$ for March 1) do not coincide completely with calendar day t (see Figure 1). In order to check on the goodness of a simulation program, it was necessary to simulate recorded data rather than the actual amounts of precipitation which fell between midnight and midnight, and the same for maximum and minimum temperatures for a calendar day.

Consider four sequences of recorded precipitation patterns over a two day period: (dry,dry), (dry,wet), (wet,dry), and (wet,wet) or respectively: DD, DW, WD, and WW. The DW refers to a precipitation pattern where day $(t - 1)$ is recorded dry and day t is recorded wet (precipitation equals or exceeds .01 inch). During the above precipitation sequences we would normally expect to find 2 maximum and 2 minimum temperatures. It also should be noted that the minimum temperatures usually occur in the early morning hours and the maximum temperatures usually occur in the afternoon. Therefore in the recorded two day precipitation sequence (7 am, day $(t - 2)$ to 7 am, day t) the expected maximum and minimum temperatures were the high temperatures for days $(t - 1)$ and $(t - 2)$, $[H_1(t - 1), \text{ and } H_1(t - 2): i = DD, DW, WD, WW]$; and the low temperatures for days t and $(t - 1)$, $[L_1(t), \text{ and } L_1(t - 1)]$, respectively.

It is of interest to note the difference between the means of these temperatures with respect to the four precipitation sequences. Table 1

gives the observed daily mean low temperatures for day t ($\hat{\mu}_{Li}(t)$), and table 2 gives the observed daily mean high temperatures for day $(t - 1)$ ($\hat{\mu}_{Hi}(t - 1)$) for the seventh day of each of the 52 weeks and for each of the four precipitation conditions. For example, the mean high temperature for day $(t - 1)$, $i = DD$, and $t = 8$ ($\hat{\mu}_{Hi}(7)$) was computed by finding the average of all the high temperatures on March 7, from 1900 to 1969 for which March 7, and March 8, were both recorded dry. Note that $\hat{\mu}_{Hi}(7)$ for day $(t - 1)$ was 38.0 degrees Fahrenheit for $i = WW$ as compared to 48.6 degrees for $i = DD$. This may be explained by the cloud cover on a WW day which acts as a reflector to prevent as much heat from the sun to pass as on a DD day. On the other hand, note that sometimes $\hat{\mu}_{Li}(t)$ is higher for $i = WW$ than for $i = DD$. For example, $\hat{\mu}_{Li}(252) = 35.25$ for $i = DD$ and $\hat{\mu}_{Li}(252) = 44.50$ for $i = WW$ on day t . This may be explained by assuming that the cloud cover which accompanies a WW period acts as an insulator reducing the energy loss through the atmosphere more than during a DD period. Clearly a model which simulates both precipitation and temperature should incorporate this phenomenon.

Note also on tables 1 and 2 the pronounced periodic effect of the temperatures with the warmest temperatures in the summer and the coldest temperatures in the winter. To remove as much of the sampling variation as possible, the means that were used in the simulation program were computed from partial sums of Fourier series for which the coefficients were determined by a least squares fit of these partial sums to the daily mean maximum and minimum temperatures, respectively. This procedure is sometimes called harmonic analysis with each set of sine and cosine terms called

a harmonic and associated with a periodic function. In figure 2 one can see how a curve with a single harmonic fits the mean daily maximum temperatures for day $(t - 1)$, $[\hat{\mu}_{H1}(t - 1), i = DD]$. One can see a need for including higher order harmonics. In figure 3 the first 2 harmonics have been fitted and results shown for the same data as in figure 2. Here one sees that the fit is quite good. Similarly for the other means (figure 4 to 18) it appeared that the first two harmonics would fit the data adequately. Thus the means that were used in the simulation program were computed from partial sums of Fourier series which included 1st and 2nd harmonics and allowed for periods of 364 days and 182 days respectively. For example, the mean low temperature for day $(t - 1)$ and for condition DW was computed from the formula:

$$\begin{aligned}\mu_{L1}(t - 1) = & 44.94 - 19.35 \cos (2\pi t/364) + 15.19 \sin (2\pi t/364) \\ & + .88 \cos (4\pi t/364) + 1.95 \sin (4\pi t/364)\end{aligned}$$

$$t = 1, 2, \dots, 364; \quad i = DW$$

The mean low temperatures for t and $(t - 1)$ were denoted as $\mu_{L1}(t)$ and $\mu_{L1}(t - 1)$ and the mean high temperatures for $(t - 1)$ and $(t - 2)$ were denoted as $\mu_{H1}(t - 1)$ and $\mu_{H1}(t - 2)$ where $i = (DD, DW, WD, WW)$. These temperatures were denoted as true means to distinguish them from the daily averages of recorded data. Table 3 lists the coefficients of the harmonic functions fitted to the means.

3. Dependence of Temperature on Antecedent Temperatures

Another phenomenon that should be incorporated into the model is that of persistence of temperatures from one day to the next. Casual observation of daily temperatures would suggest that today's maximum reading will tend to be particularly high or low depending in part on whether yesterday's temperatures were particularly high or low. Furthermore, this phenomenon should be most noticeable when considering repeated observations for a given precipitation condition. Here again the precipitation conditions would be the DD, DW, WD, and WW.

To get insight into this persistence phenomenon a multiple regression analysis was run to determine dependence of a particular maximum and minimum temperature on preceding maximum and minimum temperatures for the four different sets of precipitation conditions. The MULTREG program in the Kansas State University Statistics Laboratory was used for this analysis. To save computer time in this exploratory analysis, data for only climatological weeks 7, 20, 33, and 46 were used. The model for the analysis was:

$$L_i(t) = \alpha_{ijL} + \beta_{1Li}H(t-1) + \beta_{2Li}L(t-1) + \beta_{3Li}H(t-2) + \epsilon_{ijL}$$

$$H_i(t) = \alpha_{ijH} + \beta_{1Hi}L(t) + \beta_{2Hi}H(t-1) + \beta_{3Hi}L(t-1) + \epsilon_{ijH}$$

where

$i = DD, DW, WD, WW$

$t = 43, \dots, 49, 134, \dots, 140, 225, \dots, 231, 316, \dots, 322$

$j = 7, 20, 33, 46$

$L_i(t)$ = recorded minimum temperature on day t and for precipitation condition i ,

α_{LjL} = the regression constant for precipitation condition i , week j , and low temperature as the dependent variable,

$\beta_{1Li j}$, $\beta_{2Li j}$, and $\beta_{3Li j}$ are the partial regression coefficients on $L_i(t)$ of $H(t - 1)$, $L(t - 1)$, and $H(t - 2)$ and considered constants for precipitation condition i , week j , and low temperatures,

ϵ_{ijL} is the error term for precipitation condition i , week j , and low temperature as the dependent variable.

$L(t)$, $H(t - 1)$, $L(t - 1)$, and $H(t - 2)$ are the low and high temperature for the day number in parenthesis.

$H_i(t)$, α_{ijH} , $\beta_{1Hi j}$, $\beta_{2Hi j}$, $\beta_{3Hi j}$, and ϵ_{ijH} correspond to the parameters already defined but with the high temperature as the dependent variable.

Tables 4 and 5 give the estimates of the partial regression coefficients and their statistical significance. In most cases the third independent variable on the right side of the model was found to be non-significant. Therefore, it was decided in the interest of simplicity to use only the first two independent variables.

As pointed out earlier the $H(t - 1)$ coincides more closely with the observation period of precipitation than does $H(t)$. Regression analysis with $H(t - 1)$ and $H(t)$ as the dependent variables and with the independent variables $L(t - 1)$ and $H(t - 2)$; and $L(t)$ and $H(t - 1)$ respectively, were run. The standard deviations are shown in Table 6. In this case there was no clear-cut decision. However, since generally it appeared that the $H(t - 1)$ provided a lower variance and since $H(t - 1)$ offered a better intuitive connection with the precipitation sequence, it was chosen as the temperature to be simulated. On the other hand, since it would have been much easier to program the simulation of maximum and minimum temperatures for the same day, perhaps the $H(t)$ could have been used without a significant increase in the variance.

4. Final Model and Estimates of Parameters:

Consider the model:

$$\begin{aligned} H_1(t-1) = & \beta_{1H1}(w)[L(t-1) - \mu_{L1}(t-1)] \\ & + \beta_{2H1}(w)[H(t-2) - \mu_{H1}(t-2)] \\ & + \mu_{H1}(t-1) + \epsilon_{H1}(w) \end{aligned}$$

$$\begin{aligned} L_1(t) = & \beta_{1L1}(w)[H(t-1) - \mu_{H1}(t-1)] \\ & + \beta_{2L1}(w)[L(t-1) - \mu_{L1}(t-1)] \\ & + \mu_{L1}(t) + \epsilon_{L1}(w) \end{aligned}$$

$$i = DD, DW, WD, WW \quad t = 1, 2, \dots, 364 \quad w = 1, 2, \dots, 52$$

where

$$H(t-2), L(t-1), H(t-1), L(t), \mu_{H1}(t-2), \mu_{L1}(t-1),$$

$$\mu_{H1}(t-1), \text{ and } \mu_{L1}(t) \text{ were as defined before.}$$

$H_1(t-1)$ was the high temperature for day $(t-1)$ to be simulated given precipitation condition (i).

$L_1(t-1)$ was the low temperature for day (t) to be simulated given precipitation condition (i).

$\beta_{1H1}(w)$, $\beta_{2H1}(w)$, $\beta_{1L1}(w)$, and $\beta_{2L1}(w)$ were partial regression coefficients considered constant for week (w), on the high and low temperatures of the antecedent temperatures, for week (w), and the precipitation condition (i).

The partial regression coefficients were estimated by using a two way multiple regression analysis of the actual weather data for the period March 1, 1900, to February 27, 1970. In the multiple regression analysis for the $H_1(t-1)$, $Y = [H_1(t-1) - \mu_{H1}(t-1)]$ was the dependent variable with $X_1 = [L(t-1) - \mu_{L1}(t-1)]$ and $X_2 = [H(t-2) - \mu_{H1}(t-2)]$ as the independent variables. Likewise in the multiple regression analysis for $L_1(t)$ the dependent variable was $Y = [L_1(t) - \mu_{L1}(t)]$ and the independent variables were $X_1 = [H(t-1) - \mu_{H1}(t-1)]$ and $X_2 = [L(t-1) - \mu_{L1}(t-1)]$.

Each $\epsilon_{H1}(w)$ was assumed to be a normally distributed random variable with mean zero and variance $\sigma_{H1}^2(w)$. The variances were estimated by inserting estimates of betas from the multiple regression analysis and using the sum of squares of residuals:

$$\begin{aligned} & \sum \{H_1(t-1) - b_{1H1}(w)[L(t-1) - \mu_{L1}(t-1)] \\ & \quad - b_{2H1}(w)[H(t-2) - \mu_{H1}(t-2)] \\ & \quad - \mu_{H1}(w)\}^2 \end{aligned}$$

over all available days, for the i th condition, during week (w) of the climatological year, and over the period March 1, 1900, to February 27, 1970. Analogous assumptions and similar procedures for estimating

variances were used for $\epsilon_{L1}(w)$.

Individual betas and variances showed periodic behavior. Hence, as a further refinement in estimation, curves were fitted using partial sums (with four harmonics) of Fourier series, to the 52 values of $b_{1H1}(w)$, $b_{2H1}(w)$, $b_{1L1}(w)$, $b_{2L1}(w)$, $\sigma_{H1}^2(w)$, and $\sigma_{L1}^2(w)$, respectively. The final daily estimates of the betas and variances were computed from the harmonic function. Figures 19 to 42 show the weekly betas and variances with the harmonic curve. Table 7 gives the F-statistics for each of the four harmonics from the analysis of variance table in the harmonic analysis of betas and variances. There are some significant F-statistics for each of the harmonics. Therefore, in the interest of simplicity and uniformity all four harmonics were used in the functions. The coefficients of the harmonic functions are listed in table 8.

Thus the final model used in the simulation of maximum and minimum temperatures was:

$$\begin{aligned} H_1(t-1) = & \beta_{1H1}(t-1)[L(t-1) - \mu_{L1}(t-1)] \\ & + \beta_{2H1}(t-1)[H(t-2) - \mu_{H1}(t-2)] \\ & + \mu_{H1}(t-1) + \epsilon_{H1}(t-1) \end{aligned}$$

$$\begin{aligned} L_1(t) = & \beta_{1L1}(t)[H(t-1) - \mu_{H1}(t-1)] \\ & + \beta_{2L1}(t)[L(t-1) - \mu_{L1}(t-1)] \\ & + \mu_{L1}(t) + \epsilon_{L1}(t) \end{aligned}$$

where

$$\beta_{1H1}(t-1), \quad \beta_{2H1}(t-1), \quad \beta_{1L1}(t) \text{ and, } \beta_{2L1}(t)$$

$$t = 1, 2, \dots, 364 \quad i = DD, DW, WD, WW$$

were computed from the harmonic functions which were fit to the weekly values of $b_{1H1}(w)$, $b_{2H1}(w)$, $b_{1L1}(w)$, and $b_{2L1}(w)$, respectively, $w = 1, 2, \dots, 52$. All other terms were as defined before.

5. Simulation Program

Ison's program simulated precipitation by first using pseudo random numbers to determine if a day was dry or wet. As soon as a dry day following a wet day was simulated, the program determined the number of days in the wet spell, and then simulated the amount of precipitation for the wet period by again using a pseudo random number.

To add the simulation of temperature to this program all that was needed from the precipitation program was to know the precipitation condition for a two day period (i.e., DD, DW, WD, or WW). When the program first began to simulate it contained two appropriate temperatures (one high and one low) for the end of February and it was assumed that the last day of February was dry. After March 1, was found to be either wet or dry, these two temperatures were used in the model to simulate a high temperature for the day before March 1. The error term $\epsilon_{H1}(t - 1)$ in the model was found by using the Box & Muller method [2] to find pseudo random numbers with a standard normal distribution. The standard normal variate was multiplied by the standard deviation for day $(t - 1)$, for the high temperature, and for precipitation condition (i) (in this case i would be either DW or DD depending on whether March 1, was wet or dry). After the high temperature was found for the day before March 1, the low temperature that was inserted into the program and the simulated high temperature were used in the model to simulate the low temperature for March 1. The error term again was found by using the Box & Muller method with the appropriate standard deviation for the low temperature, $t = 1$, and $i = DW$ or DD . This low temperature was the first temperature to be

stored in the simulated weather data. Thus for each day that was found to be wet or dry, the high temperature for the previous day and the low temperature for that day were simulated. A listing of the simulation program is given in the appendix.

To save computer time in reading all the constants and to make the data cards more manageable, only every 7th value of all the means, betas, and variances were punched on data cards. The computer then interpolated the daily values between these known values.

The program for the simulation of precipitation simulated each year independently. It did not extend a wet period from February 27, to March 1, of the following year and it simulated March 1, without regard to whether February 27, was wet or dry. It could do this since for most years it didn't make any difference and the difference that did arise would not effect the mean daily precipitation values significantly for large sample sizes. However, there is a pronounced dependence on antecedent temperatures when simulating temperatures. Therefore when simulating several years of daily temperatures there is no basic alteration in the model at the end of each year. Because the precipitation values were all known at the end of each year (there was never a wet period carrying over into the next year which would mean the amount of precipitation in the last of February was unknown) it was possible to then store the full year of simulated weather data on magnetic tape following the determination of whether the next March 1, was wet or dry and consequently the determination of the high temperature on February 27. After the storage of the

weather data the computer started again by simulating the low temperature of March 1.

The information was stored in blocks of size 168. This permitted one week of data to be stored in each block (using FORMAT (42I4)). The information stored for each day of the week was the month number, day number, year number, amount of precipitation, and the maximum and minimum temperatures. The daily values of precipitation were determined by dividing the amount of precipitation in a wet period by the number of days in the wet period. This method was felt to be adequate for most uses of the simulation program. The amounts of daily precipitation were then multiplied by 100 and rounded to the nearest inch to conform to the method of storing actual daily precipitation values. The daily maximum and minimum temperatures were rounded to the nearest degree to conform to the actual temperature readings.

Thirty-one years of simulated weather data were placed on magnetic tape. Thus a 30 year period (normal period) could be used for the weather summaries when starting on January 1. The mean monthly maximum and minimum temperatures are recorded in table 9. Note the comparison between the mean monthly temperatures for the simulated data and for the actual data from the period 1941 to 1970. Note also the mean monthly temperatures computed by taking the mean of the daily mean temperatures derived by fitting two harmonics to 70 years of actual daily temperatures without taking precipitation into consideration. One can see that the simulated means appear very much like the actual means.

One of the primary uses of this simulation program could be to study

complex functional relationships between weather data (precipitation, and maximum and minimum temperatures), and weather dependent variables. To test the effectiveness of this aspect of the simulation program, it was decided to compute the Palmer Drought Index (PDI) [3] for each month in thirty years of simulated data. The PDI gives an estimate of the prevailing moisture conditions using only mean monthly temperatures and monthly precipitation amounts as well as antecedent conditions. The PDI is zero where moisture conditions are average for the area and time of year under study, positive when above average moisture conditions are encountered, and negative for below average moisture conditions. Histograms showing the frequency distributions of the PDI computed from simulated data and actual data (1939-1968) are shown in figure 43. The actual data seems to have periods with more moisture and also longer dry periods than does the simulated data. This may be indicative of some persistent general weather patterns that might appear in the actual data but has not been taken account of in this simulation program which bases its entire dependencies on a two day period.

Further study might be directed toward (1) improving the model to adequately simulate long dry and wet spells, (2) producing simulated precipitation amounts on a daily basis rather than on a wet period basis, (3) simulating 365 days of weather data in each year with a carry over of precipitation conditions from one year to the next, and (4) an investigation of the effect of antecedent temperatures on precipitation.

Table 1. Observed Daily Mean Low Temperatures for Day t

t	Dry Dry	Dry Wet	Wet Dry	Wet Wet
7	25.21	17.56	29.78	29.00
14	31.88	22.57	34.00	32.80
21	32.65	25.89	32.27	24.75
28	33.04	29.67	38.50	37.00
35	41.82	35.00	41.20	35.38
42	43.65	35.62	39.67	40.13
49	43.16	44.44	43.30	43.67
56	47.44	43.08	48.71	47.42
63	51.16	42.90	51.17	46.10
70	48.85	45.50	50.38	53.00
77	51.03	48.71	53.73	52.45
84	56.91	52.88	55.36	53.86
91	56.88	57.29	62.09	57.56
98	62.41	56.67	60.42	59.36
105	61.05	63.38	62.29	57.92
112	66.23	64.83	60.18	59.58
119	65.95	63.30	67.78	63.80
126	68.84	60.00	66.00	63.75
133	67.10	68.75	68.08	63.14
140	69.24	68.30	66.42	65.80
147	67.60	69.57	66.80	67.25
154	67.61	64.63	70.50	65.67
161	68.36	62.50	68.08	66.78
168	67.00	66.64	68.55	67.44
175	65.57	63.50	66.00	59.80
182	66.02	59.80	64.13	63.20
189	61.10	58.41	64.00	62.86
196	58.15	58.33	56.92	58.13
203	58.23	51.67	54.67	61.25
210	50.83	47.60	51.91	53.14
217	51.66	60.60	55.56	53.67
224	45.67	44.20	52.80	47.29
231	43.98	45.50	45.75	45.67
238	39.93	44.75	41.00	40.20
245	40.02	32.42	47.00	41.64
252	35.25	31.29	38.29	44.50
259	32.57	28.25	36.17	36.80
266	30.98	29.40	32.50	22.75
273	24.43	26.00	29.30	32.40
280	25.05	20.71	29.47	26.75
287	21.80	18.67	19.29	14.00
294	20.94	21.50	25.57	13.50
301	19.98	10.17	26.50	19.00
308	20.80	11.08	19.00	22.50
315	17.95	12.78	28.25	00.00
322	16.98	13.50	20.43	24.67
329	16.05	-1.50	20.92	24.00

Table 1. (continued)

t	Dry Dry	Dry Wet	Wet Dry	Wet Wet
336	18.19	12.50	17.57	-0.50
343	21.83	12.13	24.13	23.00
350	21.00	14.75	24.54	23.50
357	21.08	19.71	25.18	31.00
364	23.65	16.00	29.25	24.00

Table 2. Observed Daily Mean High Temperatures for Day (t-1)

(t-1)	Dry Dry	Dry Wet	Wet Dry	Wet Wet
7	48.63	42.80	49.44	38.00
14	55.38	51.14	51.40	50.33
21	61.11	43.13	56.75	48.71
28	62.42	60.20	55.38	58.00
35	66.11	52.11	66.43	56.22
42	68.58	59.55	70.56	56.67
49	70.13	63.00	74.36	67.80
56	71.26	67.47	69.89	63.86
63	76.24	70.79	74.40	67.75
70	75.89	75.08	78.50	67.67
77	80.34	74.42	75.50	68.71
84	82.16	73.94	80.10	76.00
91	83.53	77.90	81.78	78.40
98	86.17	79.00	84.18	79.75
105	87.11	79.25	89.43	79.88
112	91.80	82.18	87.67	80.17
119	91.24	89.73	88.15	90.25
126	93.62	87.85	92.27	86.86
133	94.28	91.71	94.36	83.92
140	96.74	87.86	91.08	86.88
147	95.07	84.89	93.91	88.33
154	94.73	96.20	89.92	89.63
161	93.54	90.73	91.36	88.14
168	93.18	89.30	92.73	90.00
175	89.30	84.80	90.38	93.75
182	90.59	79.50	90.67	85.67
189	89.20	85.00	86.27	81.71
196	85.82	79.67	82.80	80.50
203	85.24	78.22	78.91	81.25
210	80.05	70.67	75.33	72.44
217	80.89	76.56	81.44	63.50
224	75.22	68.00	79.13	70.67
231	72.87	61.75	71.82	64.33
238	70.13	57.50	74.25	47.50
245	65.19	59.90	58.33	58.86
252	60.88	61.88	59.50	44.67
259	55.49	54.71	58.63	50.25
266	54.89	45.17	57.00	45.25
273	51.79	44.22	42.57	46.83
280	50.36	45.79	36.43	47.80
287	44.18	31.78	36.67	39.00
294	41.98	31.80	43.50	42.75
301	41.42	40.83	41.78	35.00
308	39.39	33.78	45.14	40.00
315	41.47	28.25	37.50	51.00
322	41.68	36.44	33.85	41.00
329	42.88	33.73	31.11	32.00

Table 2. (continued)

(t-1)	Dry Dry	Dry Wet	Wet Dry	Wet Wet
336	40.28	30.67	36.86	24.67
343	45.06	46.00	35.57	35.67
350	47.02	41.00	35.14	37.89
357	43.98	38.33	42.10	39.00
364	50.12	43.50	41.25	39.00

Table 3. Coefficients of the Harmonic Functions for the Means

$$f(t) = a_0 + a_1 \cos (2\pi t/364) + b_1 \sin (2\pi t/364) \\ + a_2 \cos (4\pi t/364) + b_2 \sin (4\pi t/364)$$

$f(t)$	i	a_0	a_1	b_1	a_2	b_2
$I_{L1}(t)$	DD	43.75	-18.71	16.21	1.08	.11
	DW	44.74	-18.91	14.69	.37	2.32
	WD	39.93	-20.88	16.78	.59	1.38
	WW	42.64	-20.37	15.38	.28	2.56
$I_{H1}(t-1)$	DD	69.45	-20.08	16.99	1.83	2.09
	DW	67.44	-20.81	17.07	1.33	3.27
	WD	62.44	-21.82	18.07	1.13	2.43
	WW	61.39	-21.33	17.43	.95	2.25
$I_{L1}(t-1)$	DD	42.68	-18.91	16.08	1.04	-.19
	DW	44.94	-19.35	15.19	.88	1.95
	WD	43.31	-19.72	14.90	.38	2.10
	WW	45.23	-18.64	14.27	.40	2.50
$I_{H1}(t-2)$	DD	68.22	-20.30	16.82	1.73	1.80
	DW	68.12	-20.31	16.42	1.61	3.06
	WD	65.07	-21.02	17.10	1.34	2.89
	WW	65.43	-20.32	16.50	1.06	2.27

Table 4. Estimates of the Partial Regression Coefficients of $L(t)$ on $H(t-1)$, $L(t-1)$, and $H(t-2)$ with Their Student's t -Statistics*

Sample Size	i	j	b_{1Li}	Student's t	b_{2Li}	Student's t	b_{3Li}	Student's t
289	DD	7	.57	9.84	.27	4.19	-.18	-3.07
266		20	.54	8.45	.45	8.88	-.31	-4.80
336		33	.64	10.99	.49	9.46	-.28	-4.37
374		46	.54	10.02	.16	2.60	-.08	-1.78
71	DW	7	.23	2.08	.35	2.61	-.04	-.29
83		20	.24	2.86	.22	2.30	.04	.36
58		33	.39	2.86	.24	2.23	-.16	-1.39
50		46	.57	3.11	.40	2.25	-.19	-1.33
76	WD	7	.60	5.88	.36	2.91	-.17	-2.24
79		20	.57	5.62	.45	3.12	-.21	-2.21
64		33	.39	2.85	.67	4.91	-.17	-1.59
44		46	.22	.95	.93	5.25	-.33	-2.66
54	WW	7	.20	1.77	.69	5.24	-.12	-1.12
62		20	.08	.84	.34	2.62	-.00	-.03
32		33	-.12	-.63	.31	1.76	.05	.30
22		46	-.05	-.11	.72	1.66	.08	.31

*In general $t = 2$ indicates statistical significance at 5% level.

Table 5. Estimates of the Partial Regression Coefficients of $H(t)$ on $L(t)$, $H(t-1)$, and $L(t-1)$ with Their Student's t -Statistics*

Sample Size	i	j	b_{1H1j}	Student's t	b_{2H1j}	Student's t	b_{3H1j}	Student's t
289	DD	7	.38	6.45	.52	8.42	-.28	-4.72
266		20	.21	3.79	.79	17.52	-.21	-4.39
336		33	.32	6.57	.53	9.96	-.12	-2.60
374		46	.59	11.74	.35	6.26	-.04	-.67
71	DW	7	.57	5.31	.35	3.70	.10	.97
83		20	.51	3.61	.34	3.39	.11	1.03
58		33	.40	3.04	.44	3.63	.02	.17
50		46	.67	7.68	.13	1.17	.19	1.71
76	WD	7	.54	3.68	.30	2.01	-.28	-1.73
79		20	.26	2.62	.52	5.35	.01	.06
64		33	.29	2.27	.60	4.84	-.16	-1.03
44		46	.76	4.72	-.10	-.40	.23	.97
54	WW	7	.88	4.73	.04	.30	.12	.57
62		20	.29	1.50	.29	2.52	.24	1.20
32		33	.36	1.64	.05	.32	.27	1.24
22		46	.44	3.30	-.02	-.10	.34	1.32

*In general $t = 2$ indicates statistical significance at 5% level.

Table 6. Comparison of the Standard Deviations in the Models for the Dependent Variables $H(t-1)$ and $H(t)$.

Precipitation Condition	Week Number	Standard Deviation of $H(t-1)$ given $L(t-1)$ and $H(t-2)$	Standard Deviation of $H(t)$ given $L(t)$ and $H(t-1)$
DD	7	7.8	8.0
	20	4.3	4.4
	33	6.7	6.6
	46	7.6	7.7
DW	7	7.8	6.4
	20	5.0	4.7
	33	6.2	6.2
	46	7.4	5.8
WD	7	6.9	7.8
	20	5.3	4.1
	33	6.2	6.6
	46	4.5	7.4
WW	7	7.5	8.0
	20	5.2	5.6
	33	5.6	6.8
	46	4.8	5.4

Table 7. F-Statistics From the Harmonic Analysis of b_1 , b_2 , and $\hat{\sigma}^2$
 $(v_1 = 2 \text{ and } v_2 = 43)$

Dependent Variable	Precip. Sequence	Parameter	First Harmonic	Second Harmonic	Third Harmonic	Fourth Harmonic
Maximum Temperature, Day (t - 1)	DD	b_1	117.29	4.79	3.08	.53
		b_2	67.66	1.97	11.69	.66
		$\hat{\sigma}^2$	577.22	68.50	30.70	.74
	DW	b_1	4.24	3.64	1.27	.68
		b_2	.93	1.60	1.67	1.43
		$\hat{\sigma}^2$	75.26	14.24	.39	.83
	WD	b_1	2.03	.63	.52	1.66
		b_2	1.09	1.04	2.72	5.82
		$\hat{\sigma}^2$	21.16	11.57	.32	.74
	WW	b_1	.78	.27	1.79	1.67
		b_2	.61	1.20	3.18	4.87
		$\hat{\sigma}^2$	1.95	5.16	1.35	1.86
Minimum Temperature, Day t	DD	b_1	12.59	28.64	10.33	2.78
		b_2	37.98	8.69	4.15	.20
		$\hat{\sigma}^2$	175.47	35.66	13.26	5.42
	DW	b_1	2.44	1.40	.77	1.59
		b_2	3.61	2.13	.60	.92
		$\hat{\sigma}^2$	109.13	.50	1.86	.48

(continued on next page)

Table 7. (continued)

Dependent Variable	Precip. Sequence	Parameter	First Harmonic	Second Harmonic	Third Harmonic	Fourth Harmonic
	WD	b_1	14.15	.38	2.32	.88
		b_2	10.07	1.01	.73	.59
		$\hat{\sigma}^2$	51.70	1.66	4.83	3.97
	WW	b_1	.37	.96	1.56	.45
		b_2	4.26	.53	.58	.84
		$\hat{\sigma}^2$	82.51	1.62	4.61	.78

Table 8. Coefficients of the Harmonic Functions for the Betas and Variances

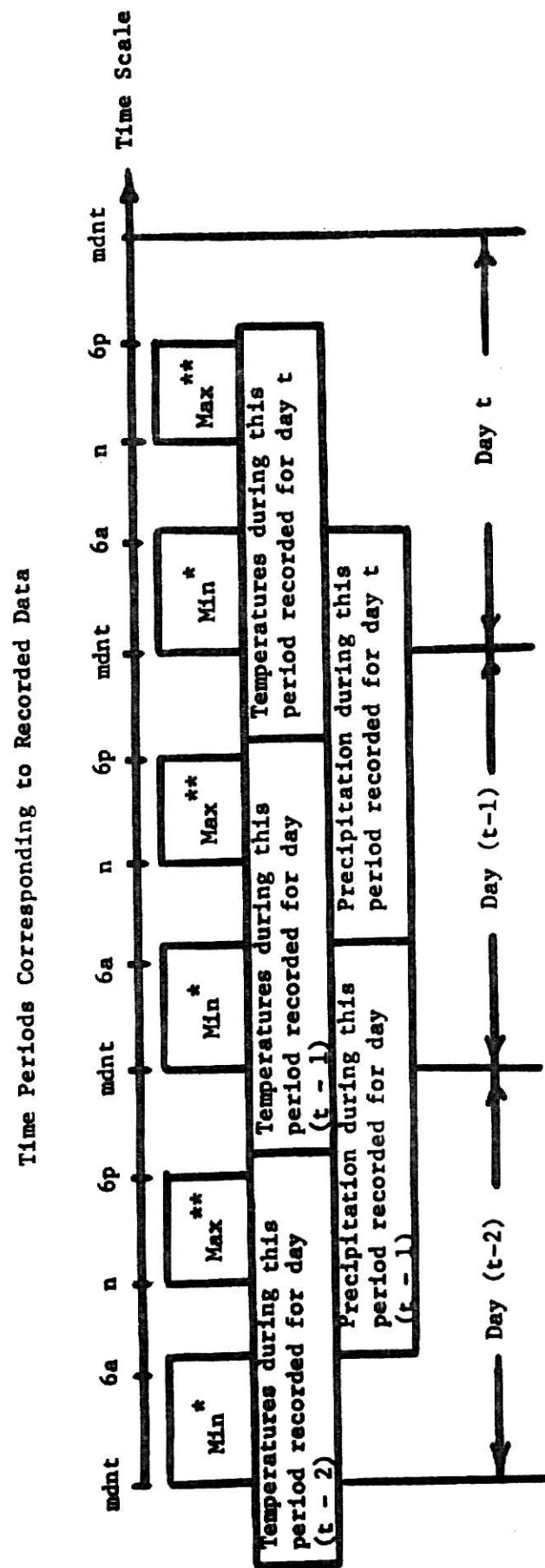
$$f(t) = a_0 + a_1 \cos(2\pi t/364) + b_1 \sin(2\pi t/364) + a_2 \cos(4\pi t/364) + b_2 \sin(4\pi t/364) + a_3 \cos(6\pi t/364) + b_3 \sin(6\pi t/364) + a_4 \cos(8\pi t/364) + b_4 \sin(8\pi t/364)$$

$f(t)$	i	a_0	a_1	b_1	a_2	b_2	a_3	b_3	a_4	b_4
$\sigma_{H1}^2(t-1)$	DD	50.25	23.37	-16.70	6.79	7.19	5.81	3.19	.91	-.48
	DW	46.99	17.13	-11.80	7.42	5.18	1.42	-.46	-2.14	-.40
	WD	41.41	9.41	-5.66	3.97	7.08	-.96	-.95	-1.77	1.05
	WW	38.40	2.84	-4.07	.75	8.05	-3.97	1.13	-4.07	2.65
$\beta_{1H1}(t-1)$	DD	.37	.17	-.09	.01	-.04	-.02	-.02	.01	.01
	DW	.34	.06	-.04	.04	-.05	.01	-.04	-.01	.03
	WD	.57	.03	.04	.01	.03	-.01	.02	-.04	.01
	WW	.62	.02	-.04	.02	-.00	-.06	-.03	-.05	-.03
$\beta_{2H1}(t-1)$	DD	.45	-.13	.06	-.01	-.02	.05	.03	-.00	-.01
	DW	.51	-.02	.01	-.04	-.00	.02	.03	.02	-.02
	WD	.33	.00	-.03	-.03	.01	.03	.03	.06	-.03
	WW	.38	.00	.03	-.01	.04	.05	.04	.07	.03
$\sigma_{L1}^2(t-1)$	DD	46.95	11.75	-9.93	2.44	6.49	-.50	-4.20	-2.43	1.19
	DW	53.30	26.12	-29.61	.87	-2.53	-2.59	-4.46	-2.53	.72
	WD	48.11	10.06	-14.53	.51	3.13	-1.32	-5.24	-.56	4.86
	WW	42.47	13.35	-22.63	-.73	-3.61	-5.48	-2.93	-2.36	-.95
$\beta_{1L1}(t)$	DD	.45	.04	.04	-.00	.08	-.05	-.01	-.03	-.01
	DW	.25	.05	-.01	.04	-.00	.02	-.02	.00	-.04
	WD	.31	-.05	.11	-.00	-.02	-.05	.02	.06	.03
	WW	.15	.02	.03	.02	-.06	-.08	-.03	.00	.04
$\beta_{2L1}(t)$	DD	.28	-.12	.00	-.01	-.06	.00	-.04	.01	-.00
	DW	.27	.03	-.07	-.03	-.05	-.03	.01	-.01	.04
	WD	.52	-.00	-.12	.01	-.04	.01	-.03	.03	-.00
	WW	.57	.10	-.15	-.02	.06	.01	.06	.07	-.04

Table 9. Mean Monthly Maximum and Minimum Temperatures

	Actual Normal Temperatures		Simulated Normals		Estimated μ 's from Harmonics	
	max	min	max	min	max	min
January	39.2	17.8	39.2	18.3	39.9	16.9
February	45.5	22.6	43.5	21.6	44.9	21.6
March	54.1	29.8	56.1	31.8	55.2	31.3
April	68.1	42.8	68.1	42.1	67.2	42.7
May	77.2	53.2	77.4	53.8	78.0	52.9
June	85.5	63.0	86.1	62.2	86.4	60.9
July	91.1	67.1	91.1	66.7	91.4	66.0
August	90.6	66.2	91.2	65.4	91.3	66.1
September	81.9	56.2	83.8	58.1	84.2	59.6
October	71.9	45.3	72.6	46.4	70.7	46.8
November	55.4	31.6	55.5	31.6	55.2	31.9
December	43.0	21.8	44.0	21.5	44.4	20.4
Annual	67.0	43.1	67.4	43.1	66.4	43.1

Figure 1.



* Most minimum temperatures occur between midnight and 7 am.

** Most maximum temperatures occur between noon and 6 pm.

ILLEGIBLE DOCUMENT

**THE FOLLOWING
DOCUMENT(S) IS OF
POOR LEGIBILITY IN
THE ORIGINAL**

**THIS IS THE BEST
COPY AVAILABLE**

Figure 2.

AVERAGE DAILY HIGH TEMPERATURES (DRY, DRY) MANHATTAN DAY (T-1)

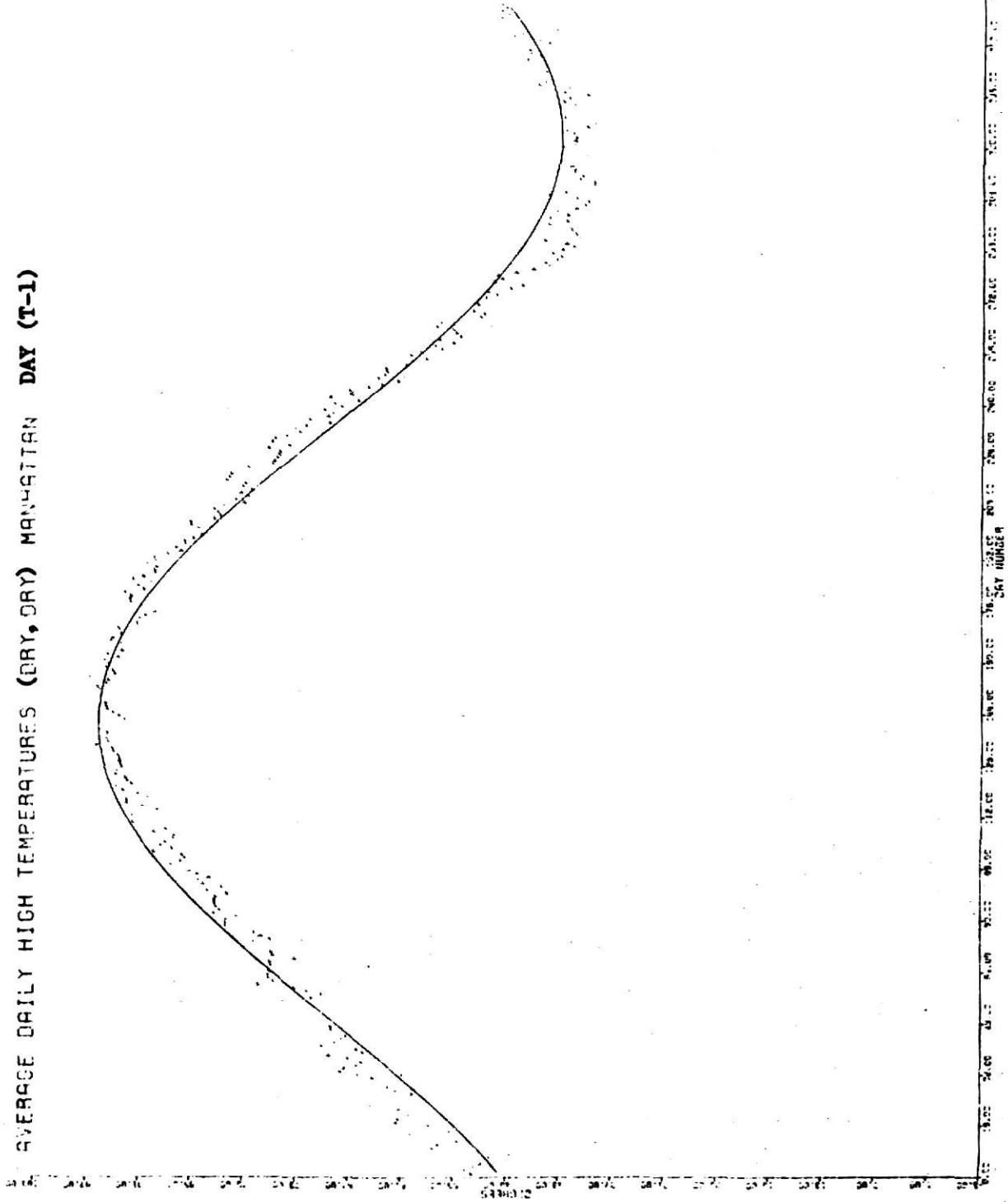


Figure 3.

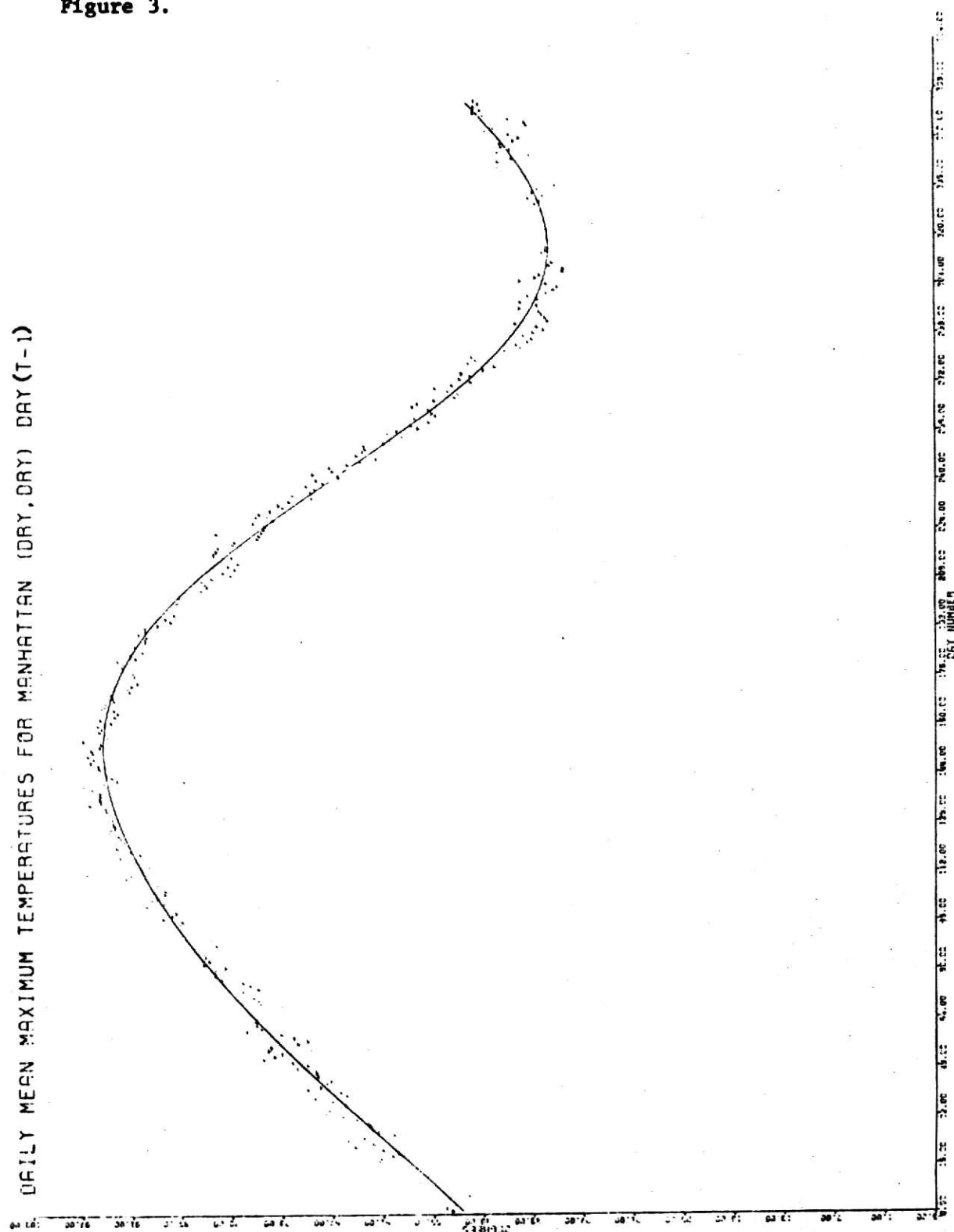


Figure 4.

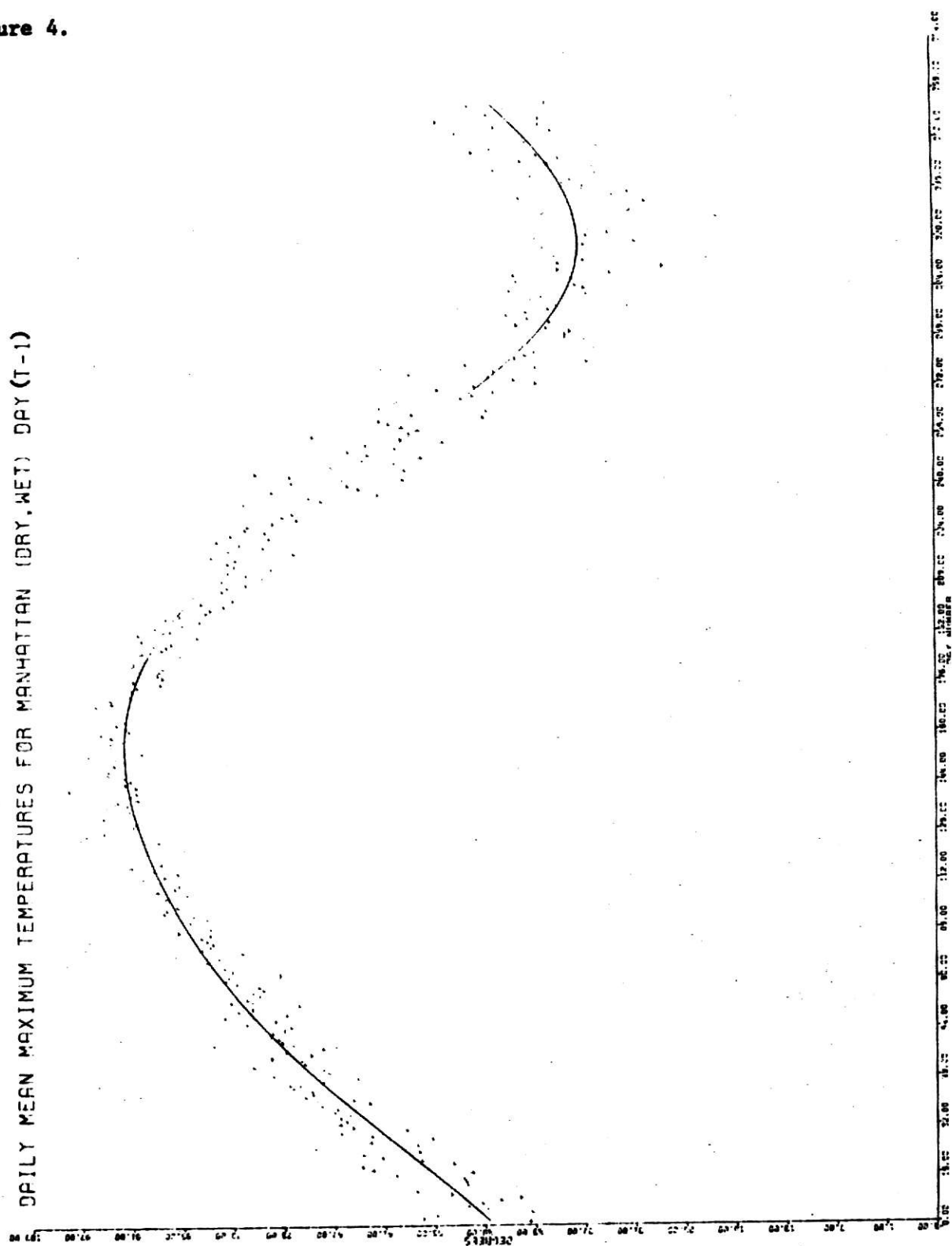


Figure 5.

DAILY MEAN MAXIMUM TEMPERATURES FOR MANHATTAN (WET, DRY) DAY (T-D)

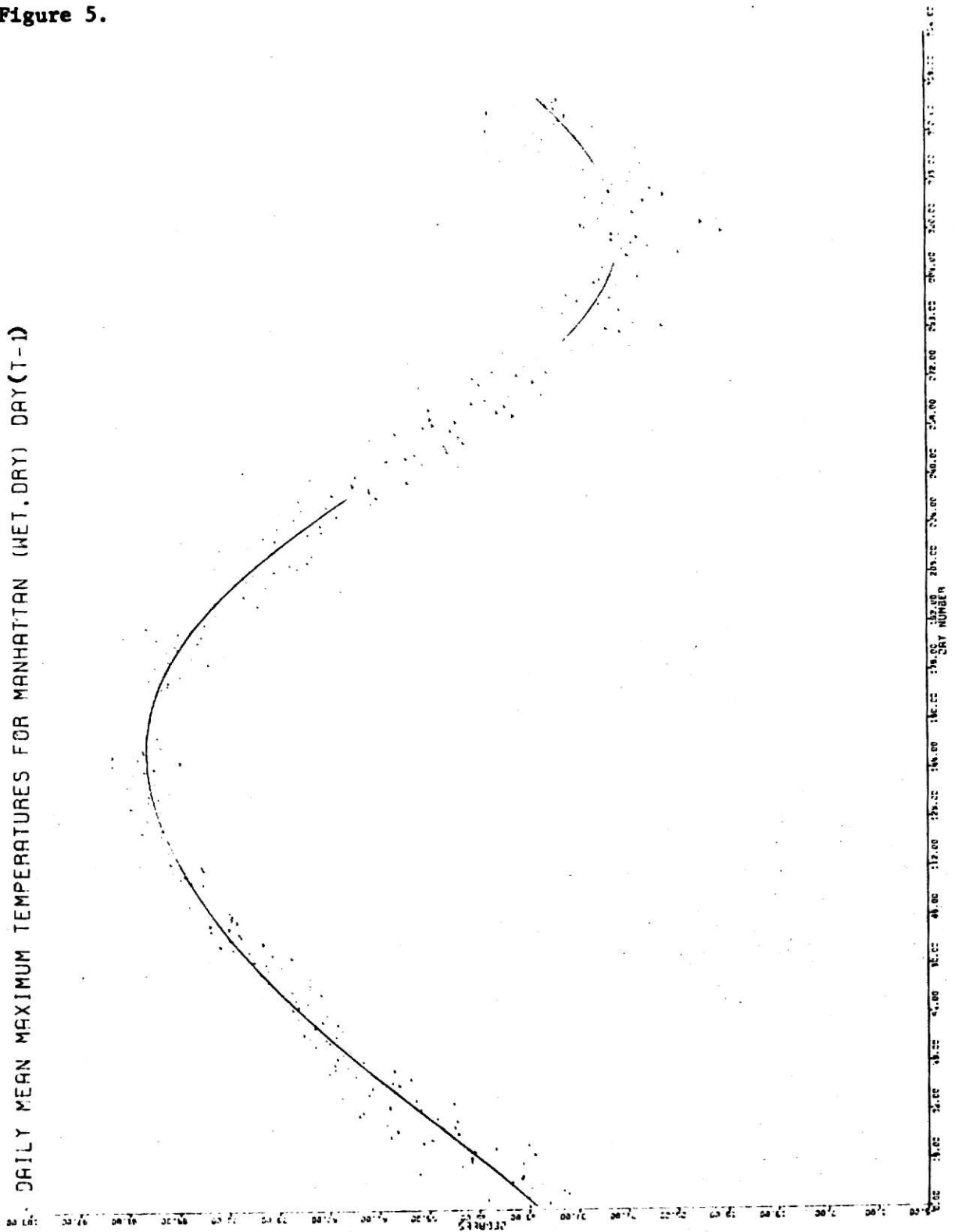


Figure 6.

DAILY MEAN MAXIMUM TEMPERATURES FOR MANHATTAN (WET, WET) DAY (T-1)

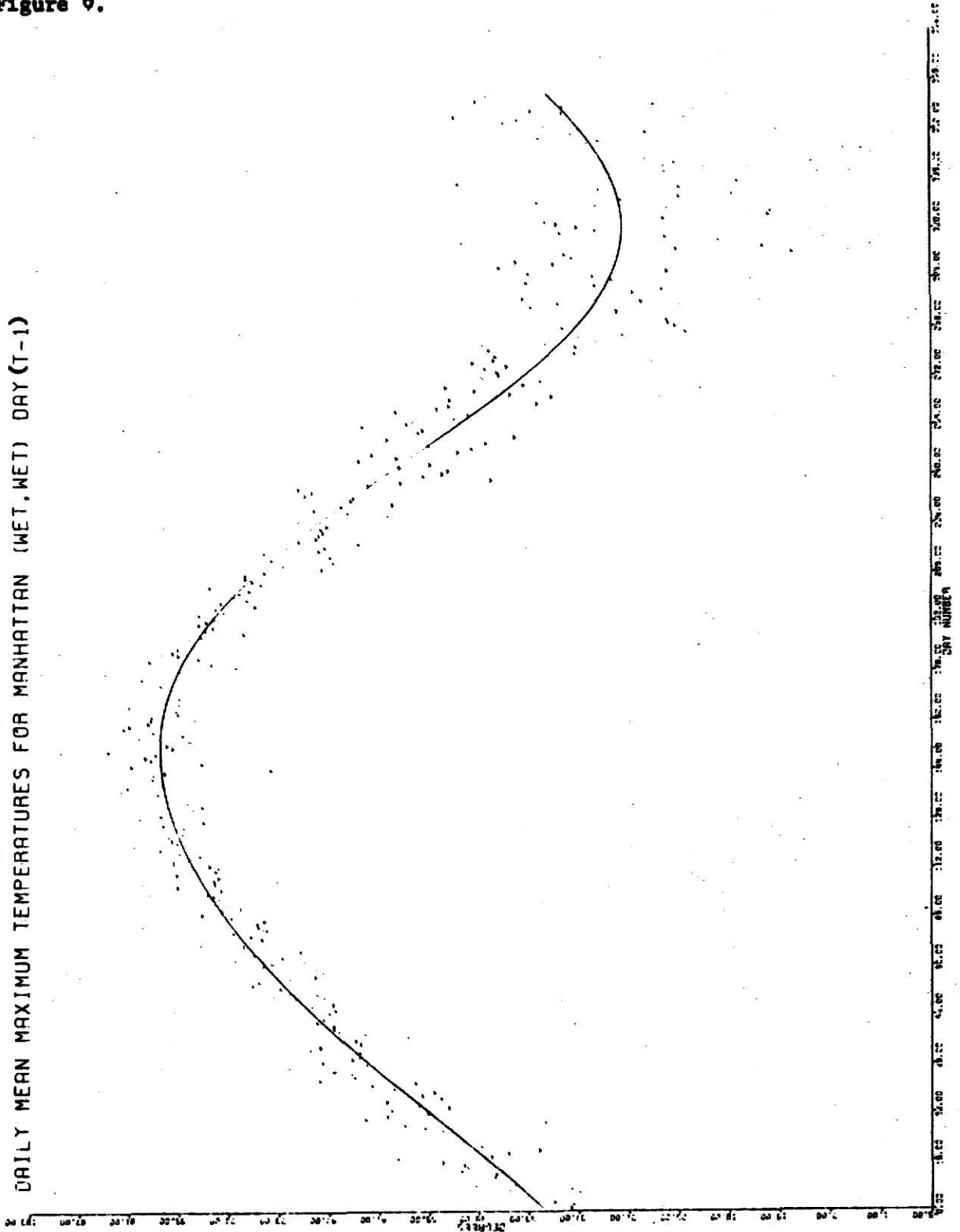


Figure 7.

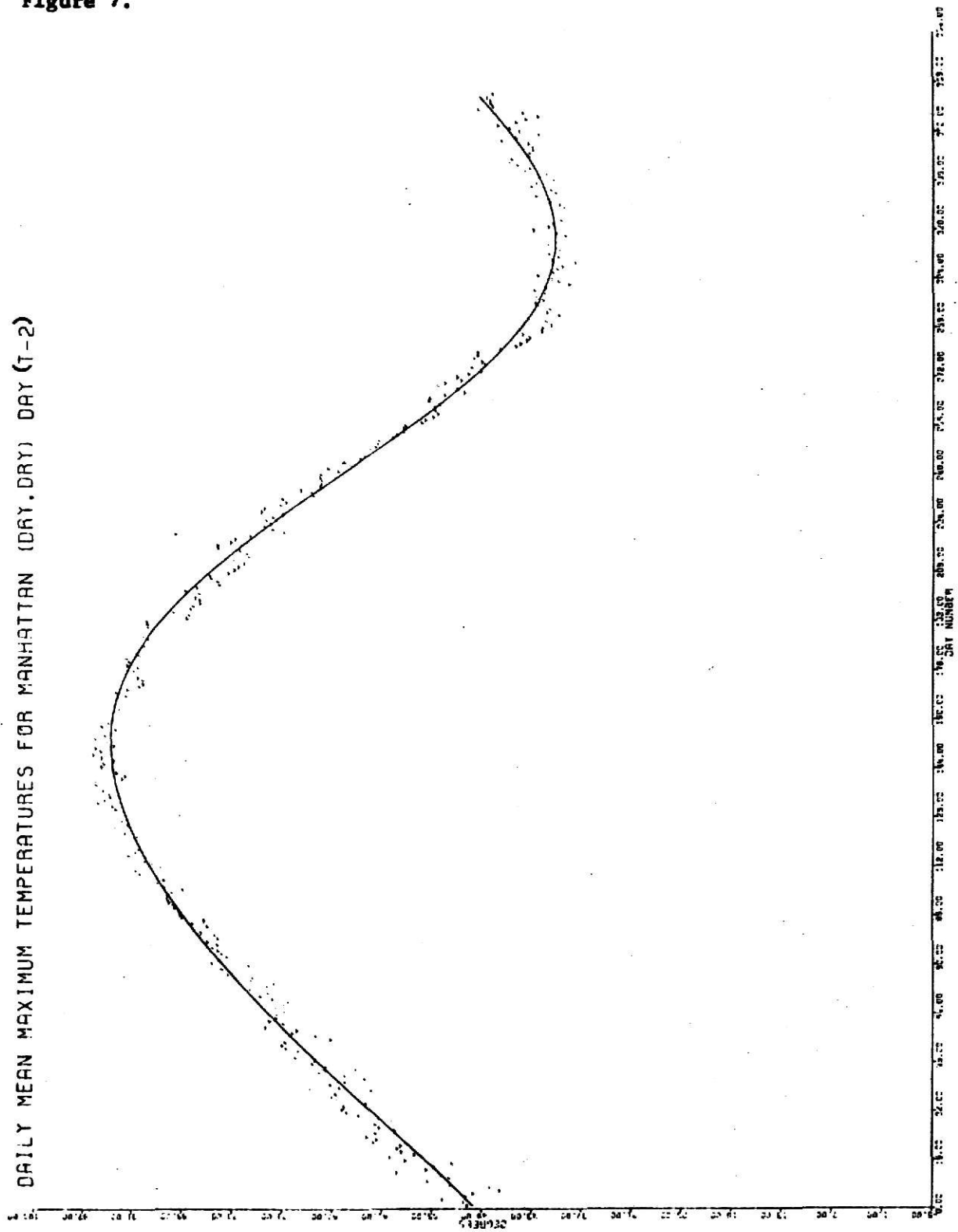


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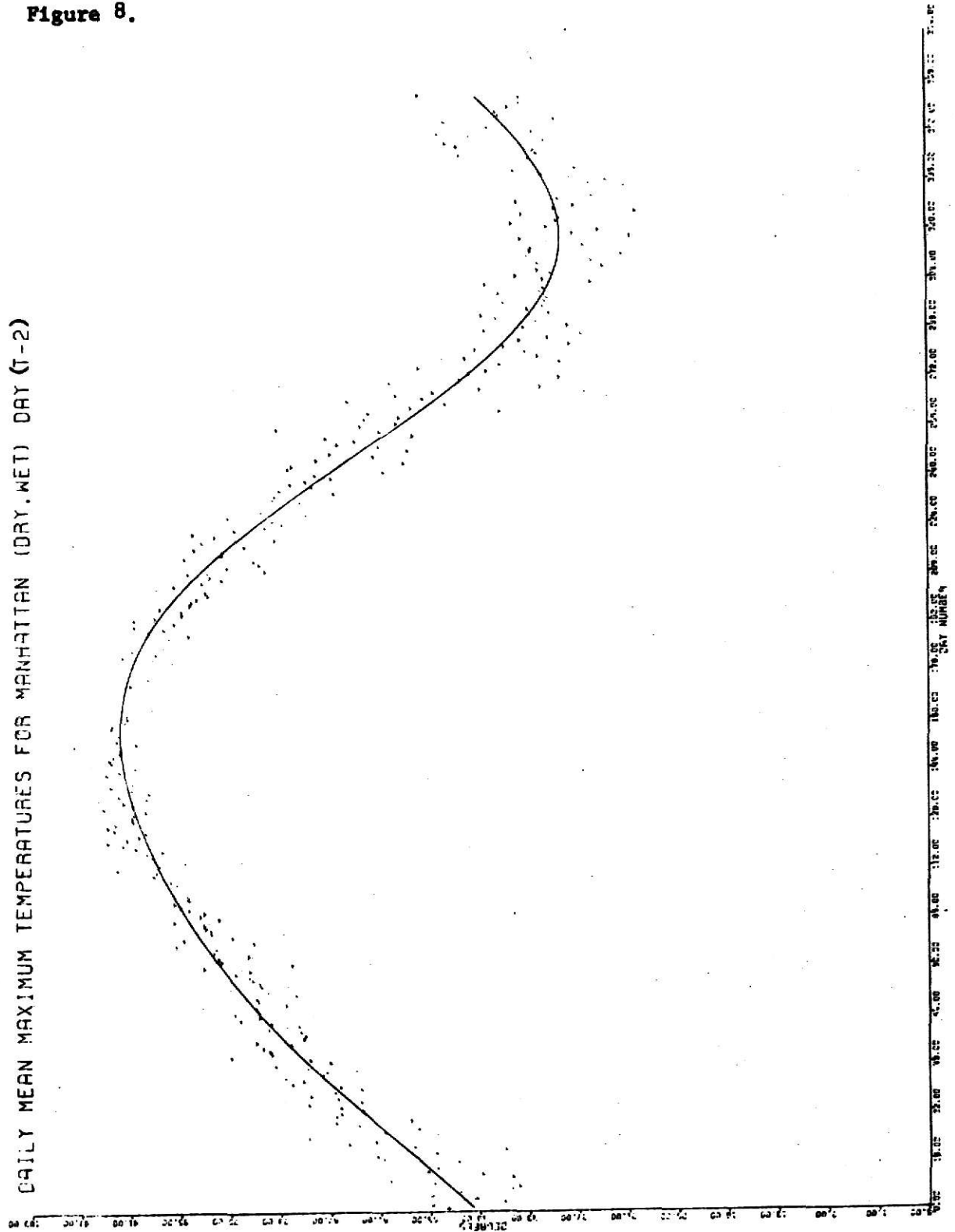


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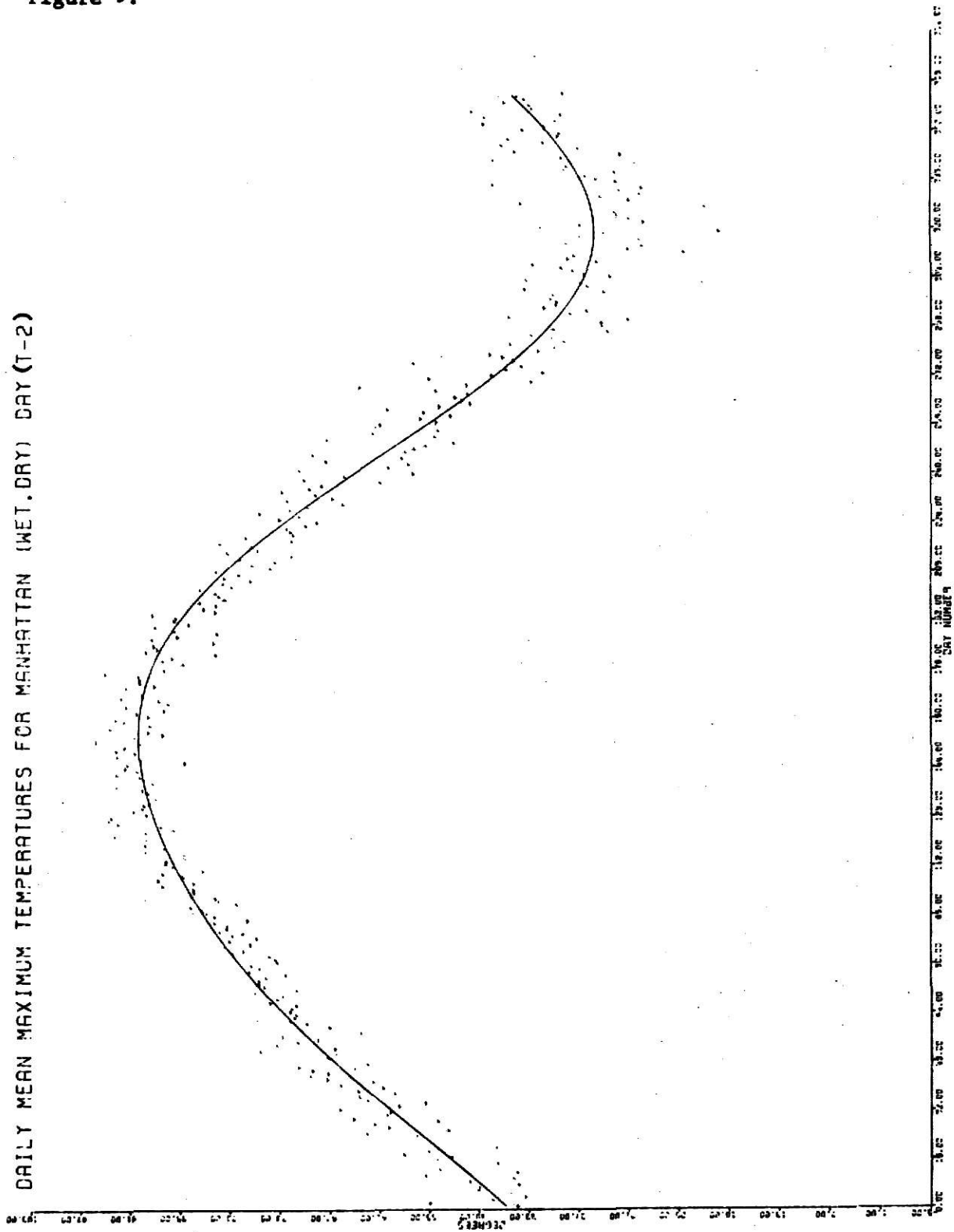


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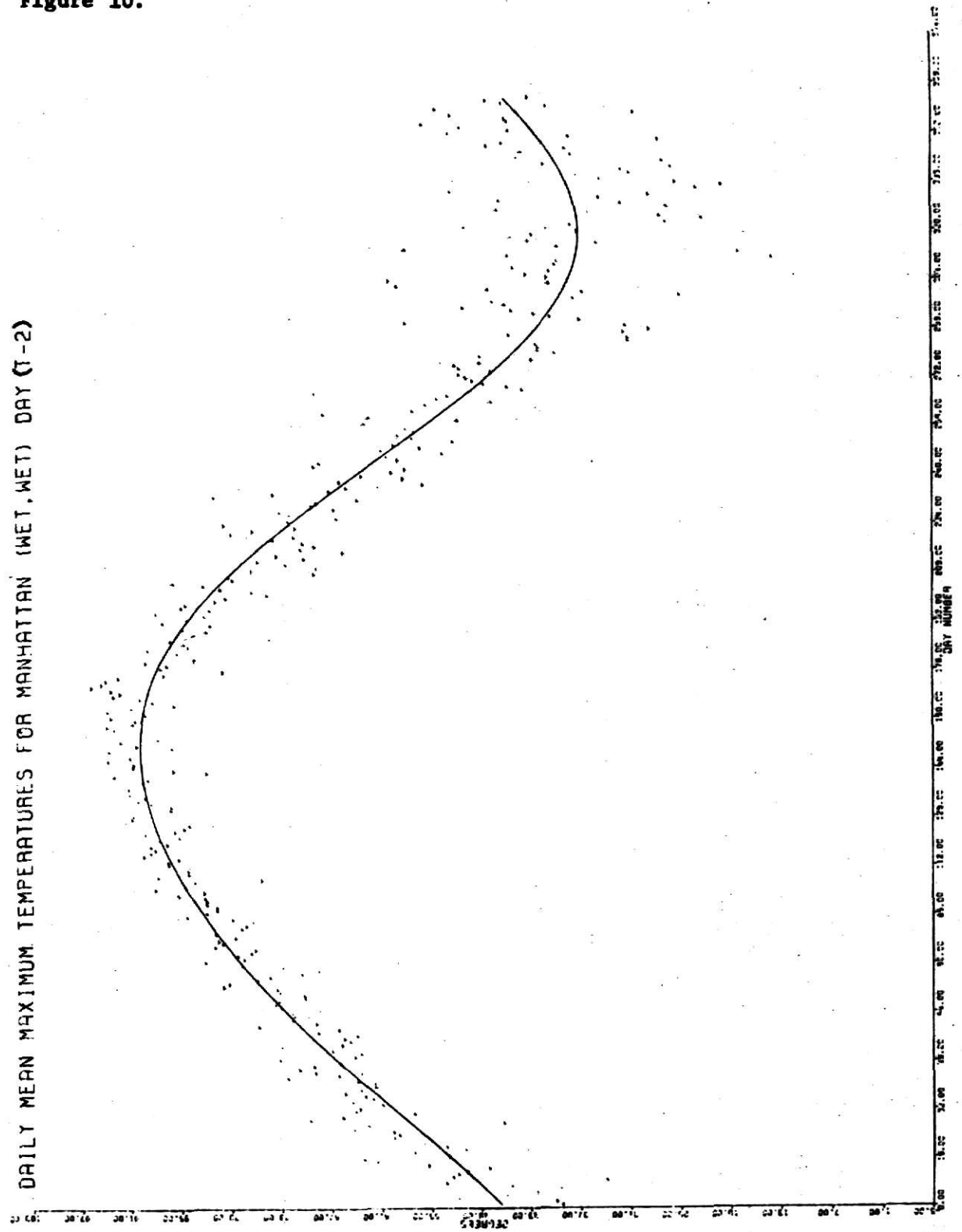


Figure 11.

DAILY MEAN MINIMUM TEMPERATURES FOR MANHATTAN (DRY, DRY) DAY T

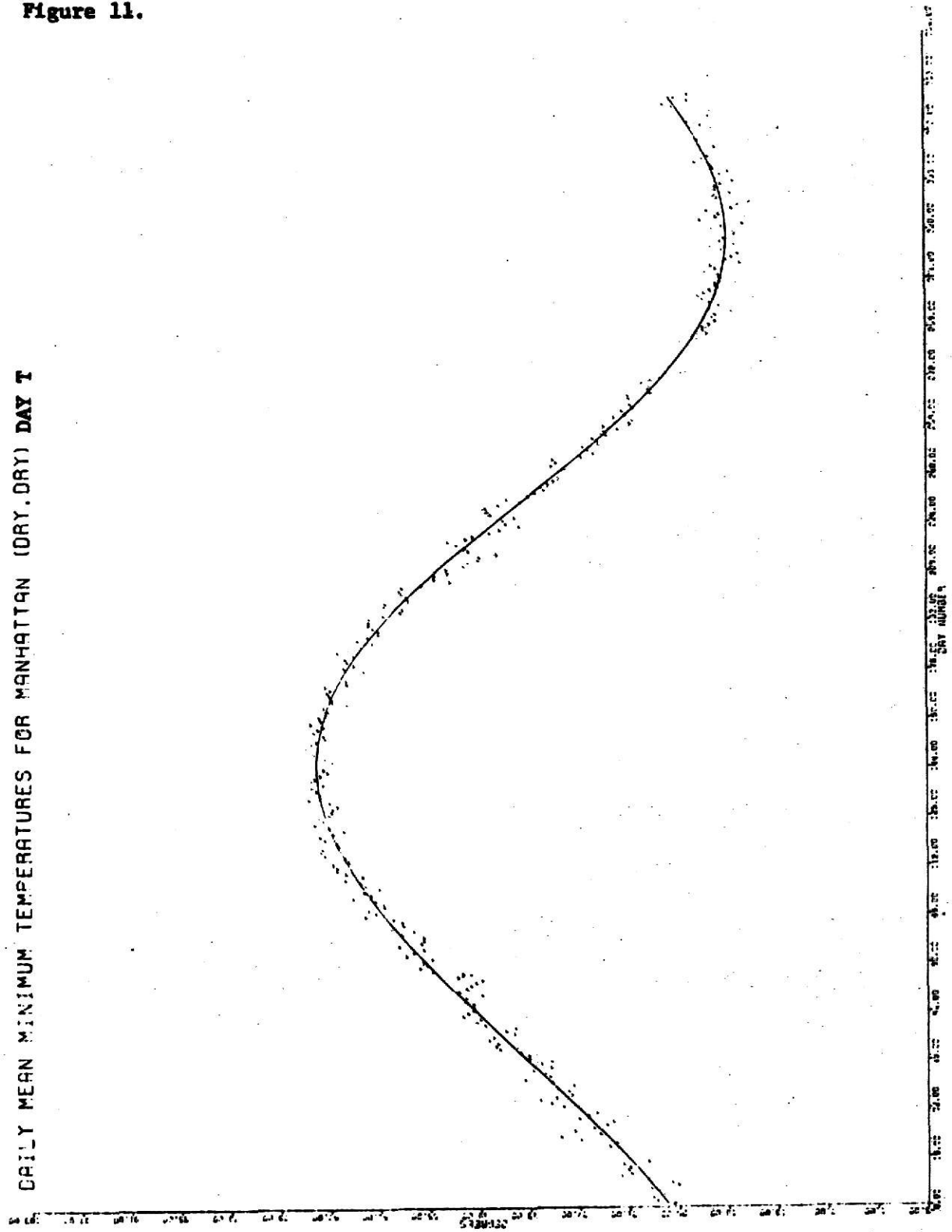


Figure 12.

DAILY MEAN MINIMUM TEMPERATURES FOR MANHATTAN (DRY, WET) DAY T

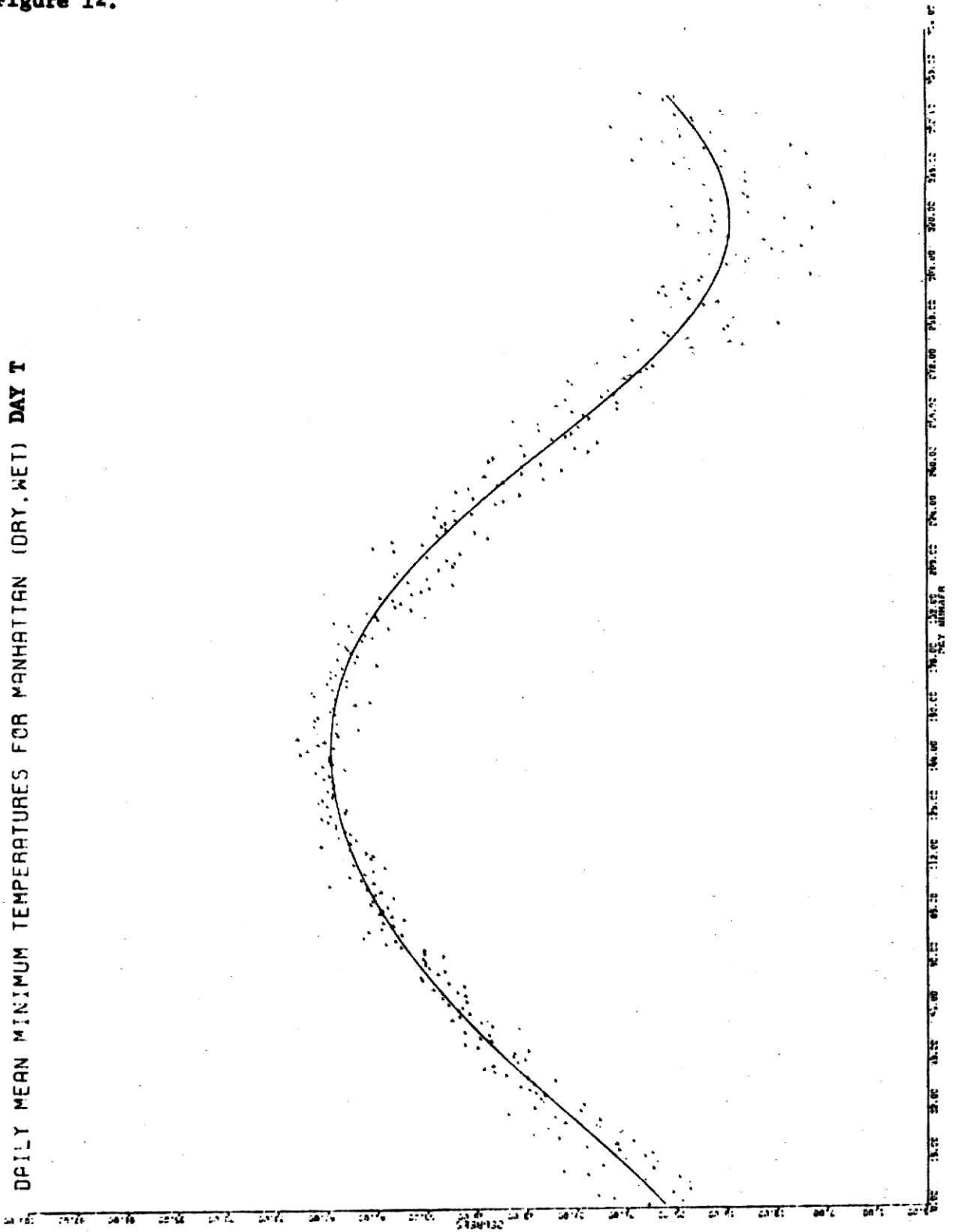


Figure 13.

DAILY MEAN MINIMUM TEMPERATURES FOR MANHATTAN (WET, DRY) DAY T

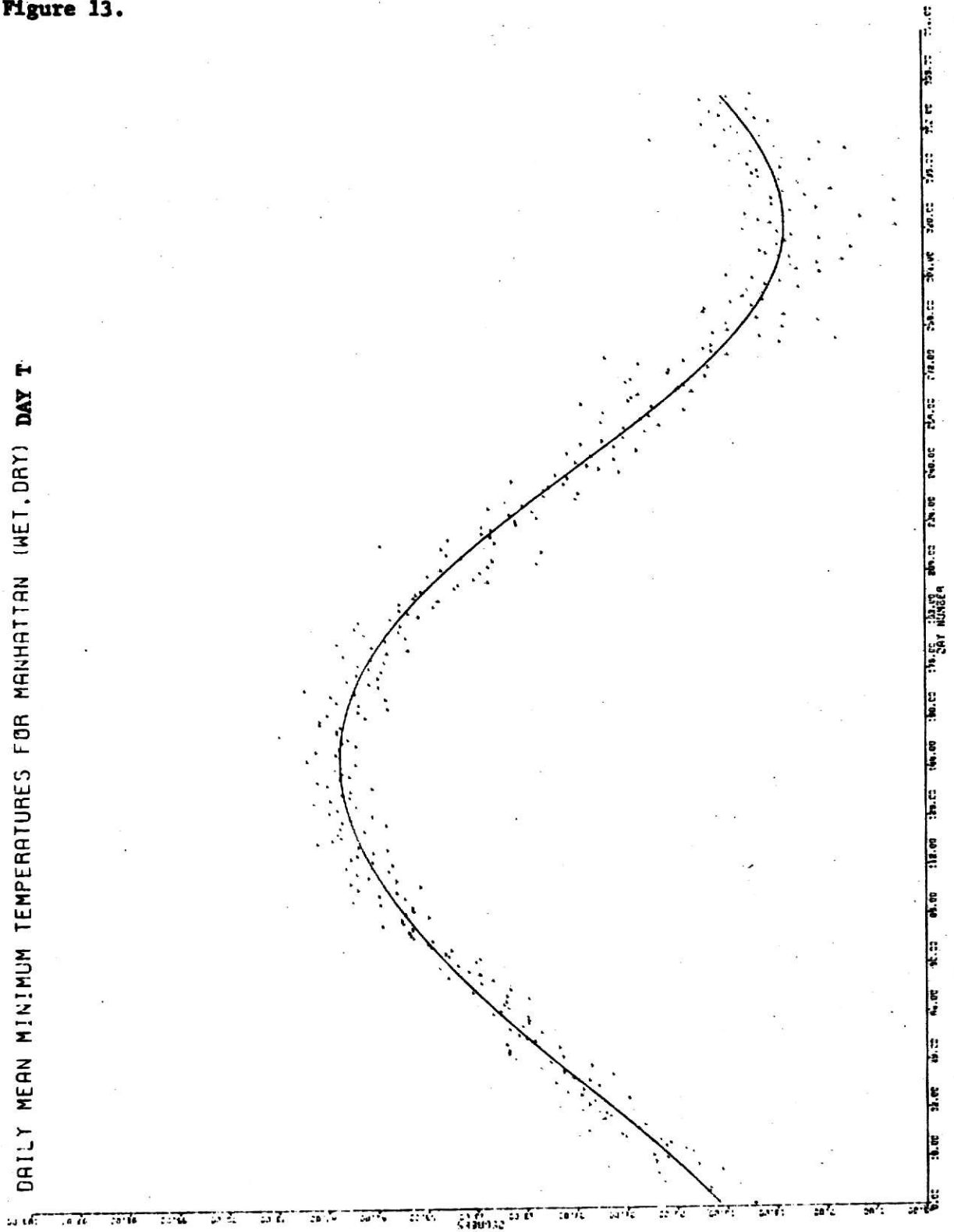


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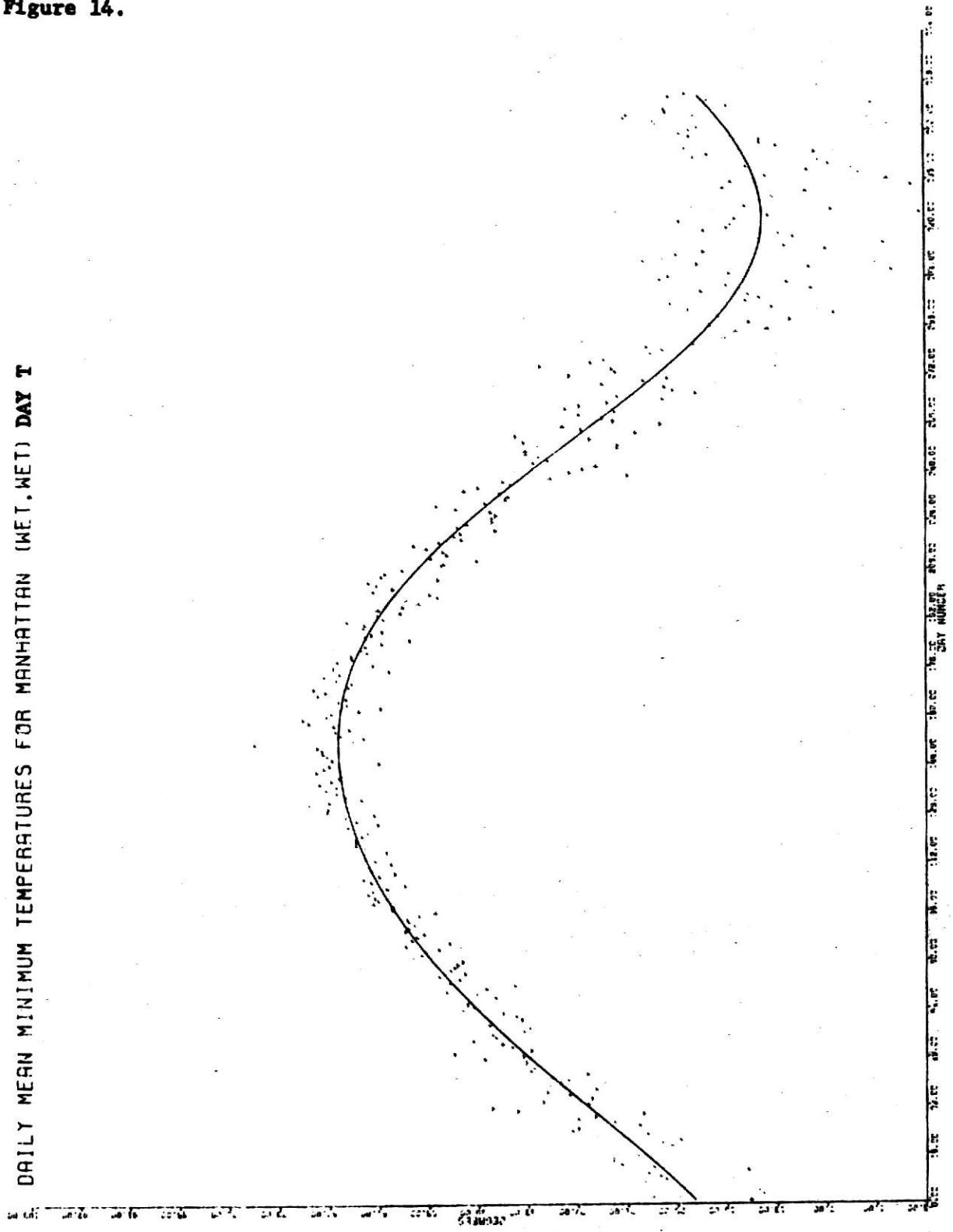


Figure 15.

DAILY MEAN MINIMUM TEMPERATURES FOR MANHATTAN (DRY, DRY) DAY (T-1)

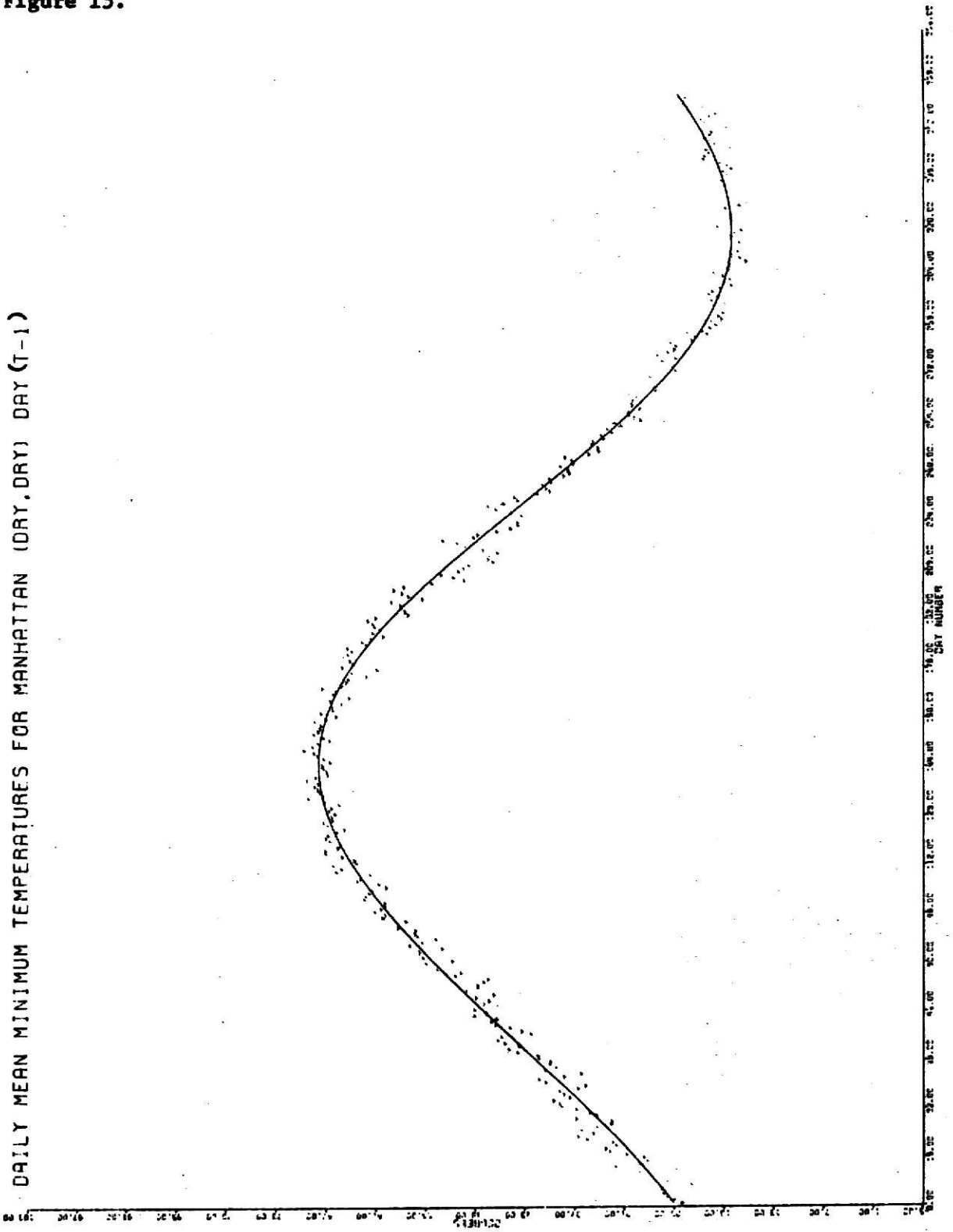


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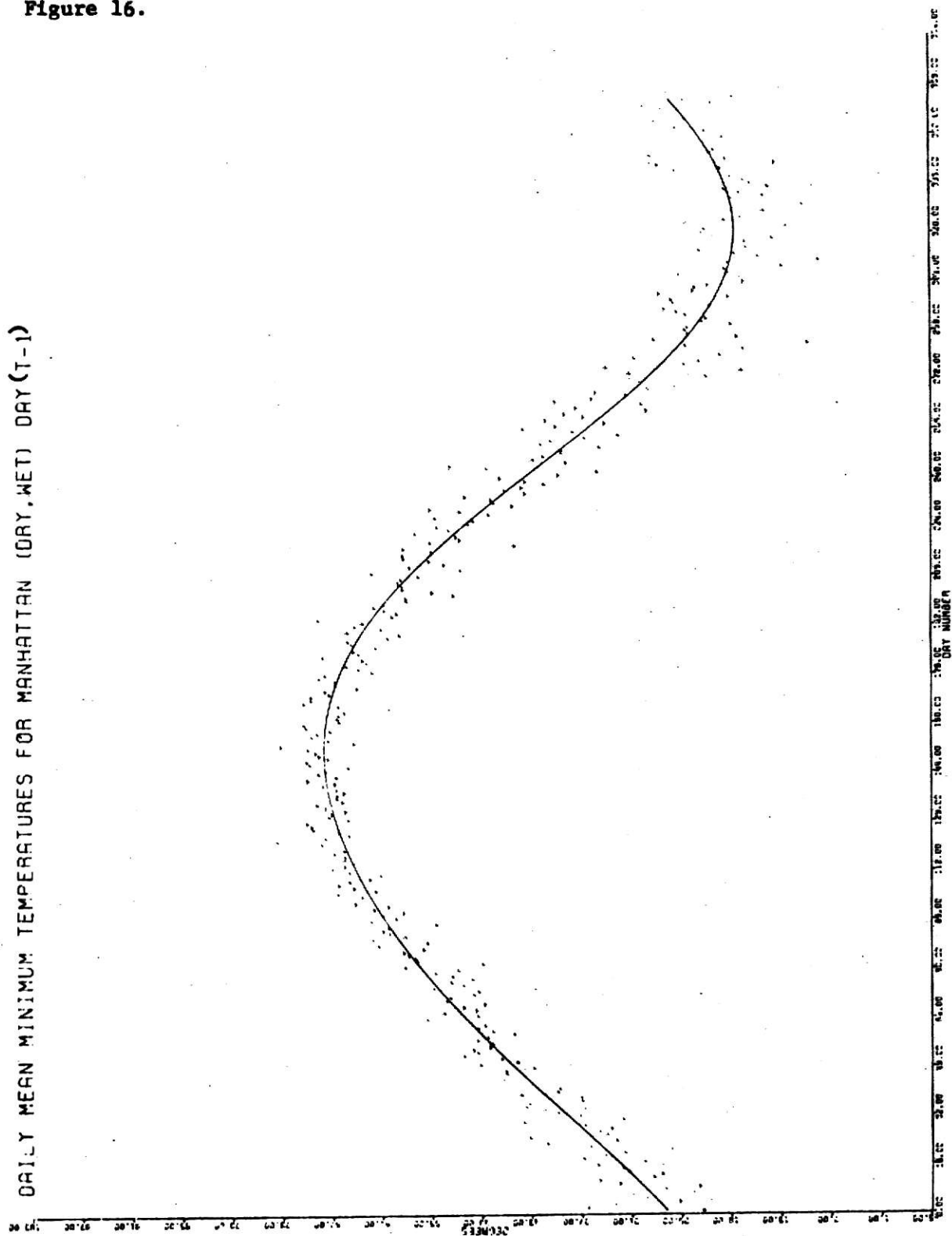


Figure 17.

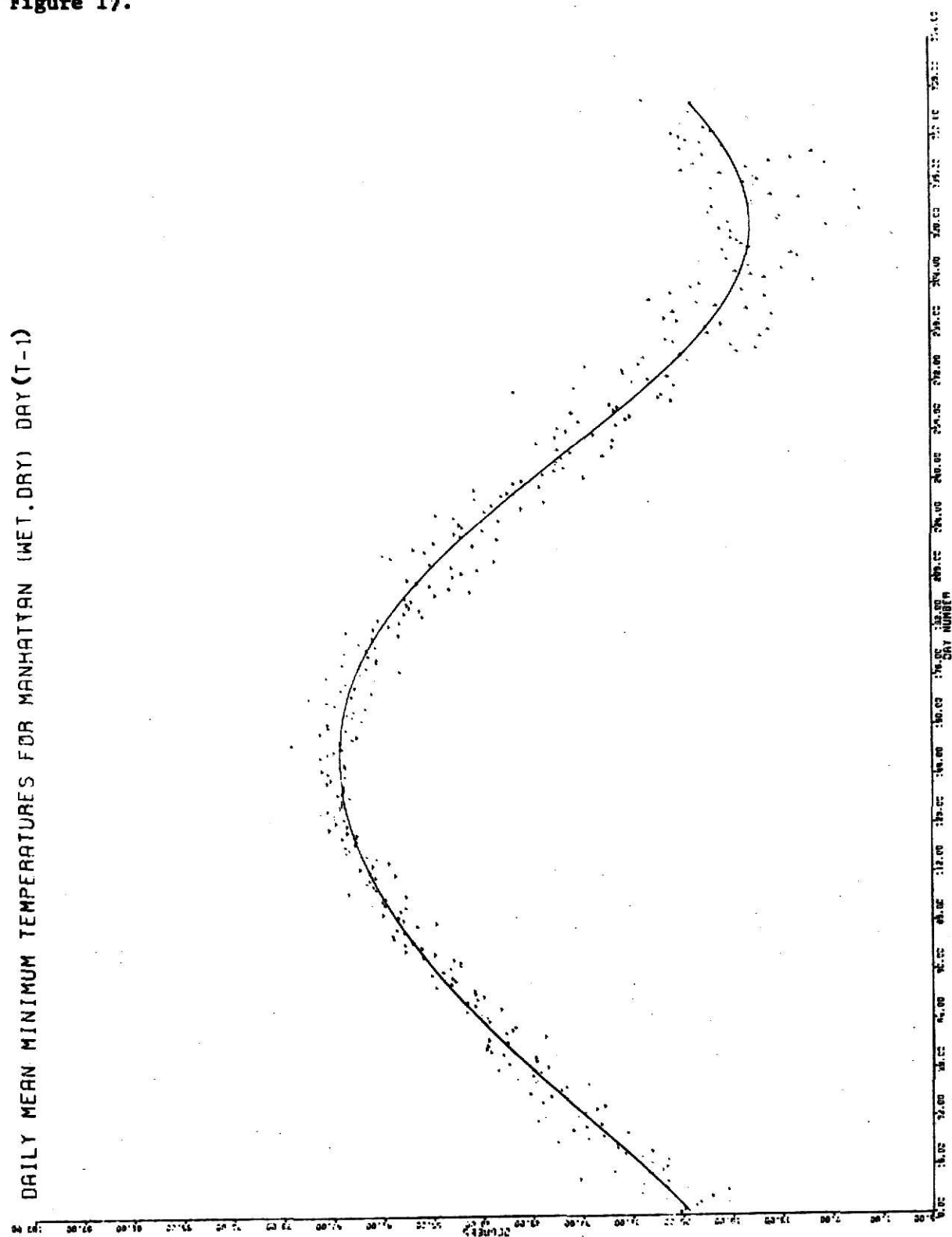


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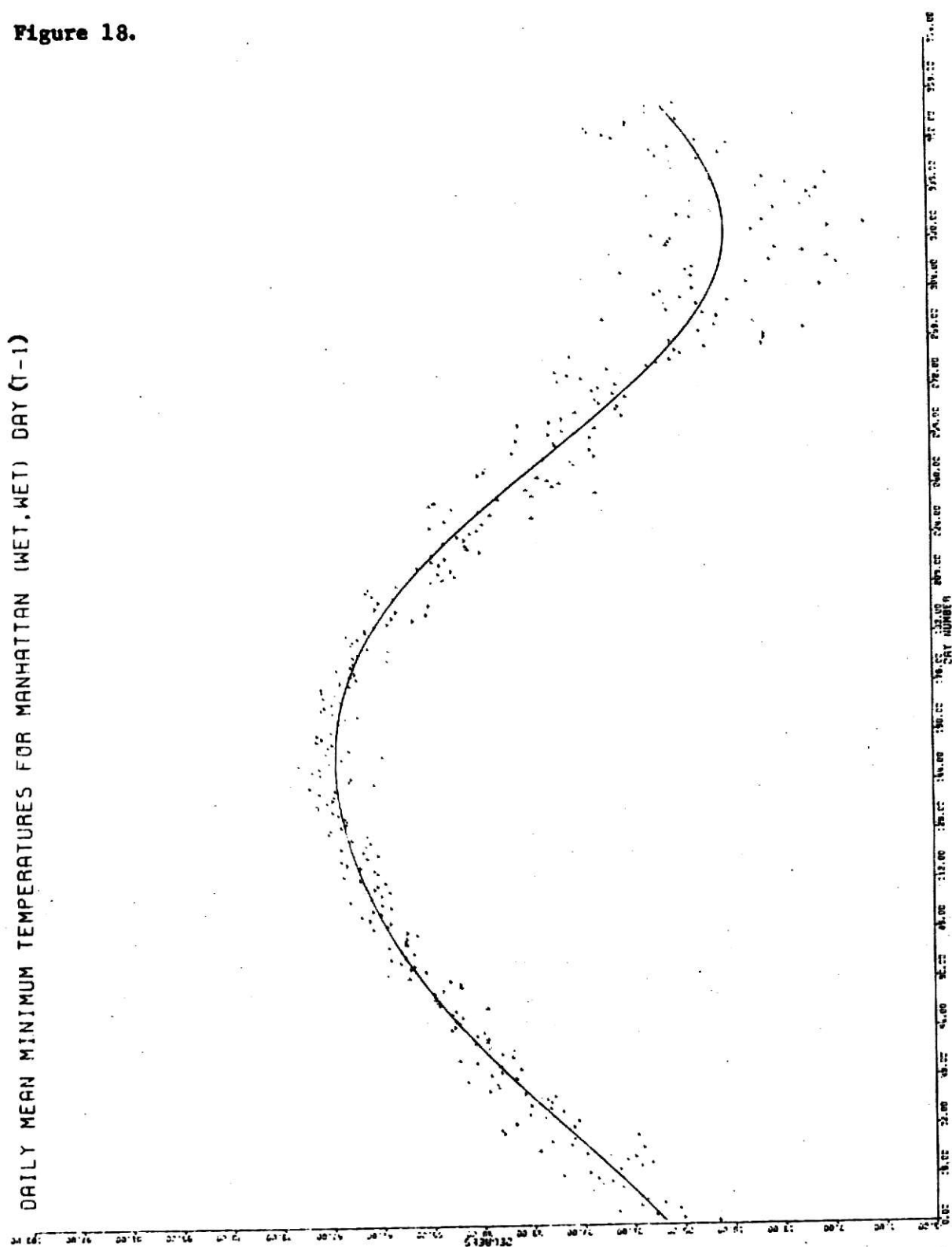


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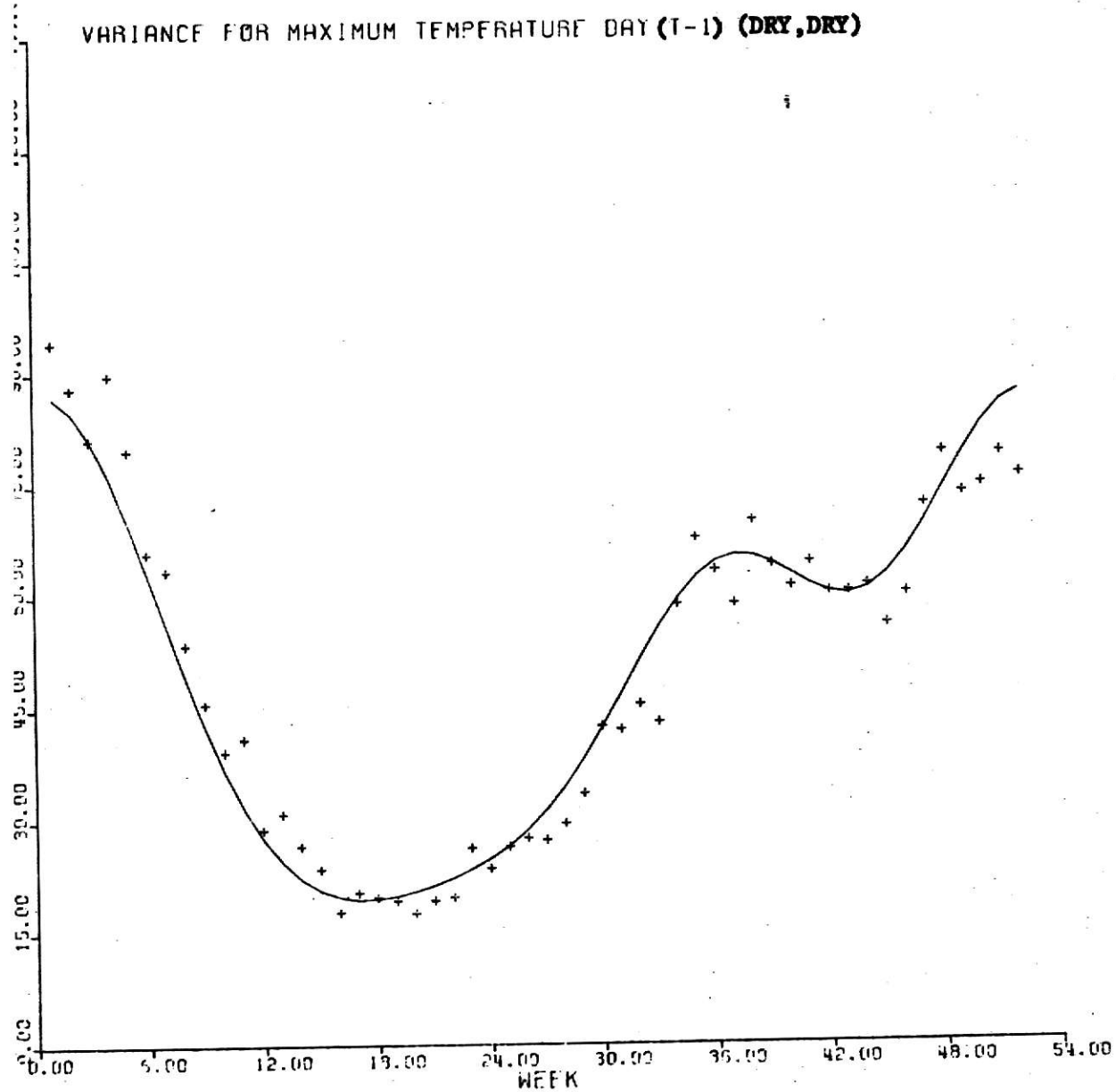


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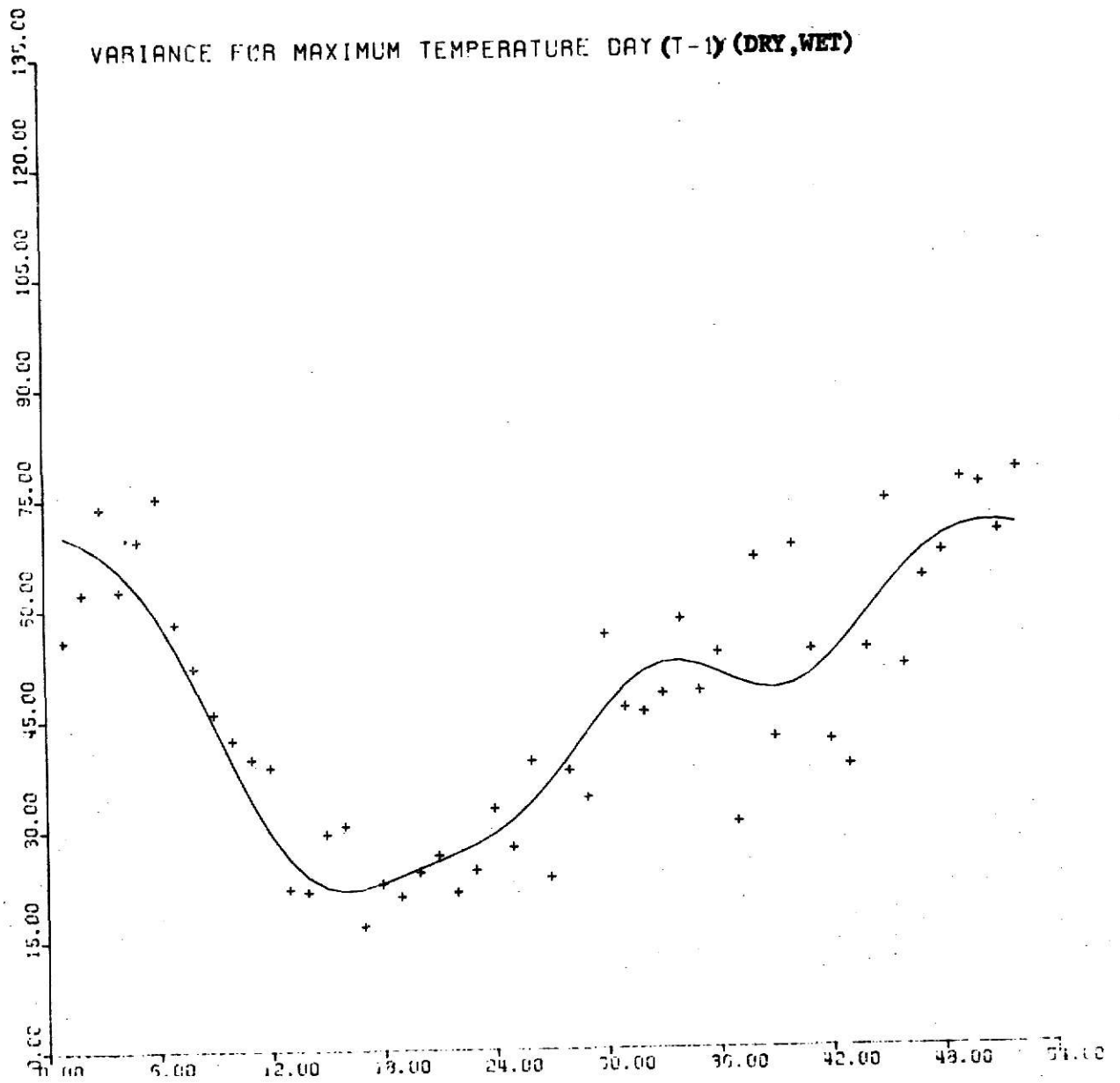


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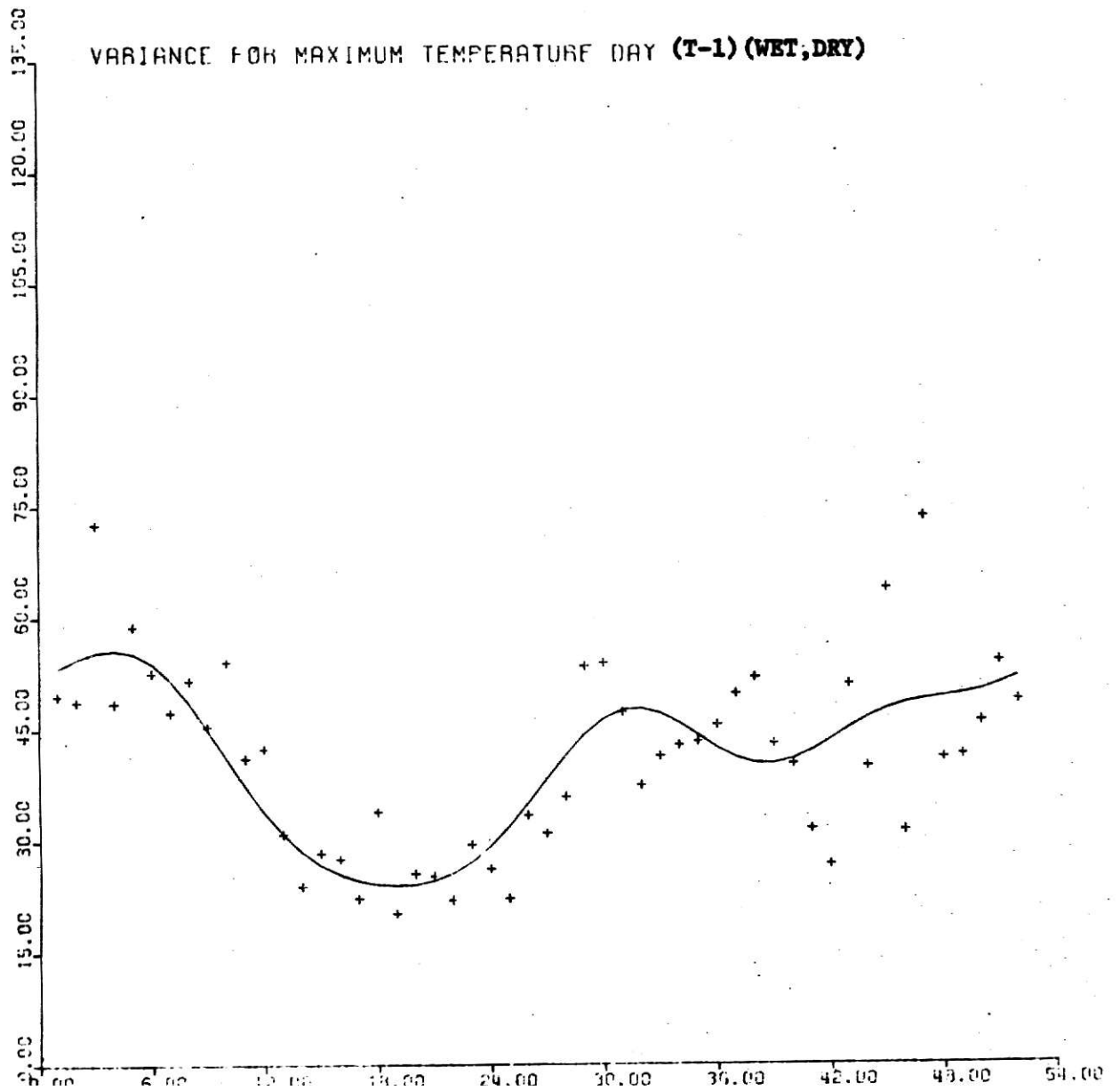


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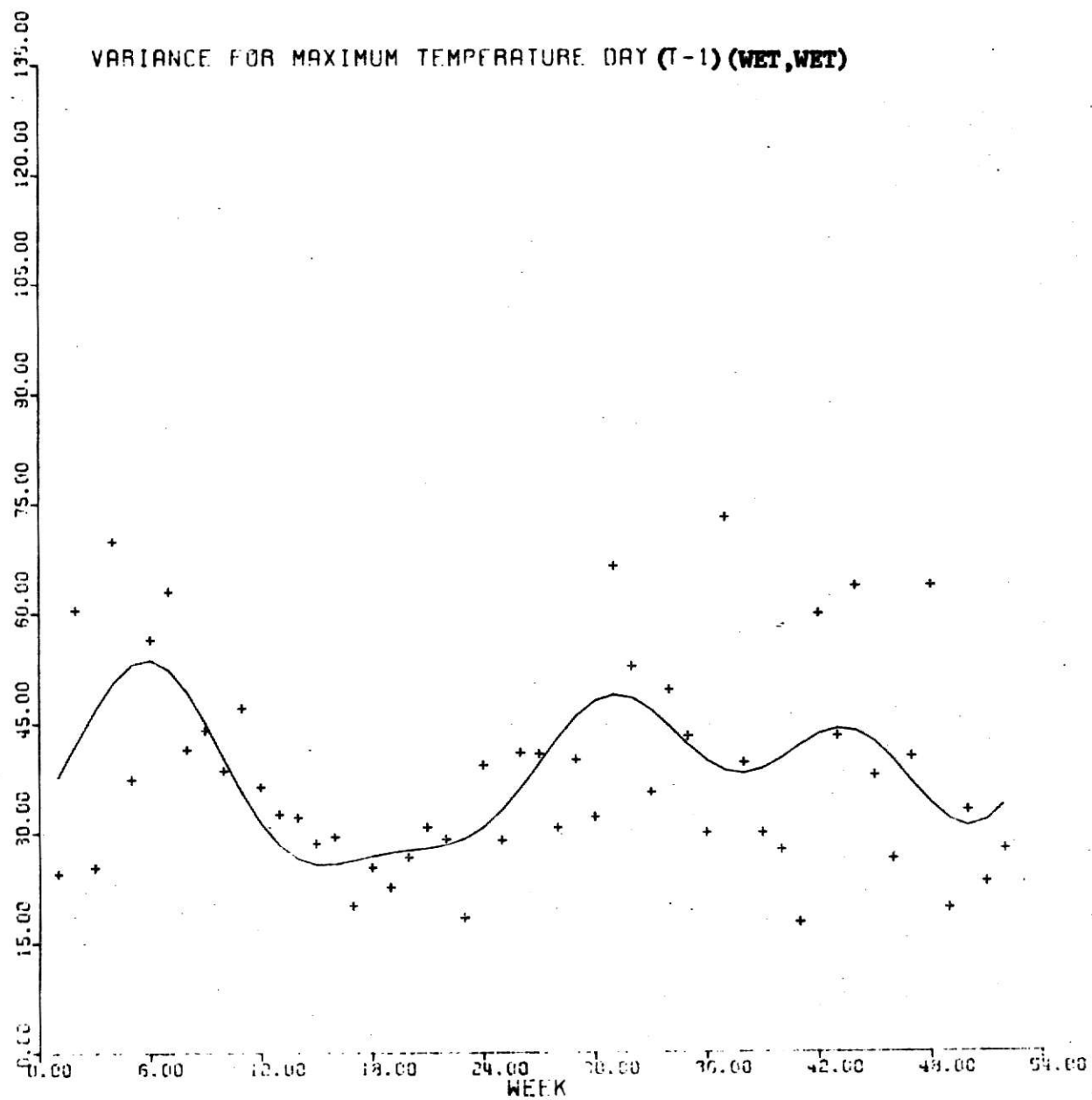


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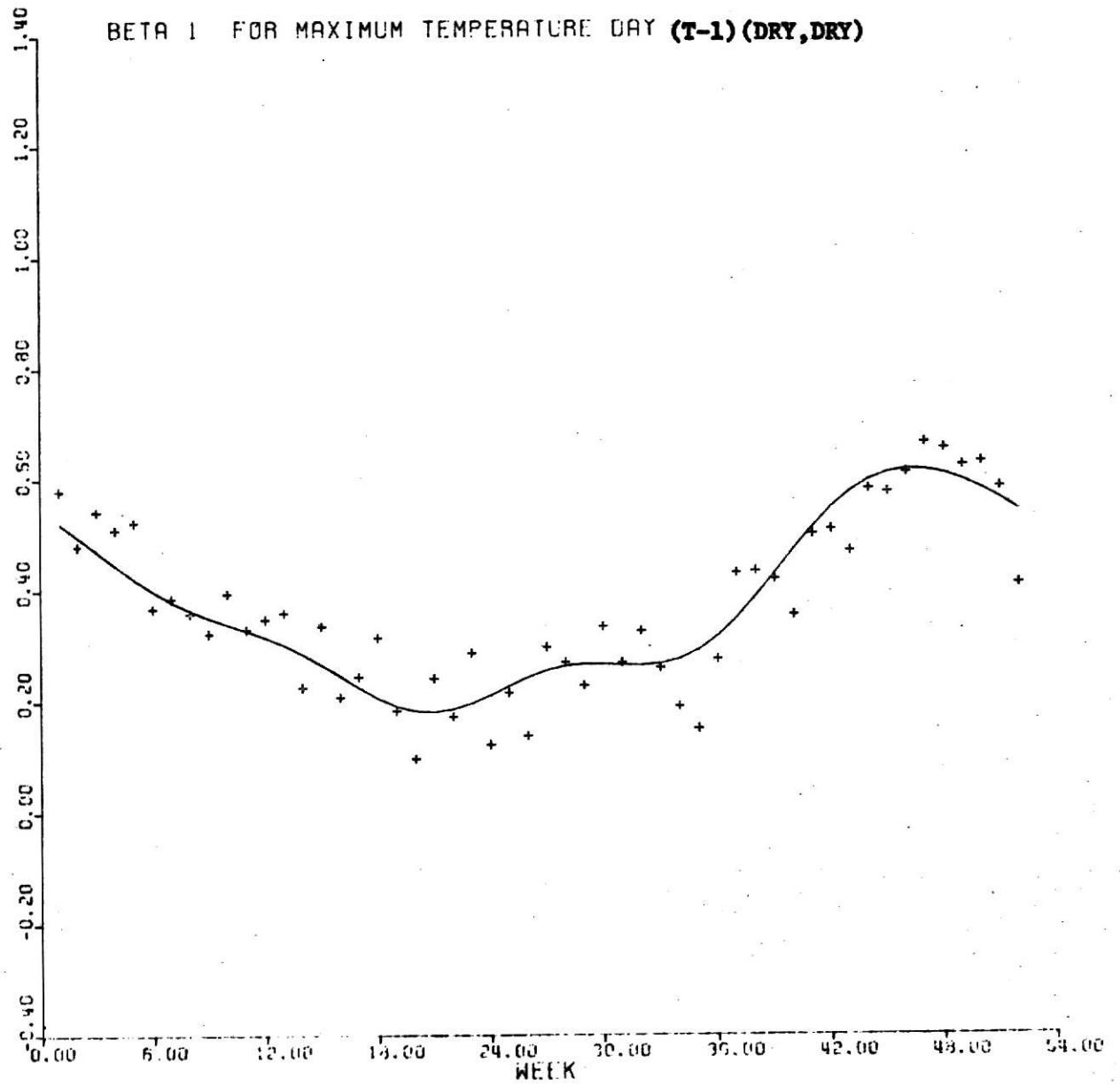


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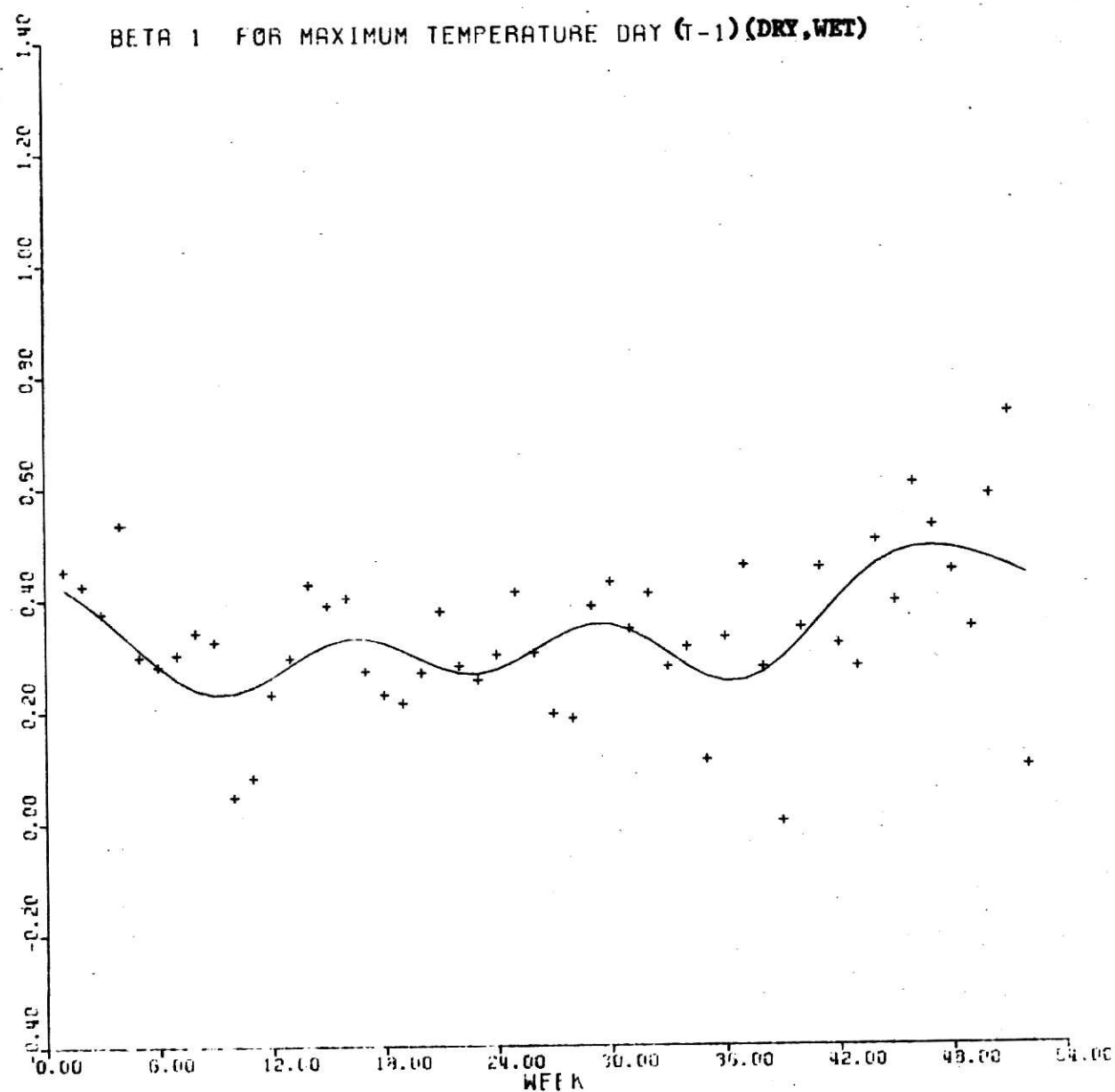


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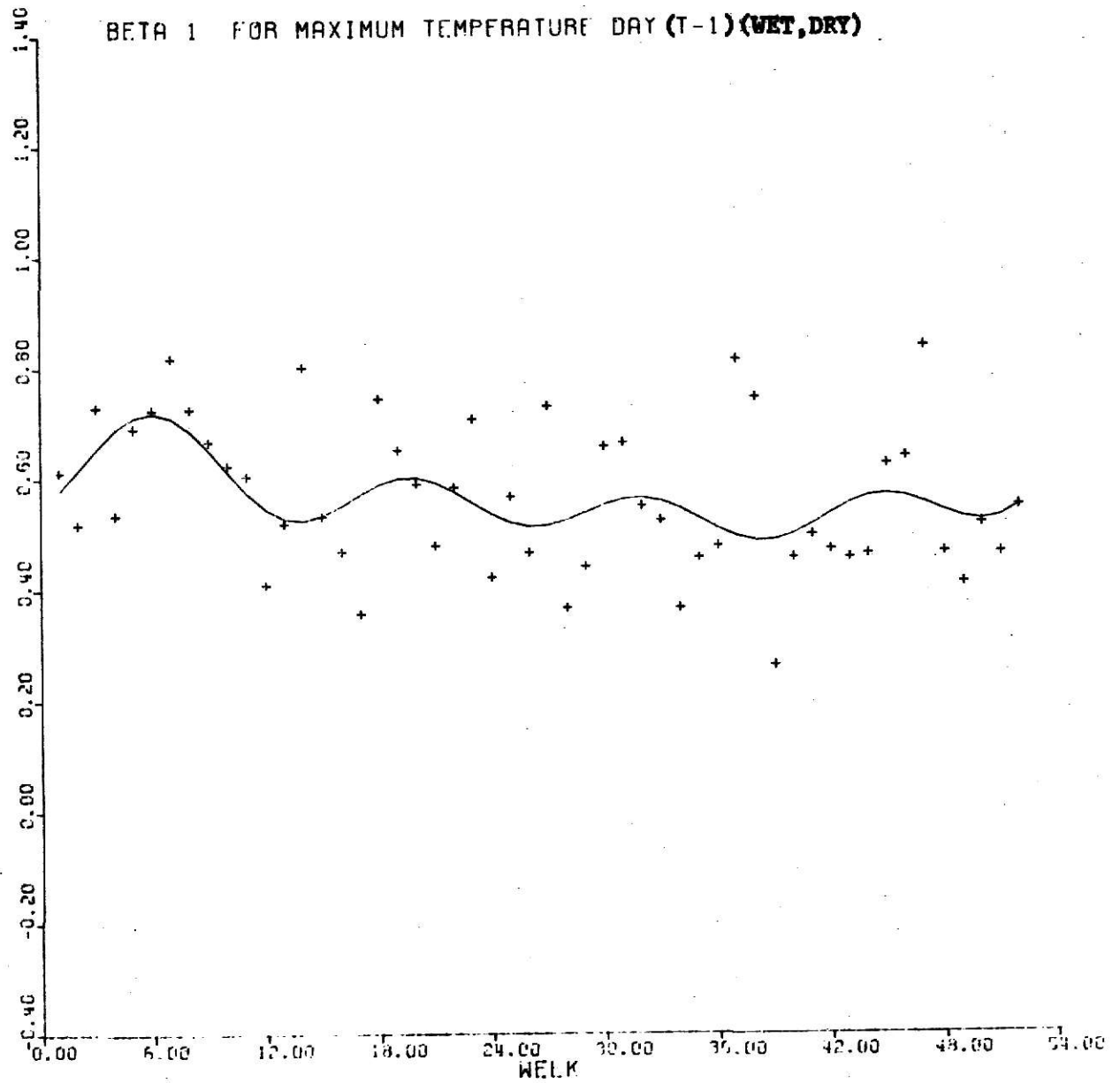


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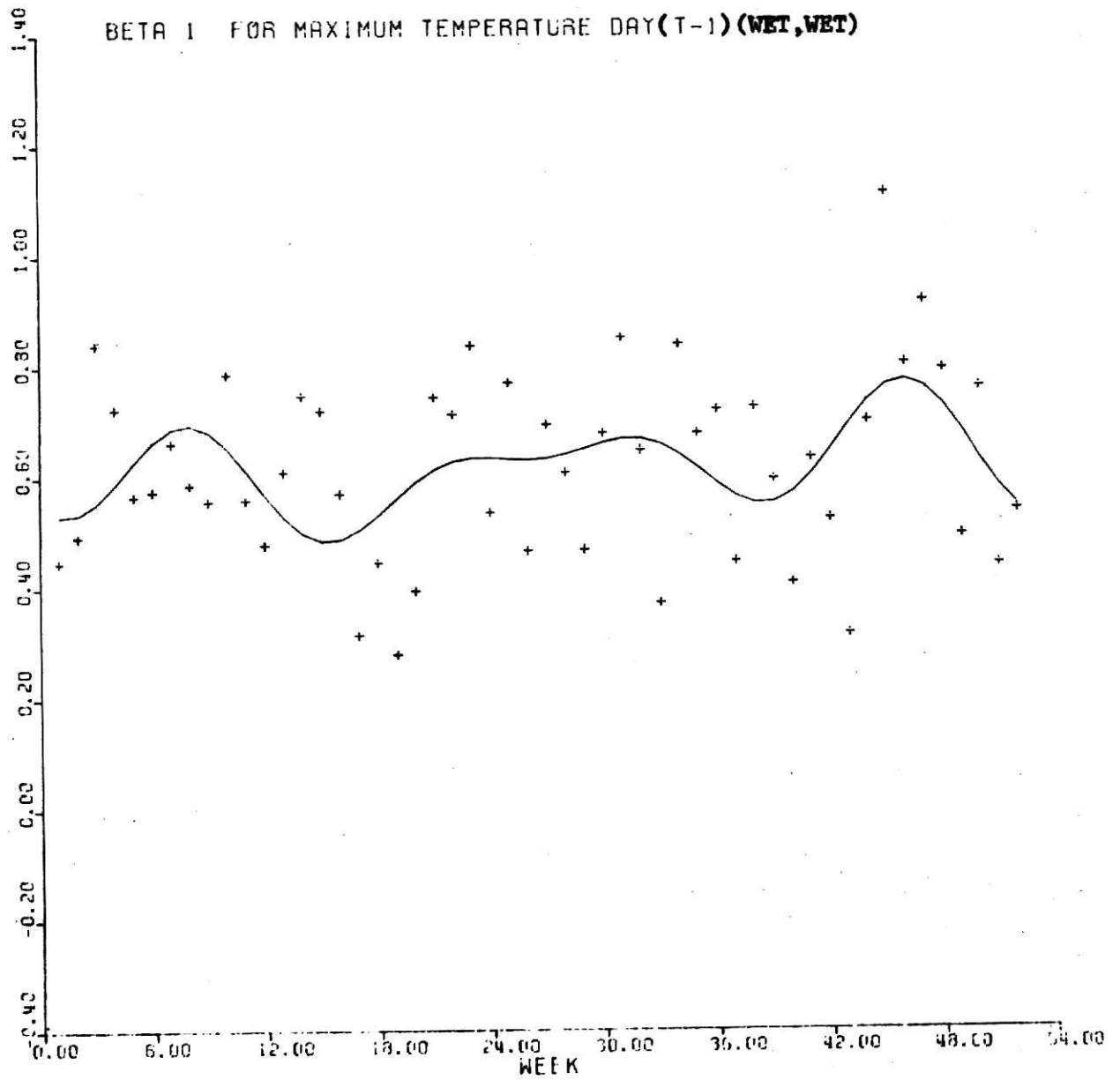


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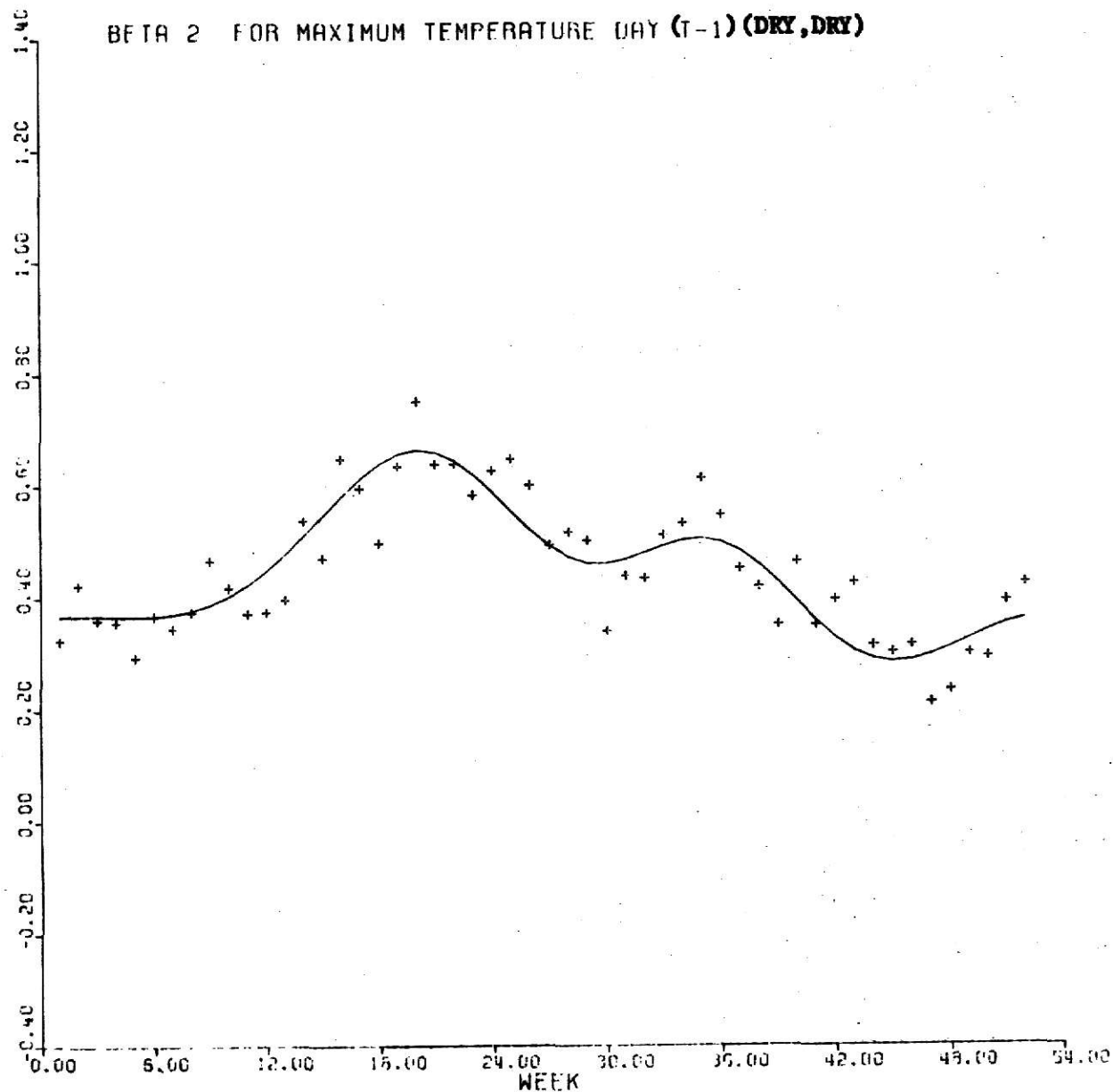


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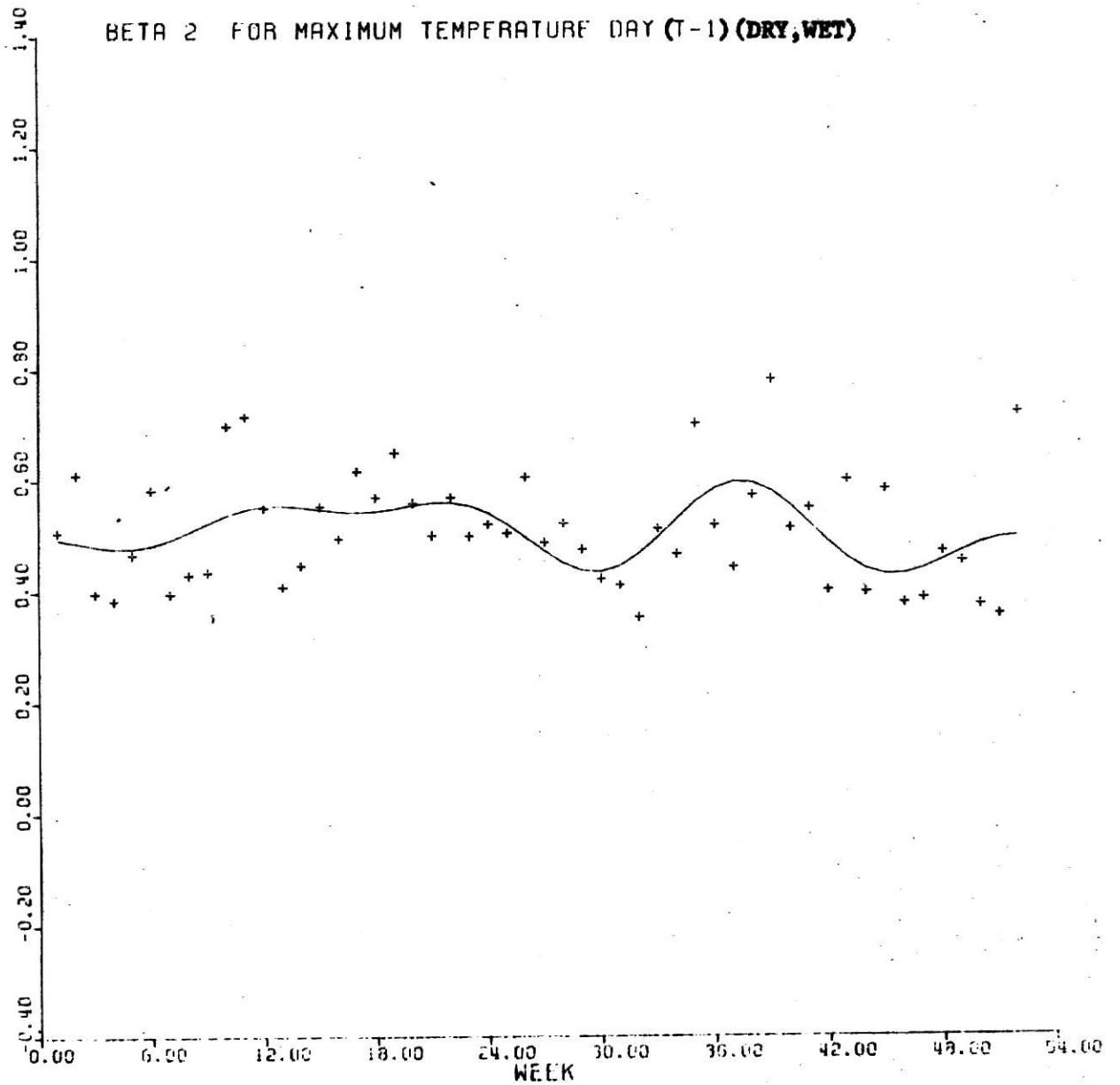


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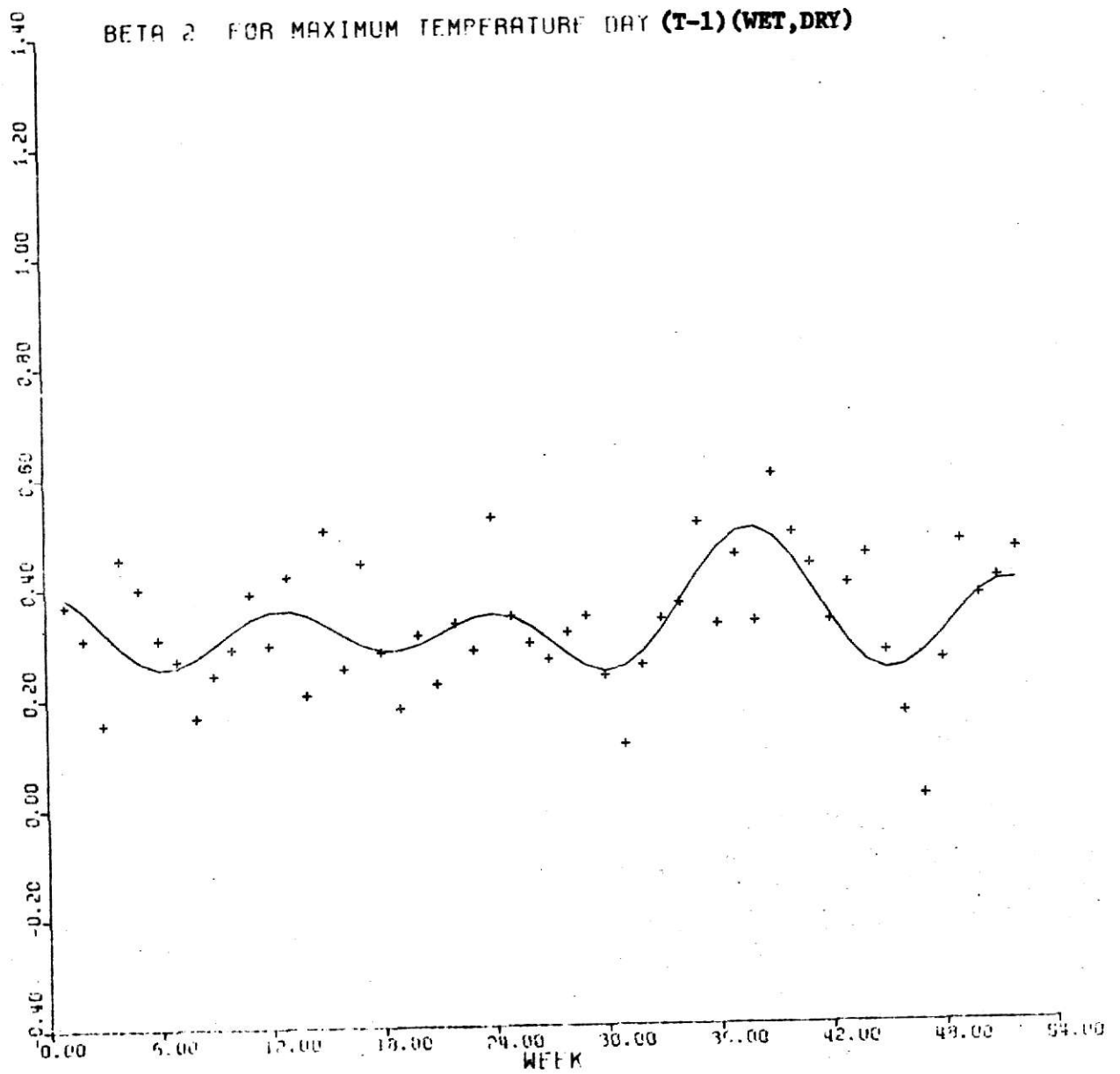


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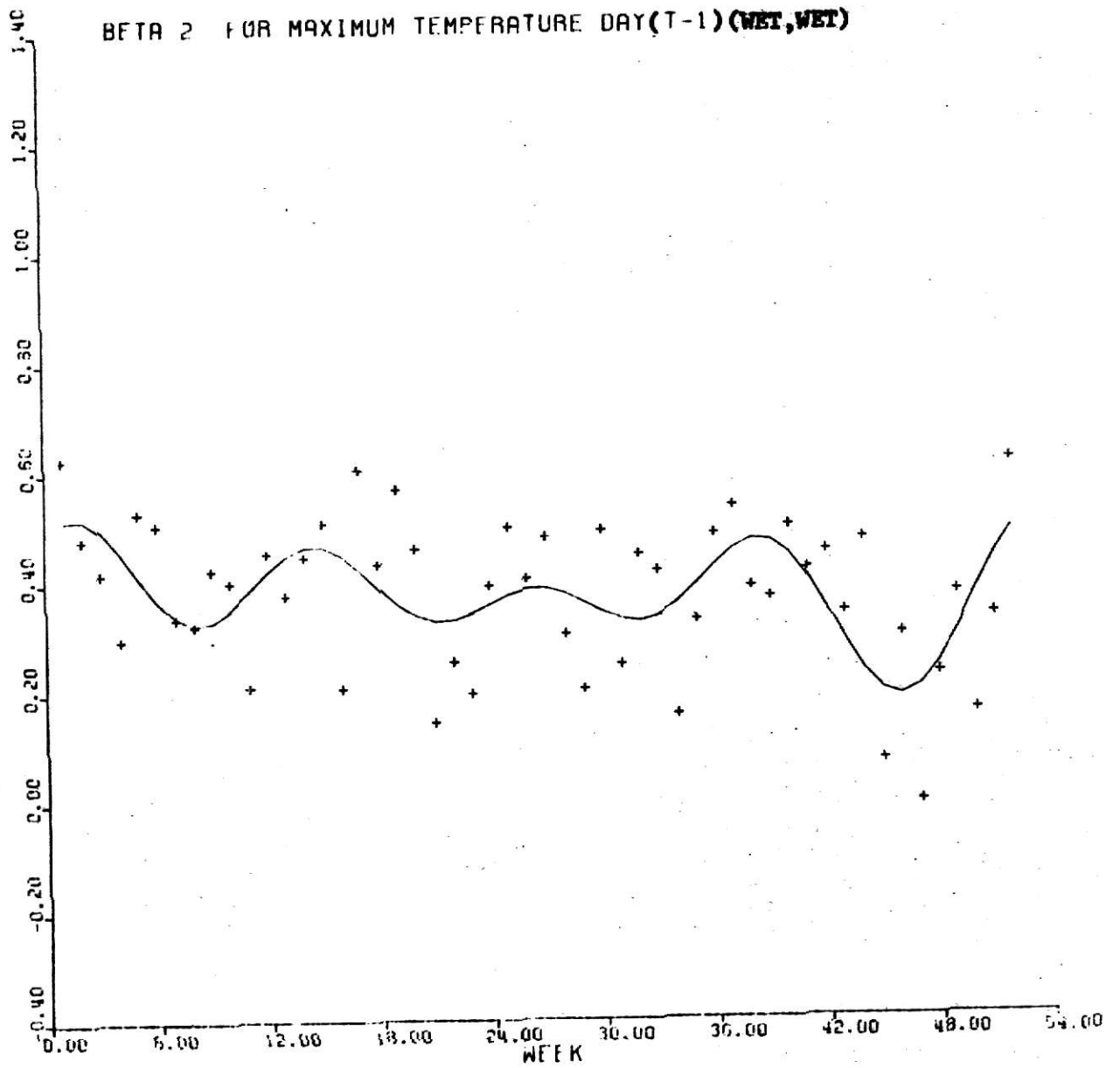


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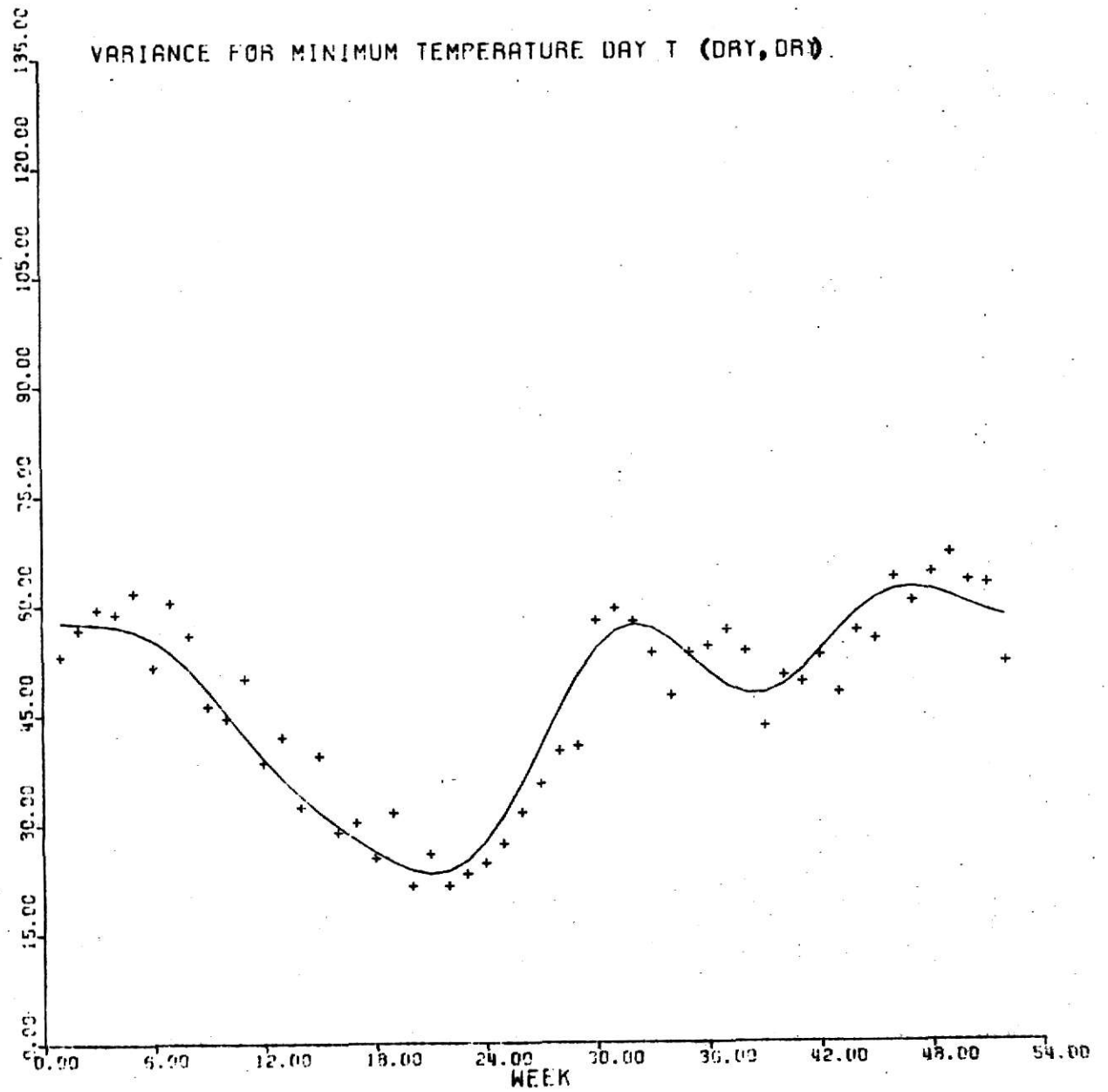


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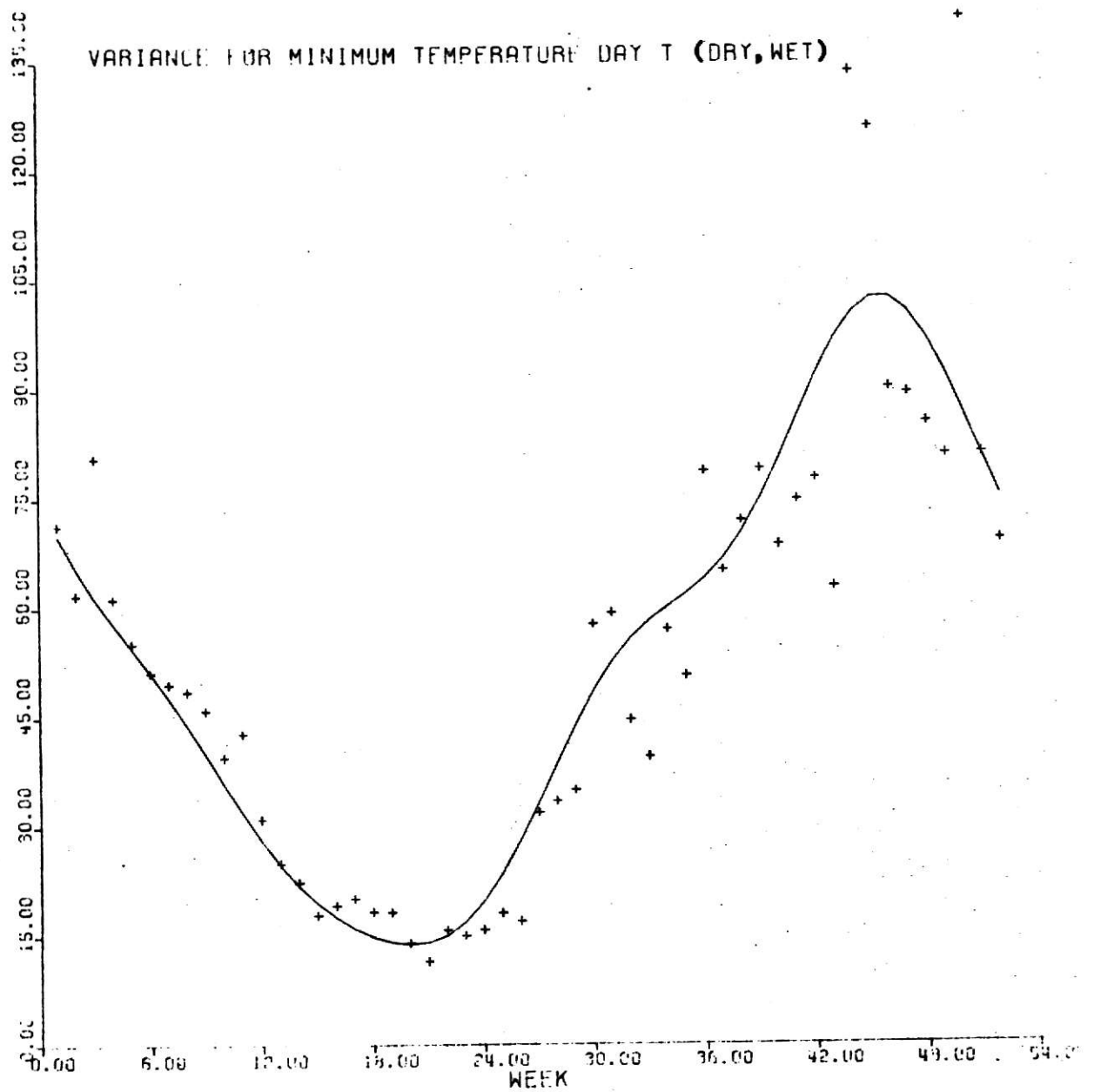


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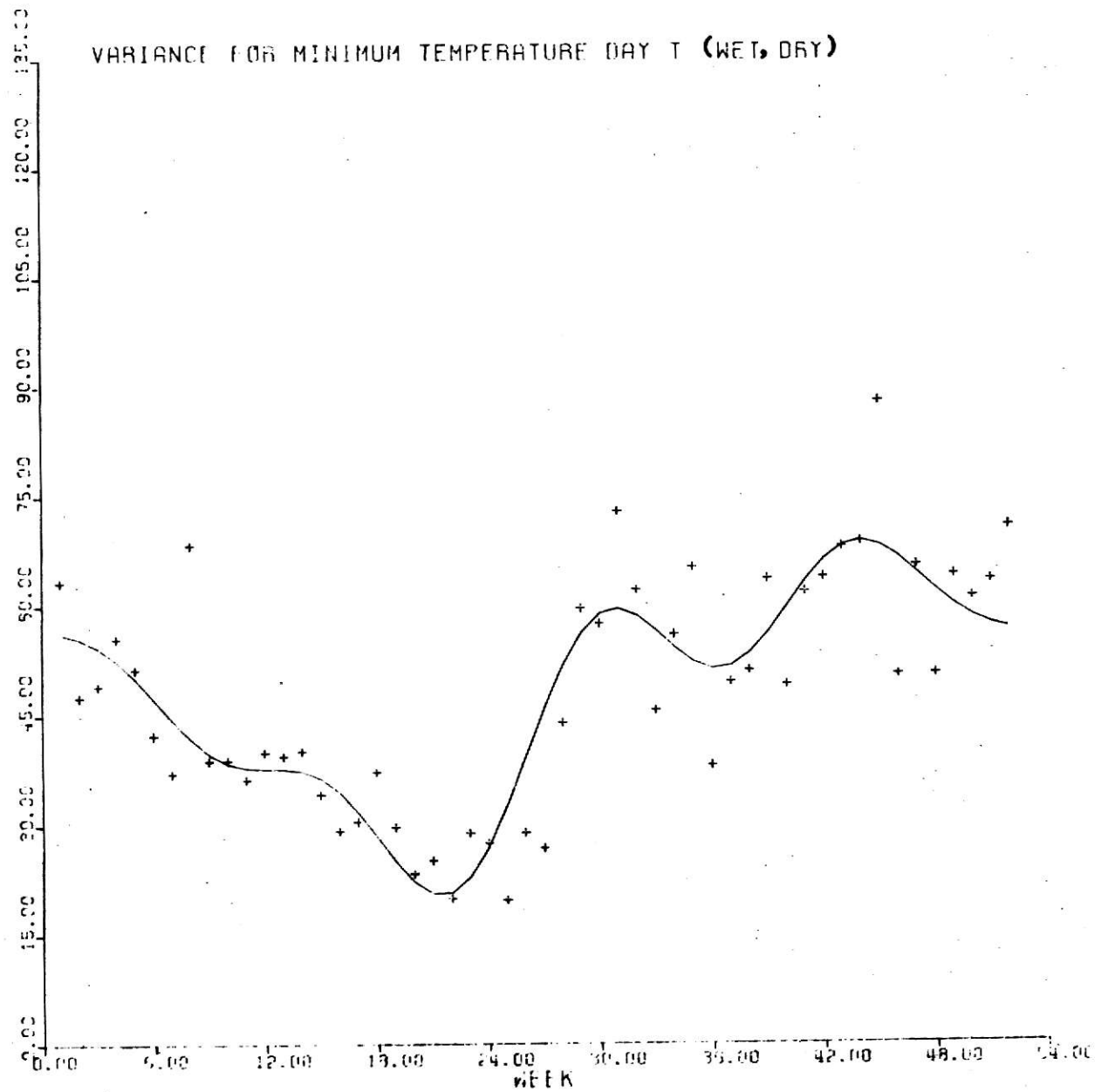


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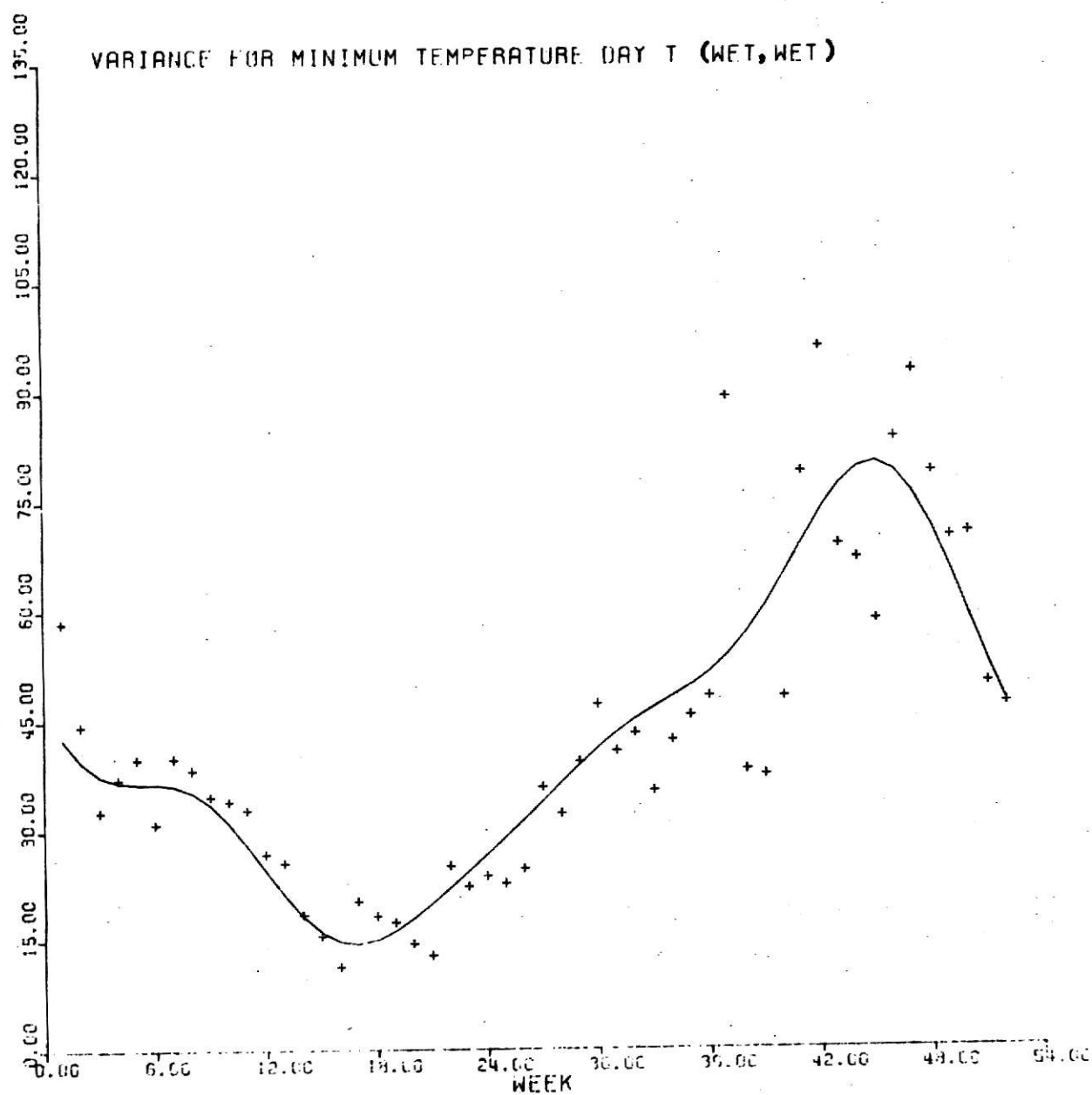


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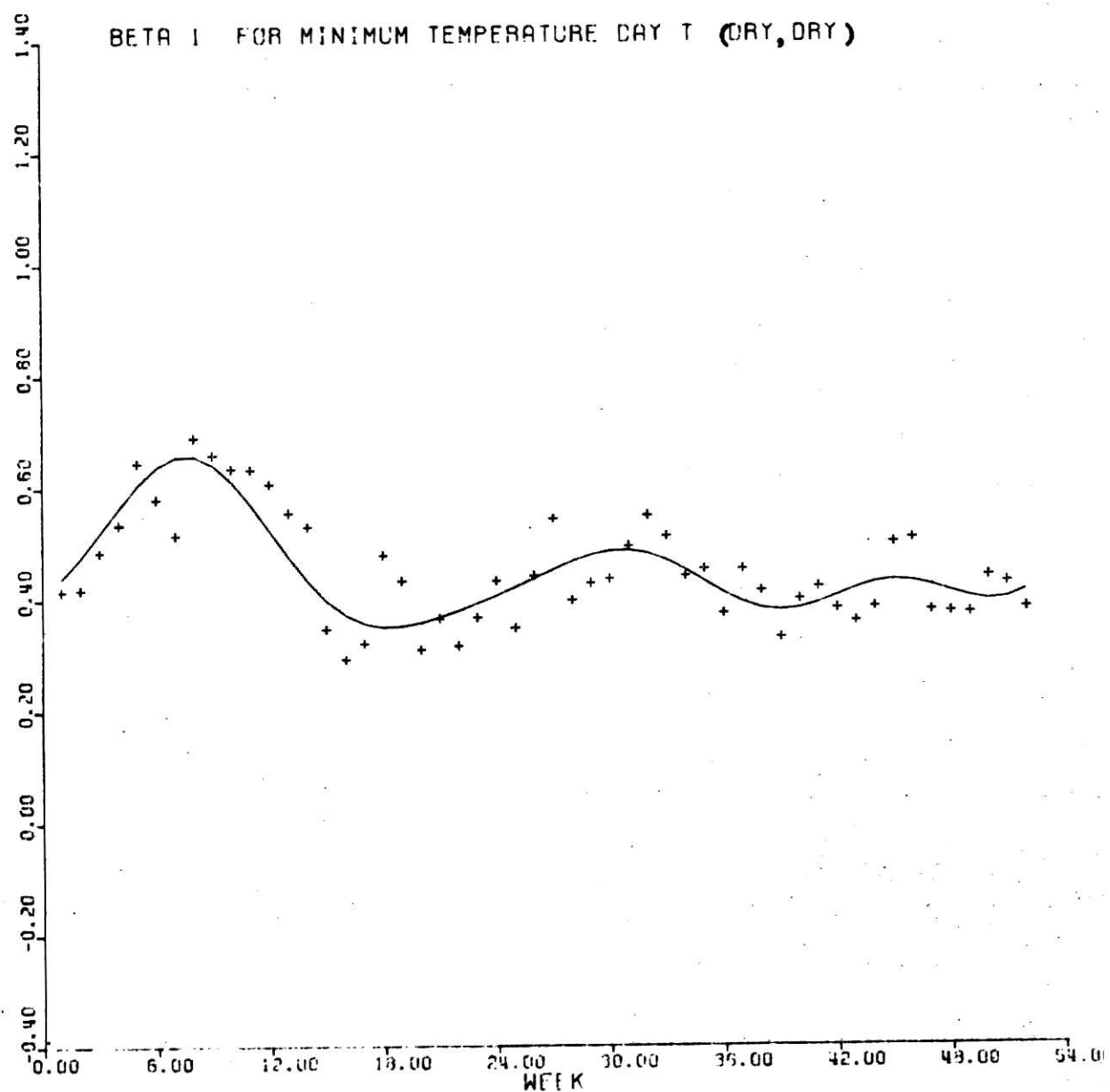


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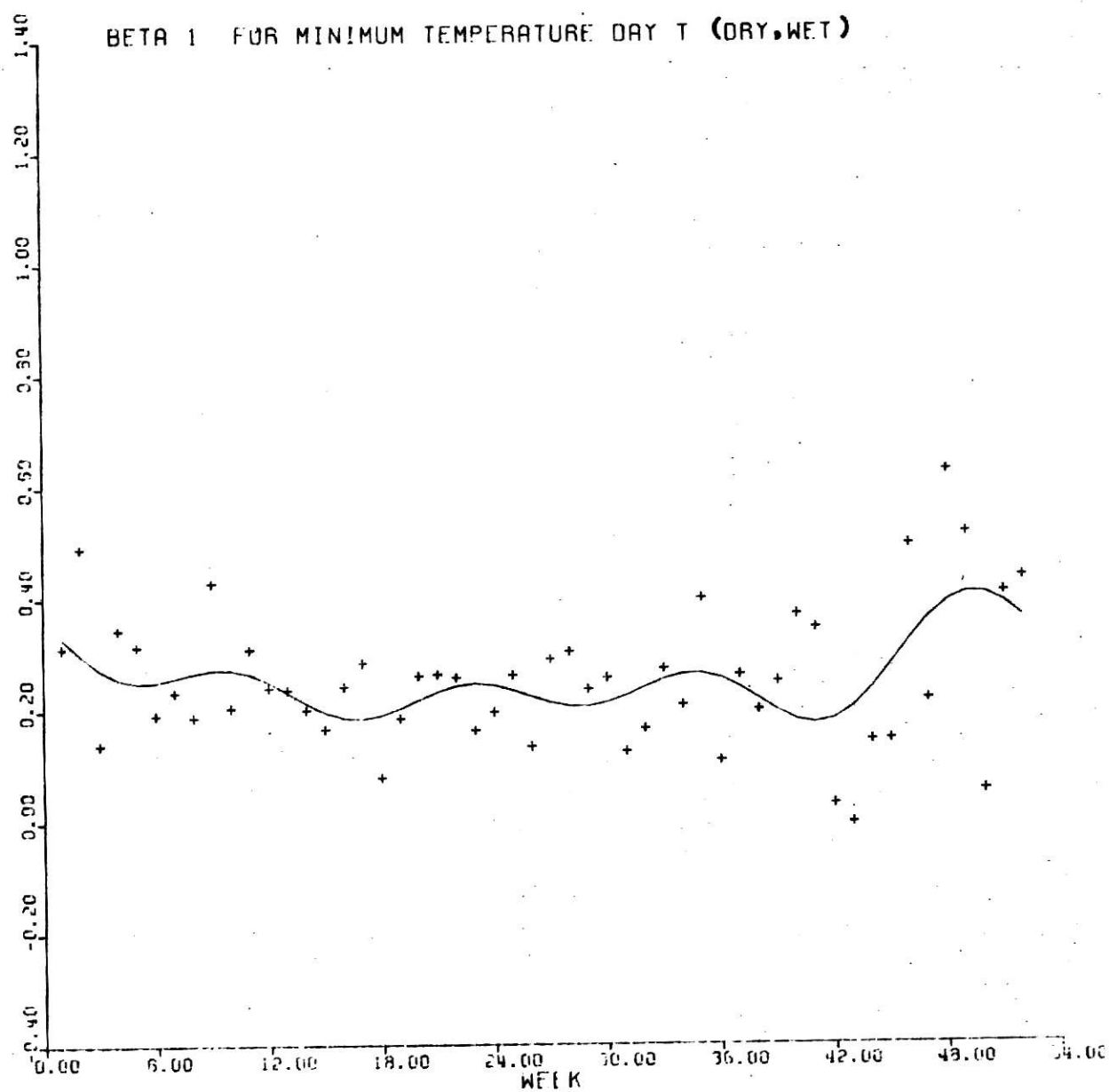


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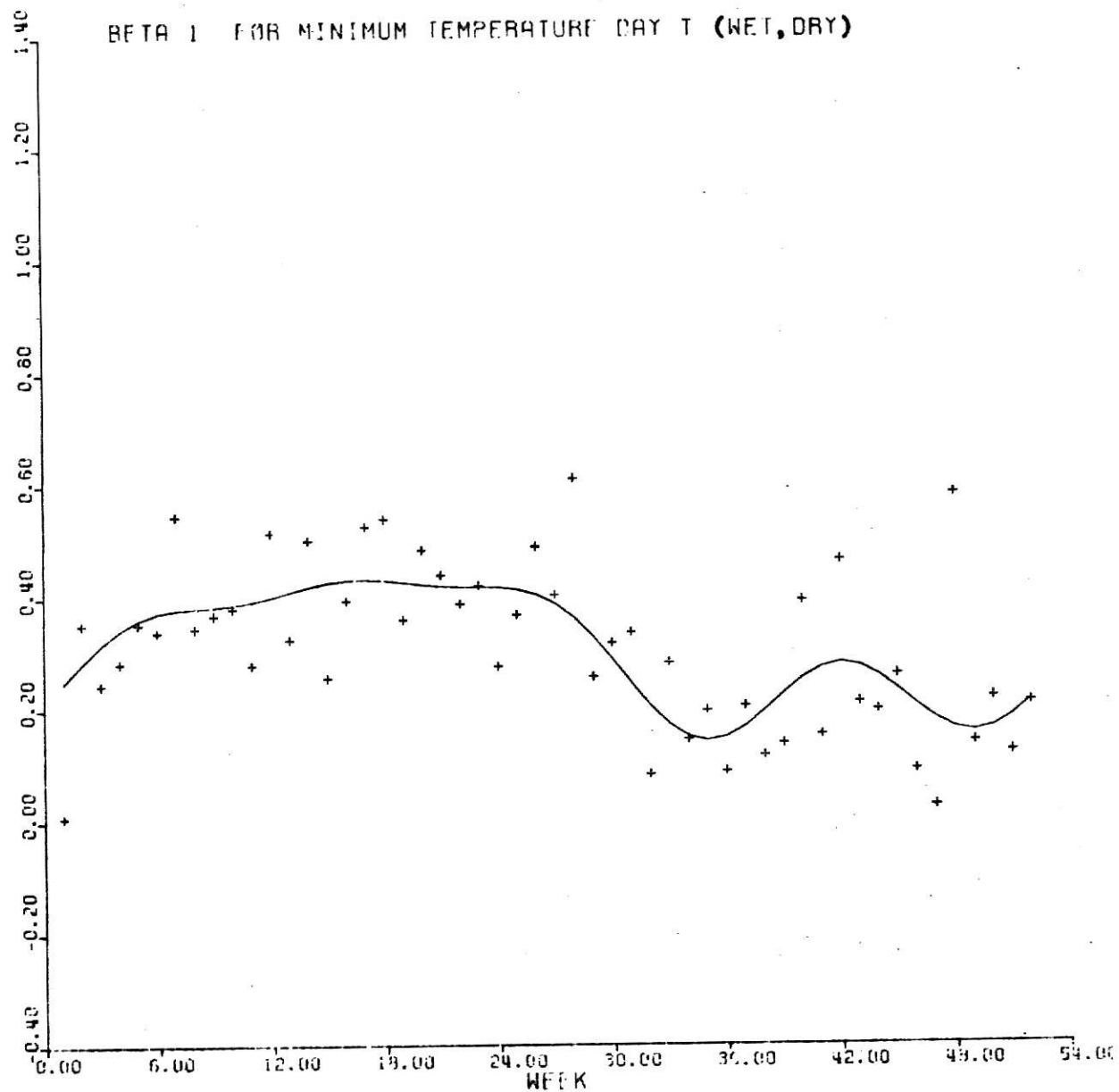


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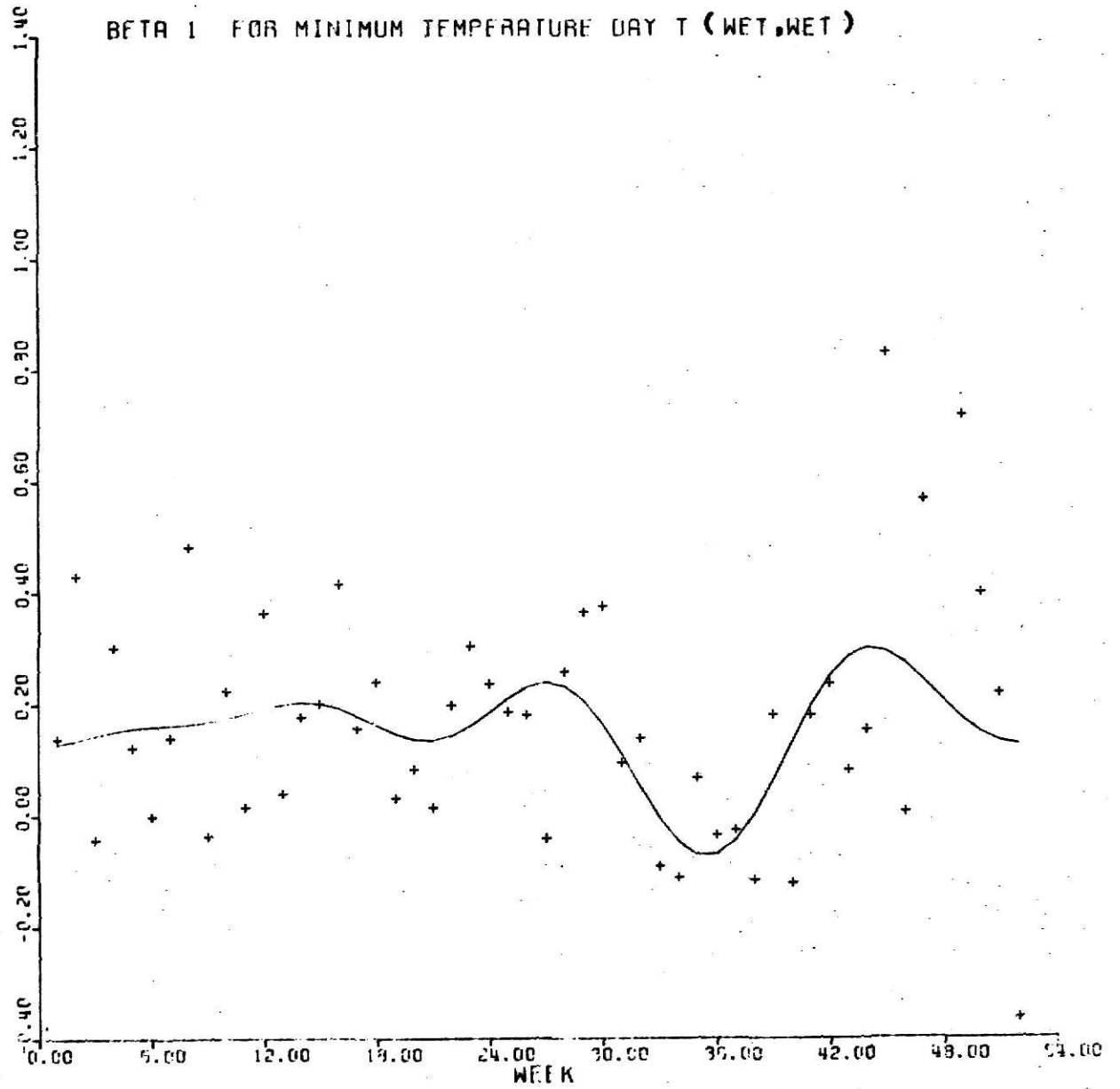


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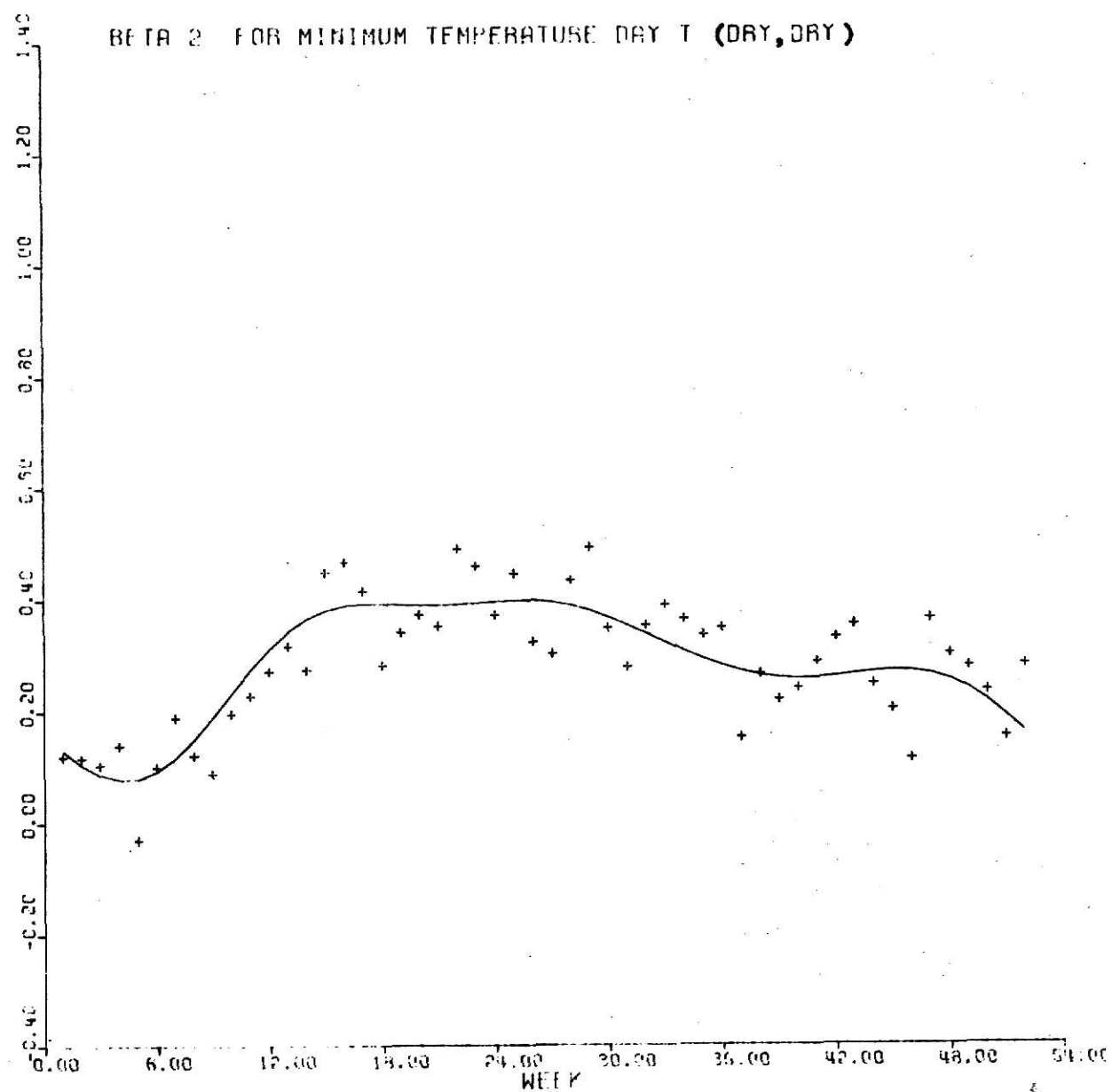


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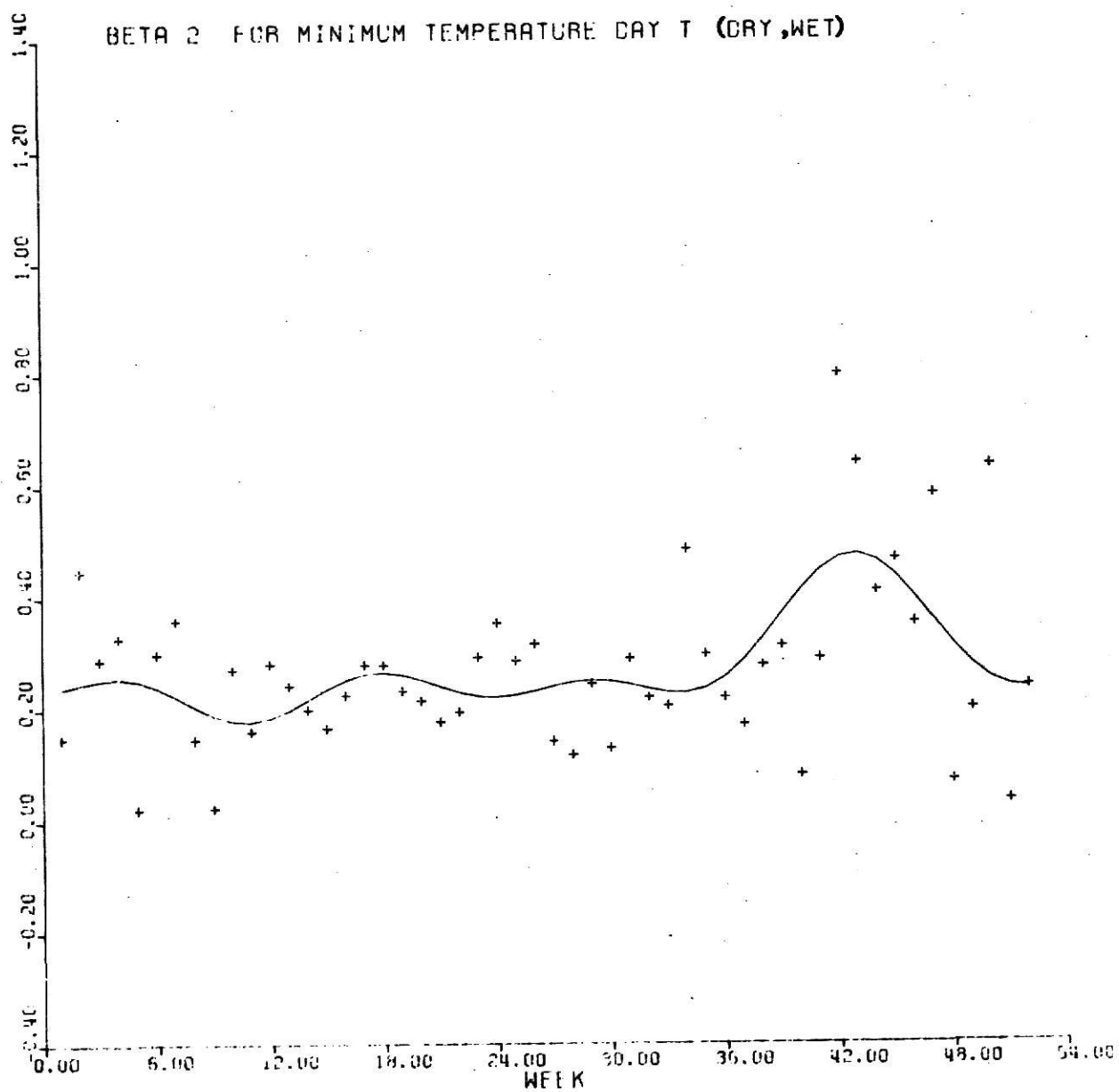


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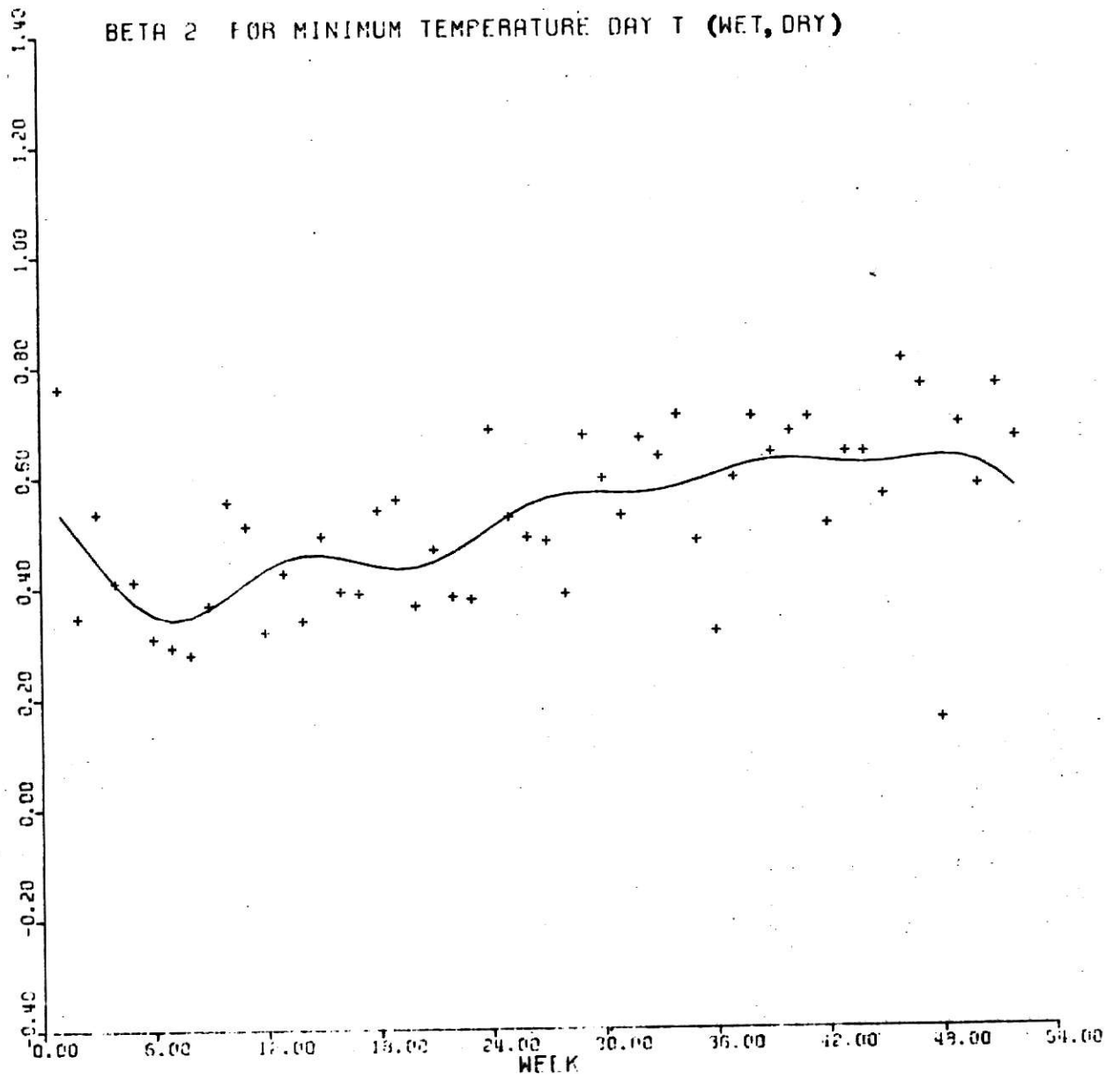


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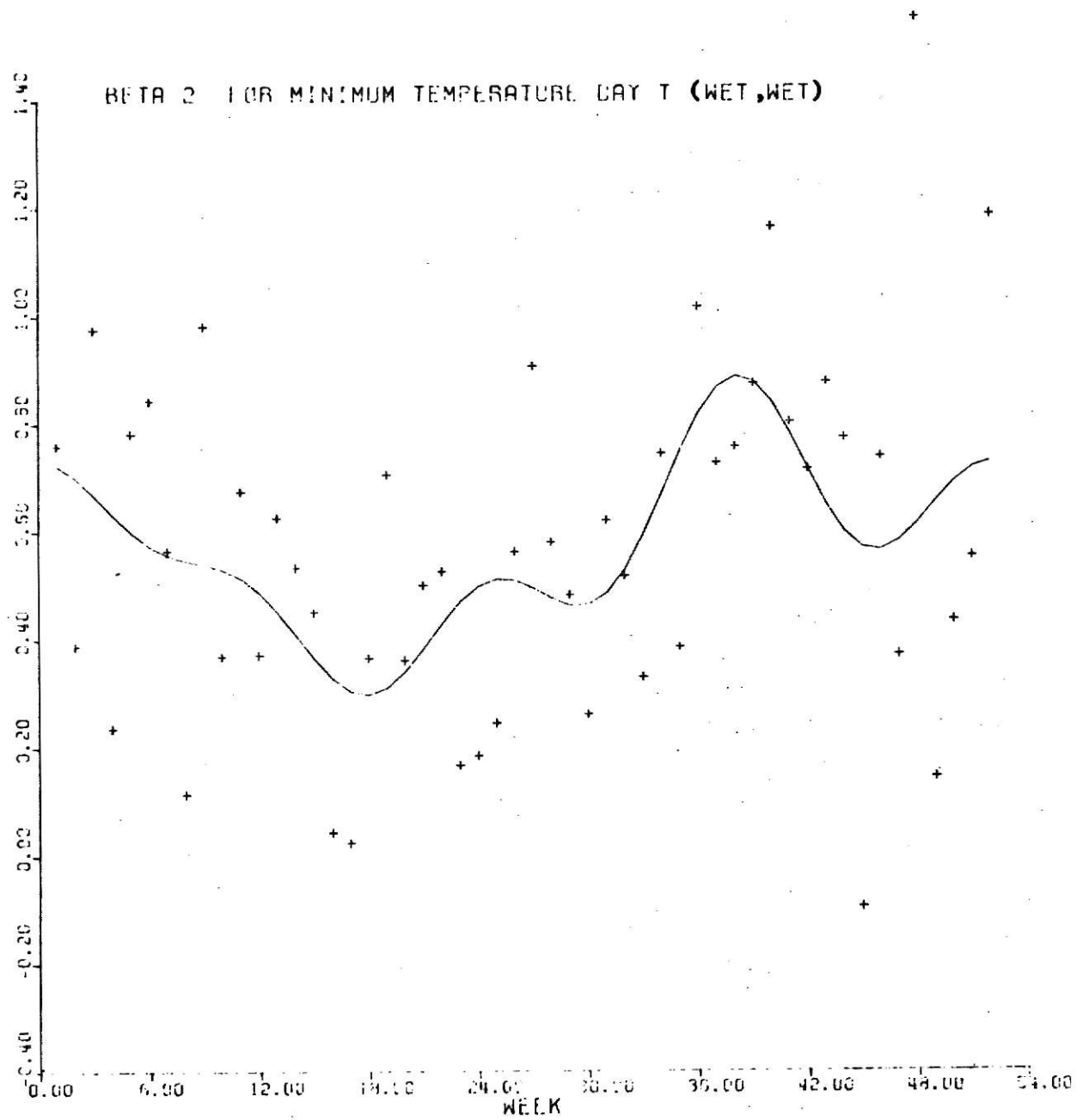
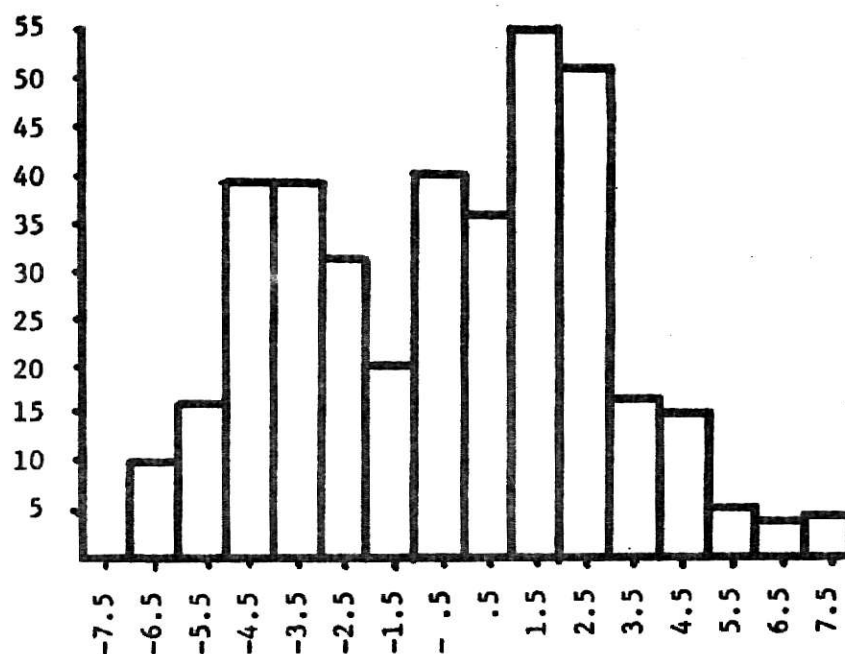
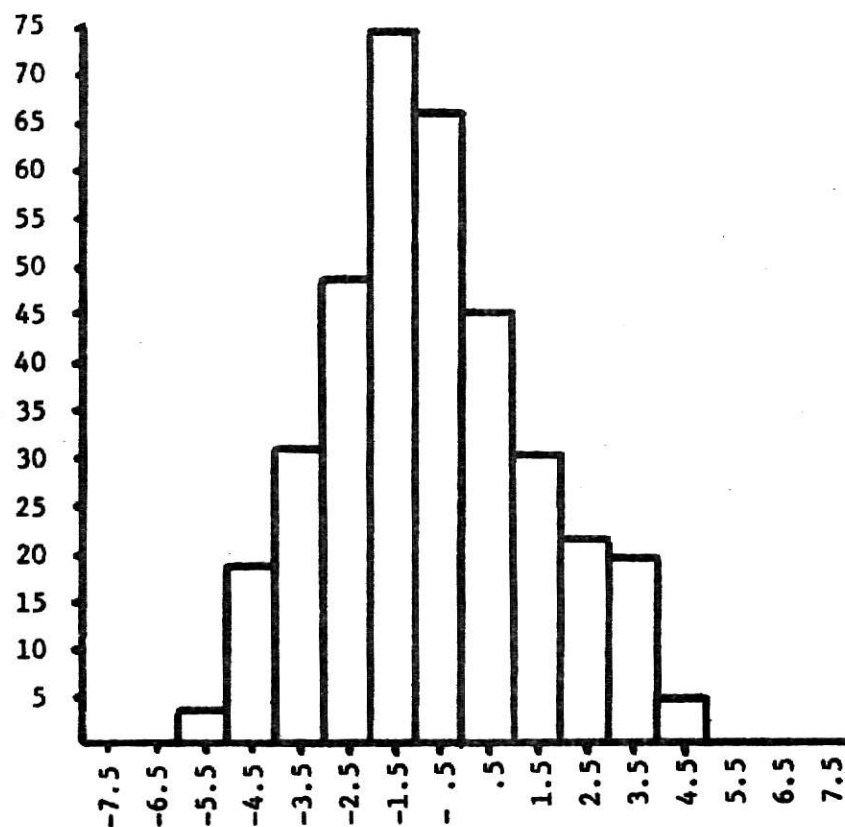


Figure 43. Distribution of Palmer Drought Index Computed from Actual Data (1939-1968)



Distribution of Palmer Drought Index Computed from Simulated Data



6. ACKNOWLEDGMENT

The writer wishes to express his appreciation to Dr. A. M. Feyerherm, Dr. L. Dean Bark, and Mr. Merle J. Brown for their advice and assistance during the preparation of this report.

REFERENCES

- (1) Ison, N. T., "A distribution Function for Amount of Precipitation During a Wet Spell.", Ph.D. dissertation, Kansas State University, 1970.
- (2) Box, G. E. P. and Muller, M. E., A Note on the Generation of Random Normal Deviates, Annals of Mathematical Statistics, Vol. 29 (1958), pp. 610-611.
- (3) Palmer, W. C., "Meteorological Drought", Research Paper No. 45, U.S. Department of Commerce. Washington, D.C.: U.S. Government Printing Office, 1965.

APPENDIX

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C      *      *      *      *      *      *      *      *      *      *      *      *
C
C      SIMULATION OF DAILY TEMPERATURES AND PRECIPITATION
C
C      PROGRAM NAME - SIMTEMPR
C
C      PROGRAMMING LANGUAGE USED:
C      FORTRAN IV
C
C      SUBPROGRAMS REQUIRED:
C      BETA
C      RANDU
C      NORMDV
C
C      REMARKS:
C      THE OUTPUT FOR THIS PROGRAM IS PLACED ON A 9-TRACK
C      MAGNETIC TAPE
C
C      *      *      *      *      *      *      *      *      *      *      *      *
C      DIMENSION CFREQT(13,80,6),SAB(80),UAB(80),TABLE(52,3)
C      DIMENSION SABS(6),UABS(6)
C      DIMENSION IFREQ(13,25,6)
C      DIMENSION SIMDA(364,3),IMDA(7,6)
C      DIMENSION MO(12),IMO(364),IDA(364)
C      DIMENSION AVH(364,2,2,2),AVL(364,2,2,2),B1H(364,2,2)
C      1  B1L(364,2,2),B2L(364,2,2),VH(364,2,2),VL(364,2,2)
C      DIMENSION B2H(364,2,2)
C      COMMON IX
C      100 FORMAT(I5/7(F10.4))
C      101 FORMAT(42I4)
C      102 FORMAT(3F10.4,40X,A4)
C      103 FORMAT(15I5)
C      104 FORMAT(2(21I4/))
C      106 FORMAT(7F10.2)
C      107 FORMAT(7F10.3)
C      111 FORMAT(7F10.4)
C      114 FORMAT('  PRECIPITATION  MAXIMUM  MINIMUM  FOR MANHATTAN ',
C      1'YEAR',I4)
C      115 FORMAT(I6,3F9.2,I6)
C      116 FORMAT('1',16X,'SIMULATION OF WEATHER CATA')
C      117 FORMAT(16F5.2)
C      118 FORMAT(4X,12F5.2)
C      120 FORMAT(I5,14F8.3)
C      125 FORMAT(2I4,14F5.2)
C
C      IN THIS SECTION THE PARAMETERS FOR THE SIMULATION OF
C      PRECIPITATION ARE READ IN
C
C      READ(1,103)NYR
C      NYR IS THE NUMBER OF YEARS THAT YOU WANT SIMULATED
C      NPD=13

```

```

NCL=68
READ(1,103)IX
C   IX IS A RANDOM NUMBER
READ(1,107)(SAB(J),UAB(J),J=1,NCL)
C   SUB & UAP ARE THE LOWER AND UPPER BOUNDS OF THE
C   PRECIPITATION CLASSES
READ(1,100)INTD,(SABS(I),UABS(I),I=1,INTD)
C   SABS & UABS ARE THE LOWER AND UPPER BOUNDS FOR THE NUMBER
C   OF WET DAYS
DO 211 I=1,NPD
DO 211 J=1,NCL
READ(1,111)(CFREQT(I,J,K),K=1,INTD)
C   CFREQT IS THE COMPUTED GAMMA PROBABILITIES FOR THE AMOUNT
C   OF PRECIPITATION
211 CONTINUE
5 DO 210 I=1,52
READ(1,102)(TABLE(I,J),J=1,3)
C   TABLE GIVES THE PROBABILITIES FOR RAIN OR NO RAIN
210 CONTINUE
C
C   IN THIS SECTION THE PARAMETERS FOR THE SIMULATION OF
C   TEMPERATURE ARE READ IN
C
DO 90 I=7,364,7
READ(1,117)((AVH(I,J,K,L),AVL(I,J,K,L)),K=1,2),L=1,2),
IJ=1,2)
C   AVH & AVL GIVE THE AVERAGE DAILY HIGH AND LOW TEMPERATURES
C   I IS THE DAY NUMBER
C   J IS THE CODE FOR THE DAY BEFORE OR TODAY
C   K IS THE CODE FOR DAY T-1 BEING WET OR DRY
C   L IS THE CODE FOR THE DAY T BEING WET OR DRY
90 CONTINUE
DO 91 I=7,364,7
READ(1,118)((B1H(I,J,K),B2H(I,J,K),VH(I,J,K)),J=1,2),K=1,2)
C   B1H,B2H, & VH ARE THE BETAS AND THE STANDARD DEVIATION USED
C   IN SIMULATING THE HIGH TEMPERATURES
91 CONTINUE
DO 92 I=7,364,7
READ(1,118)((B1L(I,J,K),B2L(I,J,K),VL(I,J,K)),J=1,2),K=1,2)
C   B1L,B2L, & VL ARE THE BETAS AND THE STANDARD DEVIATION USED
C   IN SIMULATING THE LOW TEMPERATURES
92 CONTINUE
READ(1,103)MU
C
C   IN THIS SECTION THE DAILY VALUES ARE INTERPOLATED FROM THE
C   WEEKLY VALUES
C
DO 93 J=1,2
DO 93 K=1,2
DO 93 L=1,2
A=AVH(364,J,K,L)
C=AVL(364,J,K,L)
II=1

```

```

DO 95 I=7,364,7
B=(AVH(I,J,K,L)-A)/7.0
D=(AVL(I,J,K,L)-C)/7.0
DO 94 IJ=II,I
A=A+B
C=C+D
AVH(IJ,J,K,L)=A
AVL(IJ,J,K,L)=C
94 CONTINUE
II=I+1
A=AVH(I,J,K,L)
C=AVL(I,J,K,L)
95 CONTINUE
93 CONTINUE
CALL BETA(B1H)
CALL BETA(B2H)
CALL BETA (VH)
CALL BETA(B1L)
CALL BETA(B2L)
CALL BETA (VL)

```

C
C
C

THE CONSTANTS ARE INITIALIZED

```

I=1
J=1
M=1
N=1
ID=1
NW=1
MT=28
NMO=1
IYR=1
LDAY=363
KDAY=363
NPT1=1
NORD=0
MONT=364
NCODE=0
NDATE=0
SIMDA(363,2)=30.0
SIMDA(363,3)=50.0
DO 96 J=1,364
SIMDA(J,1)=0.0
96 CONTINUE
JA=0
DO 84 I=3,14
IF(I.GT.12)GO TO 85
JMO=I
GO TO 86
85 JMO=I-12
86 K=MO(JMO)
DO 84 L=1,K
JA=JA+1

```

```

      IMO(JA)=JMO
      IDA(JA)=1
84  CONTINUE
      NCL1=NCL-1
      DO 64 LK=1,10
      CALL NORMDV(X,Y)
64  CONTINUE

C
C   THIS IS WHERE THE SIMULATION STARTS
C
15  CALL RANDU(YFL)
      NDATE=NDATE+1
      IF(NDATE.LE.MT) GO TO 20
      NPD=NMO+1
      NDATE=1
      IF(NMO.LE.NPD) GO TO 20
      IYR=IYR+1
      IF(IYR.LE.NYR) GO TO 19
      NCODE=1
      IYR=IYR-1
      NMO=NPD
      GO TO 22
19  NMO=1

C
C   IF THE RANDOM NUMBER IS LESS THAN THE PROB OF DRY -
C       THEN THE DAY IS DRY
C
20  IF(YFL.LE.TABLE(1,J)) GO TO 22

C
C       IF NOT - THEN WET
C
C       IF YESTERDAY NOT WET - THEN TODAY IS FIRST DAY OF WET SPELL
C
      IF(J.NE.3) NDY=N
      NDY IS THE FIRST DAY OF THE WET SPELL

C
      IF(N.EQ.MONT) GO TO 65
      GO TO 30

C
C       IF TODAY DRY AND YESTERDAY NOT WET GO TO 28
C
22  IF(J.NE.3) GO TO 28

C
C       IF YESTERDAY WET AND TODAY IS DRY  CHCOSE AN AMOUNT OF
C       RAINFALL
C
65  CALL RANDU(YFL)
      IF(NORD.EQ.0) NORD=1
      IF(NORD.GT.INTD) NORD=INTD
      DO 24 K=1,NCL1
      IF(YFL.LE.CFREQT(NMO,K,NCRD)) GO TO 25
24  CONTINUE
      K=NCL
      GO TO 51

```

```

25 KK=K+1
   DO 50 NI=KK,NCL
     IF(CFREQT(NMO,K,NORD).LT.CFREQT(NMO,NI,NORD)) GO TO 52
50 CONTINUE
51 FE1=SAB(K)
   FE2=UAB(NCL)
   GO TO 57
52 NI=NI-1
   FE1=SAB(K)
   FE2=UAB(NI)
57 XX=NORD
   YY=(FE1+FE2)/2.

C
C   THIS IS WHERE THE SIMULATED DAILY RAINFALL IS COMPUTED
C   AND STORED
C
   DRF=YY/XX
   NWT=N-1
   DO 77 MZ=NDY,NWT
     SIMDA(MZ,1)=DRF
77 CONTINUE
   NORD=0
28 IF(N.NE.MONT) GO TO 29
   J=1
C   J IS 1 FOR MARCH 1ST THIS MEANS WE DON'T CARE IF YESTERDAY
C   WAS WET
   GO TO 32
29 J=2
C   J IS 2 WHEN YESTERDAY WAS DRY
   GO TO 32
30 NORD=NORD+1
   J=3
C   J IS 3 WHEN YESTERDAY WAS WET
32 IF(NW.LT.7) GO TO 34
   NW=1
   I=I+1
   GO TO 36
34 NW=NW+1

C
C   IN THIS SECTION THE TEMPERATURES FOR YESTERDAY'S HIGH AND
C   TODAY'S LOW ARE SIMULATED
C
36 NPT=J-1
   IF(NPT.EQ.0)NPT=1
   CALL NORMDV(X,Y)
   B=B1H(KDAY,NPT1,NPT)*(SIMDA(LDAY,2)-AVH(LDAY,1,NPT1,NPT))
   A=B2H(KDAY,NPT1,NPT)*(SIMDA(KDAY,3)-AVL(KDAY,1,NPT1,NPT))
   C=X*VH(KDAY,NPT1,NPT)
   SIMDA(KDAY,2)=A+B+C+AVH(KDAY,2,NPT1,NPT)
   IF(KDAY.EQ.364)GO TO 42
41 B=B1L(N,NPT1,NPT)*(SIMDA(KDAY,3)-AVL(KDAY,1,NPT1,NPT))
   A=B2L(N,NPT1,NPT)*(SIMDA(KDAY,2)-AVH(KDAY,2,NPT1,NPT))
   C=Y*VL(N,NPT1,NPT)

```

```

SIMDA(N,3)=A+B+C+AVL(N,2,NPT1,NPT)
LDAY=KDAY
KDAY=N
NPT1=NPT
IF(N.LT.MONT)GO TO 38
I=1
N=1
NW=1
GO TO 40
38 N=N+1
40 GO TO 15

C
C   THIS IS WHERE THE SIMULATION ENDS
C
C   STORE THE SIMULATED DAILY VALUES OF PRECIPITATION AND
C   MAXIMUM AND MINIMUM TEMPERATURES ON MAGNETIC TAPE
C   AND MINIMUM TEMPERATURES ON MAGNETIC TAPE
C
42 DO 88 JC=1,52
DO 83 JB=1,7
JE=JC*7-7+JB
IMDA(JB,4)=SIMDA(JE,1)*100.0+.5
IMDA(JB,5)=SIMDA(JE,2)+.5
IMDA(JB,6)=SIMDA(JE,3)+.5
IMDA(JB,1)=IMO(JE)
IMDA(JB,2)=IDA(JE)
IF(JE.EQ.307)M=M+1
IMDA(JB,3)=M
83 CONTINUE
WRITE(8,101)IMDA
88 CONTINUE
DO 82 J=1,364
SIMDA(J,1)=0.0
82 CONTINUE
IF(NCODE.EQ.0) GO TO 41
REWIND 8
DO 87 JD=1,104
READ(8,101)IMDA
WRITE(3,104)IMDA
87 CONTINUE
END

```

```

C      *      *      *      *      *      *      *      *      *      *      *      *
C
C      SUBROUTINE BETA
C
C      PURPOSE:
C          THIS SUBROUTINE INTERPOLATES DAILY VALUES OF THE PARTIAL
C          REGRESSION COEFFICIENTS AND THE STANDARD DEVIATIONS
C          BETWEEN EVERY SEVENTH DAILY VALUE
C
C      PROGRAMMING LANGUAGE USED:
C          FORTRAN IV
C
C      *      *      *      *      *      *      *      *      *      *      *      *
C      SUBROUTINE BETA(BT)
C      DIMENSION BT(364,2,2)
C      DO 10 J=1,2
C      DO 10 K=1,2
C      A=BT(364,J,K)
C      II=1
C      DO 11 I=7,364,7
C      B=(BT(I,J,K)-A)/7.0
C      DO 20 IJ=II,1
C      A=A+B
C      BT(IJ,J,K)=A
C 20 CONTINUE
C      II=I+1
C      A=BT(I,J,K)
C 11 CONTINUE
C 10 CONTINUE
C      RETURN
C      END

```

```

C      *      *      *      *      *      *      *      *      *      *      *      *
C
C      SUBROUTINE RANDU
C
C      PURPOSE:
C          THIS SUBROUTINE COMPUTES UNIFORMLY DISTRIBUTED PSEUDO
C          RANDOM NUMBERS BETWEEN 0.0 AND 1.0
C
C      PROGRAMMING LANGUAGE USED:
C          FORTRAN IV
C
C      *      *      *      *      *      *      *      *      *      *      *      *
C      SUBROUTINE RANDU(YFL)
C      COMMON IX
C      IY=IX*65539
C      IF(IY)5,6,6
C 5  IY=IY+2147483647+1
C 6  YFL=IY
C      YFL=YFL*.4656613E-9
C      IX=IY
C      RETURN
C      END

```



```

C      *      *      *      *      *      *      *      *      *      *      *
C
C      SUBROUTINE NORMDV
C
C      PRUPOSE:
C          THIS SUBROUTINE GENERATES PSEUDO RANDOM NUMBERS WITH:
C          A STANDARD NORMAL DISTRIBUTION BY USING THE BOX & MULLER
C          METHOD
C
C      PROGRAMMING LANGUAGE USED:
C          FORTRAN IV
C
C      SUBPROGRAMS REQUIRED:
C          RANDU
C
C      *      *      *      *      *      *      *      *      *      *      *
C      SUBROUTINE NORMDV(X,Y)
C      COMMON IX
C      CALL RANDU(YFL)
C      TLOG=SQRT(-2.*ALOG(YFL))
C      CALL RANDU(YFL)
C      X=TLOG*COS(6.2832*YFL)
C      Y=TLOG*SIN(6.2832*YFL)
C      RETURN
C      END

```

**A MODEL FOR SIMULATING DAILY
TEMPERATURE AND PRECIPITATION READINGS**

by

JAMES CHARLES LUNDGREN

B.A., Bethany College, 1970

AN ABSTRACT OF A MASTER'S REPORT

**submitted in partial fulfillment of the
requirements for the degree**

MASTER OF SCIENCE

Department of Statistics

KANSAS STATE UNIVERSITY

Manhattan, Kansas

1972

This report dealt with the problem of creating a statistical model for simulating weather data. The model was developed using data from weather station 4972, in Manhattan, Kansas, for the period March 1, 1900, to February 27, 1970. Ison's method was used to simulate precipitation and this study dealt primarily with the simulation of maximum and minimum temperatures.

Four precipitation conditions were considered: (dry,dry), (dry,wet), (wet,dry), and (wet,wet), where (dry,wet) designates a condition for which day $(t - 1)$ is dry, and day t is wet ($t = 1, 2, \dots, 364$). The model assumed that for a given precipitation condition and given antecedent low and high temperatures, the high temperature for day $(t - 1)$ and the low temperature for day t were normally distributed random variables with a given mean and variance.

A two-way multiple regression analysis was used to estimate the partial regression coefficients involved in estimating the means for each of the four precipitation conditions. This same analysis also gave an estimate of the variances. To take into consideration the variation of temperatures with time of year the independent and dependent variables used in the multiple regression analysis were the differences between the actual high and low temperatures, and the daily mean high and low temperatures, respectively for the pertinent precipitation condition.

The means, partial regression coefficients, and variances used in the simulation program were smoothed values determined from partial sums of Fourier series for which the coefficients were determined by a least squares fit to the estimated parameters.

A computer program was written to simulate weather data and 31 years of simulated data were placed on magnetic tape. The normal mean monthly temperatures computed from this data appeared to be very close to the actual normal temperatures computed for the period 1941 to 1970. However, a more complex function (Palmer Drought Index) indicated that, the simulated data might be deficient in persistent weather conditions.