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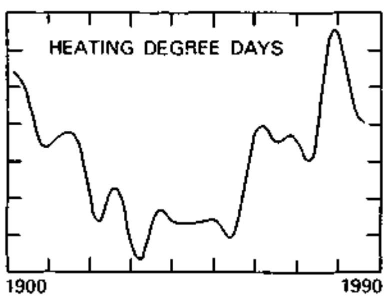
STATE OF ILLINOIS
DEPARTMENT OF ENERGY AND NATURAL RESOURCES

The Appropriate Use of Climatic Information in Illinois Natural-Gas Utility Weather-Normalization Techniques

by WILLIAM E. EASTERLING, JAMES R. ANGEL, and SCOTT A. KIRSCH



ILLINOIS STATE WATER SURVEY
CHAMPAIGN
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Title: The Appropriate Use of Climatic Information in Illinois Natural-Gas Utility Weather-Normalization Techniques.

Abstract: Historical climate data from 41 sites in Illinois were used to determine the optimal averaging period for predicting hearing degree day accumulations up to 5 years ahead. This was done by examining all possible averaging periods between 1 and 30 years and using four different evaluation techniques. In general, an 11-year mean best predicted heating degree days 1 yearahead.while a 19-year mean performed best for predicting beyond 1 year. To illustrate the effect of using climate means with different averaging periods, a simple weather-normalization model was developed in which selected heating degree day means from historical cases were employed. The use of simulated price and sales data in this model permitted an illustration of the relative dollar differences achieved through using contrasting climate means.

Reference: Easterling, William E., James R. Angel, and Scott A. Kirsch. The Appropriate Use of Climatic Information in Illinois Natural-Gas Utility Weather-Normalization Techniques. Illinois State Water Survey, Champaign, Report of Investigation 112, 1990.

Indexing Terms: Averaging periods, climate normals, climatic data, degree days, economic models, Illinois, natural gas utilities, prediction, temperature, utility rates, weather normalizing, weather patterns.

STATE OF ILLINOIS
HON. JAMES R. THOMPSON. Governor

DEPARTMENT OF ENERGY AND NATURAL RESOURCES
Karen A. Witter, M.S., Director

STATE WATER SURVEY DIVISION
RICHARD G. SEMONIN, Chief

2204 GRIFFITH DRIVE
CHAMPAIGN, ILLINOIS 61820-7495

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INTRODUCTION

A well-known relationship exists between variations in weather and variations in residential-space heating energy consumption (Quayle and Diaz, 1980). In particular, departures of weather conditions from "normal" can markedly affect an energy utility's annual heating fuel sales revenues. The colder it gets, the more fuel is sold by the company for space heating. (In the case of this report, the fuel is natural gas.) And the reverse occurs as temperatures warm.

Normally, the relationship between weather and natural gas sales becomes problematic only when a gas company proposes a change in its price rate schedules. Such a proposal is typically brought before a state regulatory body (public utility commission), which reviews the rate change request and issues a ruling, either denying the request or granting it, with or without modifications. A fundamental issue before the reviewing body is whether or not the proposed rate change is predicated on extraordinary conditions such as "abnormal" weather. The implications of this are elaborated on below.

The accepted protocol for an Illinois natural gas utility in proposing a rate change is to prepare a "test-year case" for the ruling body (Illinois Commerce Commission, or ICC). A test-year case is essentially a simulation of a utility's current production costs and sales revenues over a hypothetical year. Test-year cases can be based simply on historical patterns, or historical patterns can be adapted to project cost and revenue trends into the next year, thus creating a "future test-year case."

The Pennsylvania Public Utility Commission (1980) ruled that "extraordinary occurrences such as abnormal weather conditions, atypical economic conditions, or strikes should not be reflected in test year levels." This suggests that the occurrence of atypical weather conditions is not a valid basis for revising rates. Also implicit is that abnormally beneficial weather conditions (that increase sales revenues) will be offset by negative weather conditions during the time in which a particular rate schedule is in effect.

Therefore it is assumed that neither of these conditions should have a skewing effect on revenues over the life of the rates. That is, for the life of the rates, positive and negative weather conditions will be symmetrically grouped around an unchanging climatic mean.

Partly in response to the above reasoning, many utility companies have begun developing and implementing techniques to "weather-normalize" their revenues and costs before seeking a rate change ruling. Weather normalization is the adjustment of the test-year data to depict the level of sales and operating costs that would occur during a year of normal weather conditions if all else were equal.

Stated differently, the purpose of weather-normalization adjustments is to eliminate the impact of improbable weather conditions on revenues. From the standpoint of the natural gas utility, decreases in revenues that occur after normalization has been performed are likely to build a stronger supporting case for a rate change. For more on weather-normalization techniques with applications to Illinois, see Gillan (1984).

No single agreed-upon method is used by all utility companies to weather-normalize revenues. However, most methods that are in use incorporate climate information in the form of accumulated heating degree days (HDDs). HDDs are calculated on a daily basis as the arithmetic difference between a standard base of 65°F (19.3°C) and the mean daily temperature (65°F minus mean daily temperature equals daily HDDs). If the mean daily temperature is greater than 65°F, then the daily HDD value goes to 0.

Thus if the mean daily temperature is 55°F, there are 10 HDDs on that day; and if the mean daily temperature is 70°F, there are 0 HDDs on that day. Daily HDDs can be summed over longer time periods, such as months or seasons, to represent an index of accumulated cold.

One obvious premise of the use of HDDs in this context is that people turn on their furnaces when the mean daily temperature drops below 65°F. The reliability of this premise has been widely debated, the most common counter-argument being that 65°F may be too warm for a home heating threshold (Lehman and Warren, 1978).

However, it is not the purpose of this study to further the debate on the reliability of the 65°F HDD base. Rather, it is acknowledged that most of the energy industry accepts HDDs as they are now calculated. Moreover, applied climate research has demonstrated a strong correlation between accumulated HDDs and energy usage (Quayle and Diaz, 1980).

Several specific techniques have evolved for weather normalizing. Indeed, many regulatory commissions have developed basic criteria for evaluating various aspects of normalizations. For example, with respect to climate data, questions naturally arise concerning which climate reporting stations were used, as well as the manner in which the data were integrated within the normalization models.

The central issue addressed in this study is the precise manner in which HDDs are now implemented within a typical Illinois weather-normalization model. It has been pointed out that the most critical problem in weather-normalizing sales revenues to develop a test-year case is to determine what constitutes "normal" weather in order to measure the degree of abnormality of actual weather conditions (New York Public Utility Commission, 1960; Gillan, 1984).

The traditional approach in weather normalization is to use the 30-year means computed by the National Weather Service (NWS) for HDDs (ICC, personal communication, 1987). Two potential problems can occur in using NWS 30-year means to perform normalizations, both relating to the now commonly accepted knowledge that climate varies over time scales that are shorter and longer than 30 years.

The first problem is that the NWS 30-year means are calculated only once every 10 years, at the beginning of a new decade. Thus it is conceivable that a mean describing a 30-year period that ended 10 years previously could be used in a current normalization. An example of this situation would be a hypothetical weather normalization performed in late 1989 that relies on an NWS 30-year mean constructed from 1951-1980 data.

The second problem, perhaps more important, is that it is questionable whether a 30-year averaging period is the ideal length for establishing the normal climate at any point. For example, the 30-year mean for 1941-1970, which might have been used in a 1970s Illinois normalization, included the century's warmest temperatures and lowest HDD totals to that point (Changnon, 1984) and thus described a climatic regime different from that of the 1970s. Indeed, in a study conducted partly at the request of the ICC, Lamb and Changnon (1981) found that seasonal temperature normals integrated over a short time interval (five years) outperformed the 30-year mean in predicting seasonal temperatures one year in advance across Illinois.

This study had two specific objectives. First, we reexamined the 1981 Lamb and Changnon study to determine optimal HDD normals for use in the development of test-year cases in Illinois. This involved a detailed examination of the spatial variation of optimal normals across Illinois and the specific adaptation of the normals to rate-change decision making, both of which built onto the Lamb and Changnon analysis. These normals will be referred to as means.

Second, a simple weather-normalization model was developed, and different HDD means were used in the model in an after-the-fact evaluation. The use of simulated price and sales data in this model permits an illustration of the relative dollar differences achieved through use of contrasting climate-averaging periods.

In accordance with these two objectives, this report has two main sections. The first is a discussion of optimal means for use in Illinois weather-normalization schemes. The second is an overview of the development and implementation of a generic weather-normalization model, along with an analysis of the model output.

Acknowledgments

This report was prepared under the general direction of Richard G. Semonin, Chief of the Illinois State Water Survey, and with the general guidance of Peter J. Lamb, Head of the Survey's Climate and Meteorology Section. The research was funded by a grant from the Illinois Department of Energy and Natural Resources. John Brother provided the drafting, and Gail Taylor edited the report.

The report was reviewed by Stanley A. Changnon and Peter J. Lamb, and their comments and encouragement are appreciated. Data collected by the U.S. National Weather Service at its first-order and cooperative stations made this study possible.

A CLIMATOLOGY OF ILLINOIS HEATING DEGREE DAY NORMALS

A primary requirement of natural gas utility weather-normalization models is an assessment of the "normality" of present and near-future climatic conditions. This section investigates the optimal averaging period for describing the current "normal" climate and for predicting the climate over individual years ranging from 1 to 5 years in advance, as well as for predicting the average climate for the entire 5-year period. Five years was selected because that time period represents the typical upper boundary for the lifetime of a given set of rates for a particular utility company (ICC, personal communication, 1987).

A body of research exists on determining the normal climate and how well it can predict future climate (for example, Court, 1968; Lamb and Changnon, 1981; Dixon and Shulman, 1984; Sabin and Shulman, 1985). Until recently, climate has been considered stable, with only a random variation around some mean value. This mean or average value is labeled the "normal." This determination ties in with traditional statistical concepts of central tendency and implies that confidence in the mean increases with more observations (i.e., more years of data). Therefore the stations with the longest records provide the best mean.

As Court (1968) has pointed out, this assumption has two faults. First, climate is now understood to fluctuate over many time scales (National Academy of Sciences, 1975, pp. 19-23 and Appendix A), which can cause the standard deviation of a climate measurement to increase over time. Second, longer records are likely to include non-homogeneous data caused by changes in instrumentation, exposure, and method of observation. To minimize these effects, in the mid-1950s the United States adopted the 30-year mean for first-order stations (U.S. Weather Bureau, 1958) and cooperative substations (U.S. Weather Bureau, 1955).

Court (1968) suggests that the best empirical test of reliability for appropriate climatic means is their ability to predict the future. In a review of five other studies and his own research, he concludes that for predicting one year in advance, a mean of approximately 20 years is superior to the standard 30-year mean.

In a case dealing specifically with Illinois, Lamb and Changnon (1981) studied four stations and concluded that a 5-year mean best predicts seasonal temperatures for the next year. Building on Lamb and Changnon's analysis, Dixon and Shulman (1984) examined heating degree days for six stations across the United States and found running means from 10 to 30 years in length to be better for prediction.

Dixon and Shulman (1984) were critical of the method used by Lamb and Changnon (1981) for two reasons. First, only selected running means were used (5,10,15,20,25 and 30 years). They noted that in this approach, the individual best predictors must be constrained to those that are among the particular means tested; and therefore the selection and number of means could act as an artifact to influence the results. Second, although the 5-year mean most frequently is the best predictor of the next year's climate, it also produces the largest prediction errors when it fails. Regardless of these criticisms, Lamb and Changnon clearly brought into question the use of traditional 30-year averaging periods for portraying normal weather.

In seeking the optimal averaging period for use in weather normalization, we examined all possible interannually aggregated averaging periods (from 1 to 30 years) by using a variety of evaluation techniques that are sensitive to different aspects of prediction error. These techniques were used to evaluate the various averaging periods in terms of their predictive ability for the whole year, for winter (defined as December-February), for extended winter (defined as October-April), and for each month, averaged for the entire state. The spatial distribution over the state for the whole year was also examined.

Daily temperature data from 41 stations in Illinois (for the period 1901-1984) were used to calculate HDD amounts. These amounts were then summed into monthly, seasonal, and annual totals. Four methods were used to determine the best base period for constructing a climatic normal. The base periods examined ranged from 1 to 30 years in length and were calculated as running means (discussed below). The 30-year period was chosen as the maximum because earlier research (for example, Lamb and Changnon, 1981; Dixon and Shulman, 1984) suggests that the optimum is less than 30 years.

The results for each method were ranked according to the predictive accuracy of the averaging period (best to worst), and an assessment was made of the differences in the results. An examination of the top-ranked means across Illinois for each method and for each prediction period (1 to 5 years) provides a basis for choosing the best overall running mean.

Running means, also known as moving averages, are first calculated for a given base period (for example, 18 years). Then the base period is shifted forward one time unit (in this case, 1 year), and a new mean is calculated. For example, an 18-year running mean would use 1967-1984 data to predict a 1985 value. In the next step, the mean would use 1968-1985 data to predict a 1986 value.

Although running means are normally used to smooth a time series, the primary advantage of using them in this study to predict a year's HDD value is that they make it possible to use the most recent time period to calculate the averaging period. For this study, running means were calculated for the period 1901-1984.

Data and Methodology

The temperature data (converted to HDDs) used in this study were obtained from the National Climatic Data Center (NCDC). Forty-one stations across Illinois were chosen to provide representative spatial coverage (figure 1). Data were obtained for the period 1901-1984 (with the exception of Kankakee, where recording began in 1917). These 41 stations are a subset of a network of 61 high-quality data stations in Illinois (Changnon, 1979).

On average, 2 percent of the data, or roughly seven days of data per year, were missing for each station. Missing temperature data were filled in from nearby stations with similar topographies and observation times (when known). This addition is considered appropriate because, on average, temperatures do not vary much between stations on the order of 50 to 100 kilometers (31 to 62 miles) apart.

The HDD year begins on July 1 and ends on June 30 of the following year. The traditional winter (December-February) makes the largest contribution to the yearly total. An examination of the daily distribution of heating degree days for all 41 sites shows that 90 percent of the HDDs fall between the third week of October and the second week of April (figure 2). This period increases from the southern sites to the northern sites and is about two weeks longer in the north than in the south.

HDD totals for both the traditional and extended winter (October-April) seasons were examined. The definition of extended winter used here agrees well with winter as defined by Dixon and Shulman (1984). Some discussion has occurred (for example, Gillan, 1984) about whether annual, seasonal, or monthly HDD totals should be used in normalization. Because we feel that this matter is unresolved in both theory and practice, we performed an interannual analysis of HDD averaging periods aggregated all three ways (by month, season, and year).

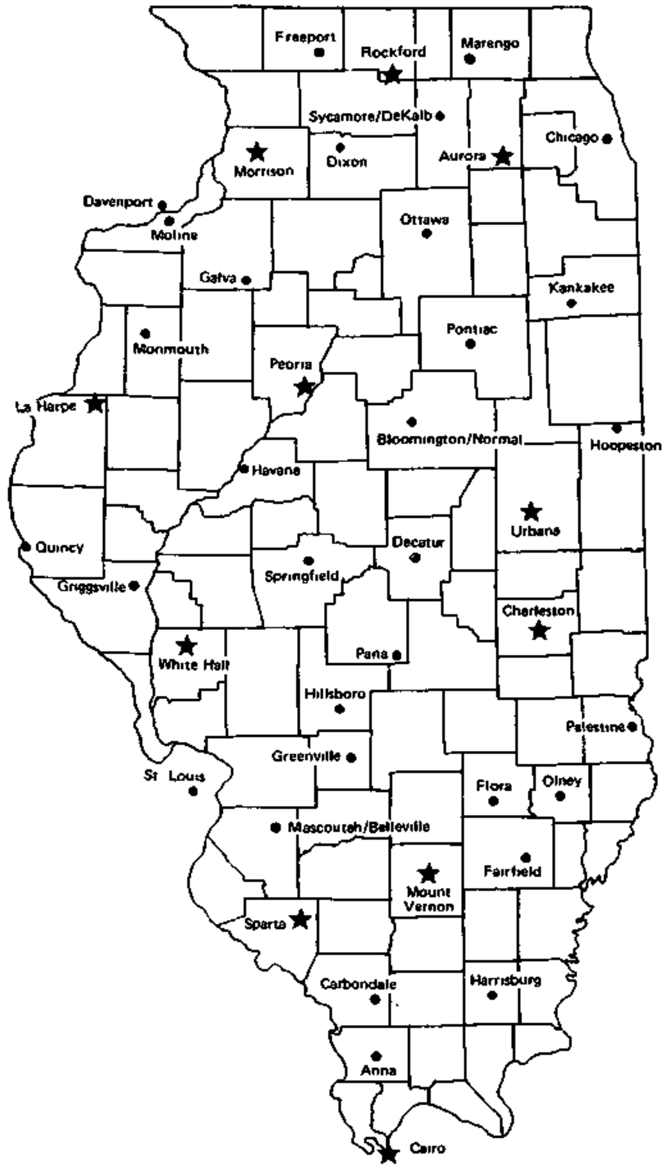

Figure 1. Climate stations in Illinois used in this study (Stations denoted by a star were also used in the weather-normalization model analysis)

Four statistical methods were used to evaluate the predictive ability of the running means: root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), and the "WINS" method. Basically, in each method, an HDD running mean is calculated and subtracted from the HDD value of the year for which a prediction is being made. This difference is called the predictive error (AX).

For example, a 10-year extended-winter HDD running mean covering 1961-1970 would be subtracted from the extended-winter HDD total for 1971. Relatively large values of AX indicate poor predicta-

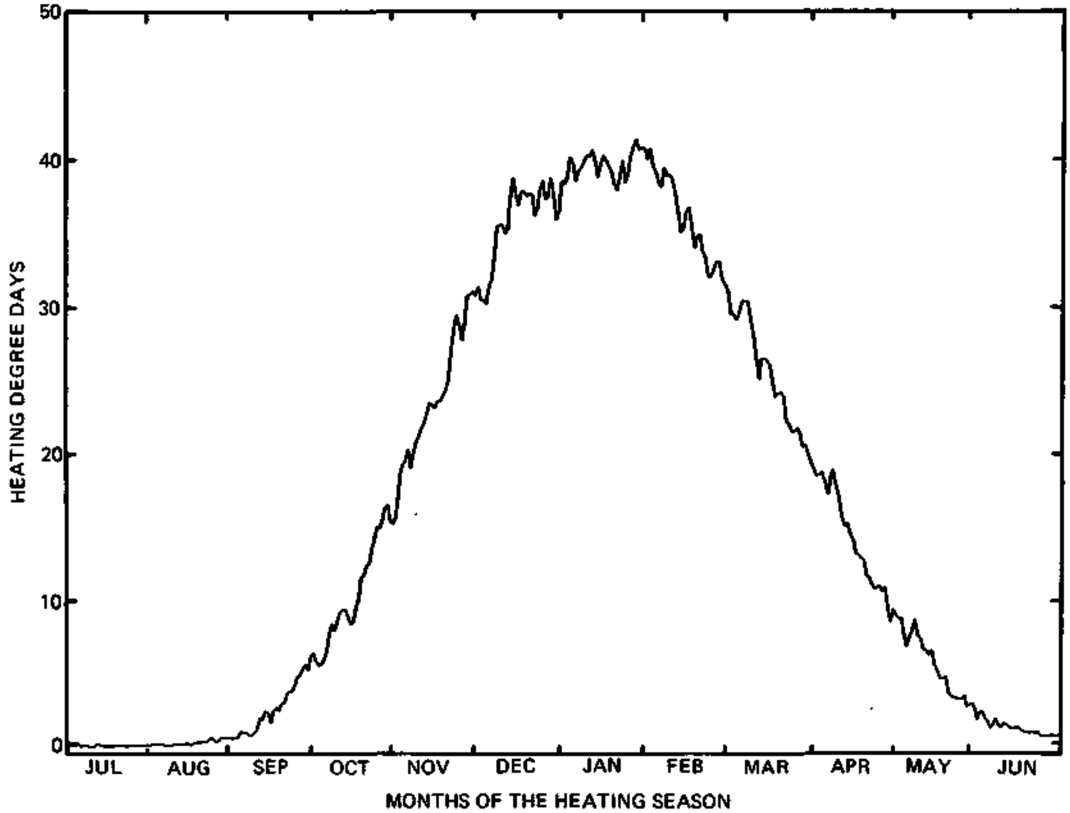

Figure 2. Annual distribution of mean HDDs (1901-1984) for Urbana

bility by the moving mean, and low values indicate good predictability.

The first and most commonly used evaluation method in previous studies is the root mean square error (RMSE). As the running mean moves through the time series, the predictive errors, ΔX, are squared to remove the sign and accumulated. This accumulation is then divided through by the number (n) of predictive errors accumulated, and the square root is taken of this quotient (equation 1):

$$\mathrm{RMSE} = [1/n \sum (\Delta X)^2]^{1/2} \quad (1)$$

The second method used in this study is the mean square error (MSE). It is the same as the RMSE except that the final square root is not taken (i.e., MSE = RMSE^2). The primary difference between the MSE and the RMSE is that the MSE magnifies the differences between the selected movingmeans. While this has no effect on the rankings for individual sites, it can lead to differences when a summation is made across the state. That is, the sum of a set of numbers and the sum of the squares of a set of numbers can lead to changes in the relative rankings.

The third method is the mean absolute error (MAE). In this method, the absolute values of the predictive errors are accumulated and divided by n (equation 2):

$$\mathrm{MAE} = 1/n \sum |\Delta X| \quad (2)$$

As Dixon and Shulman (1984) point out, it is desirable to choose a predictor that gives a low mean error and minimizes the large errors. RMSE and MSE are functions of the square of the errors, whereas MAE is a mean of their magnitude. Therefore the RMSE and MSE methods have the attractive property of magnifying the importance of large prediction errors.

The final method — the WINS method — is derived from Lamb and Changnon (1981). It involves tabulating the number of times a particular mean has the lowest prediction error for a given year compared to all other means. This method is referred to as WINS because it is based on summing the wins over time for a particular mean.

The results for these four methods were ranked according to the scores accumulated over the time series, allowing a comparative assessment of all means in a given instance. The selected means were used to see how well each could predict individual years from 1 through 5 years in advance. The prediction errors were also summed over the entire 5-year period.

Running means of 1 through 30 years in length were examined, as well as the 30-year NWS means for each site (calculated only once per decade). Although the NWS did not use 30-year means before the 1960s, in this study the NWS 30-year means were calculated retroactively back to 1930. Table 1 shows the calculated NWS 30-year means and the corresponding series of years that the NWS means were used to predict.

The analysis included 1- to 30-year averaging periods; and because 1931 was the first year preceded by 30 years for which data were available, it was the first year used in the analysis. The last year used in the analysis was 1979, because predictions were made for up to 5 years in advance and our data collection for most sites ended in 1984.

Results and Discussion

Background Climatology

To provide a background climatology of HDDs, time-series plots were made for all 41 sites. The time-series plot of all the sites averaged together reveals a downward trend in annual HDDs from 1901 to the mid-1930s (figure 3). From the mid-19303 to the mid-1950s, HDDs leveled out before beginning an upward trend to 1980. The last few winters have been relatively warm, contributing to a downward trend approaching levels of roughly the same magnitude as at the beginning of the time series.

Thus there are three distinct periods (or epochs) that span, in order, 35, 20, and 25 years. These epochs alone suggest that shorter means (that is, shorter than the epochs themselves) will make better predictors for the next year. One hypothesis that follows from these time series is that means shorter than 30 years could outperform the National Weather Service 30-year means (which are updated every 10 years) in describing temporally homogeneous climate patterns.

Mapped 1901-1986 mean annual HDD totals show a consistent pattern of increasing values from southern to northern Illinois (figure 4). The spatial difference in HDD totals is about 2,500 more HDDs in far northern Illinois than in the southern tip (a 50 to 60 percent difference, depending on the sites). Not unexpectedly, this increase is directly related to latitude.

Table 1. Calculated NWS 30-Year Means and the Corresponding Series of Years That the NWS Means Were Used to Predict

30-year mean	*Corresponding years predicted*
1901-1930	1931, 32, 33, . . . , 40
1911-1940	1941, 42, 43, ... 50
1921-1950	1951, 52, 53, . . . , 60
1931-1960	1961, 62, 63, . . . , 70
1941-1970	1971, 72, 73, . . . , 80
1951-1980	1981, 82, 83, 84

Evaluation Method Results

In tables 2 through 5, the 1- to 30-year running means and the NWS 30-year means are ranked from 1 to 31 in predicting annual HDDs, according to the four evaluation methods. These tables reflect predictions of annual HDD totals for individual years 1 through 5 years in advance, as well as predictions of the 5-year average. It is important to note that although the results in these tables are based on HDD totals, they are a derivative of temperature. The results for temperature means would be similar.

Spearman's rank-order correlation analysis was used to measure how well the rankings of each method matched the rankings of the other three. The rank-order correlation is a nonparametric test obviating the need for assumptions about normality. With 31 observations, the correlation matrix contains simple r values, all equal to or greater than 0.90 and significant at a = 0.05. This suggests that the four different methods produce essentially the same ranks.

Therefore the results of this study can be attributed to the data and not to artifacts of the methods used in measuring the prediction error. Moreover, this ability to reproduce the results with different methods increases the confidence in those results.

The study generated values for four methods, 41 sites, and 12 months plus two different winter seasons and annual HDD totals for each of 31 means (4 x 41 x 15 x 31). Because this represents a large data matrix, only summary results are presented here. The entire data set will be made available on request.

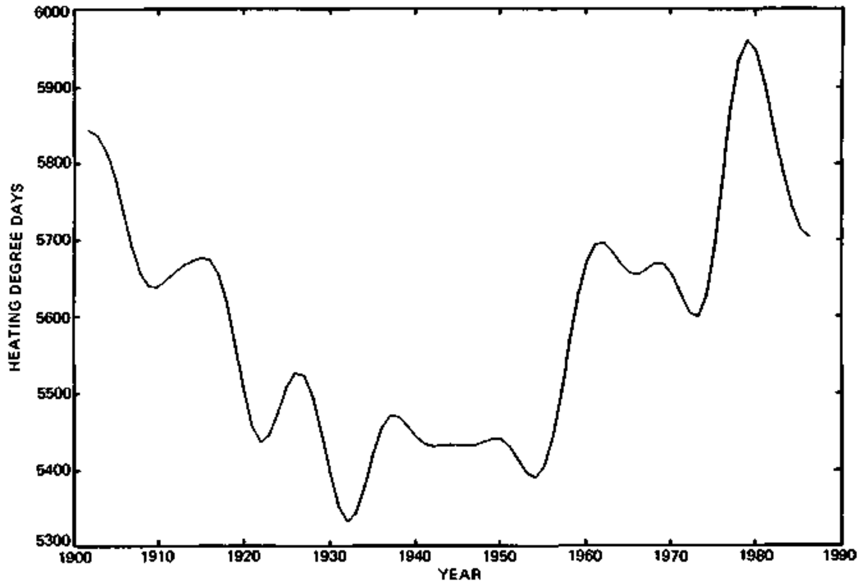

Figure 3. Smoothed, spatially averaged annual HDD totals over time for the 41 stations in Illinois

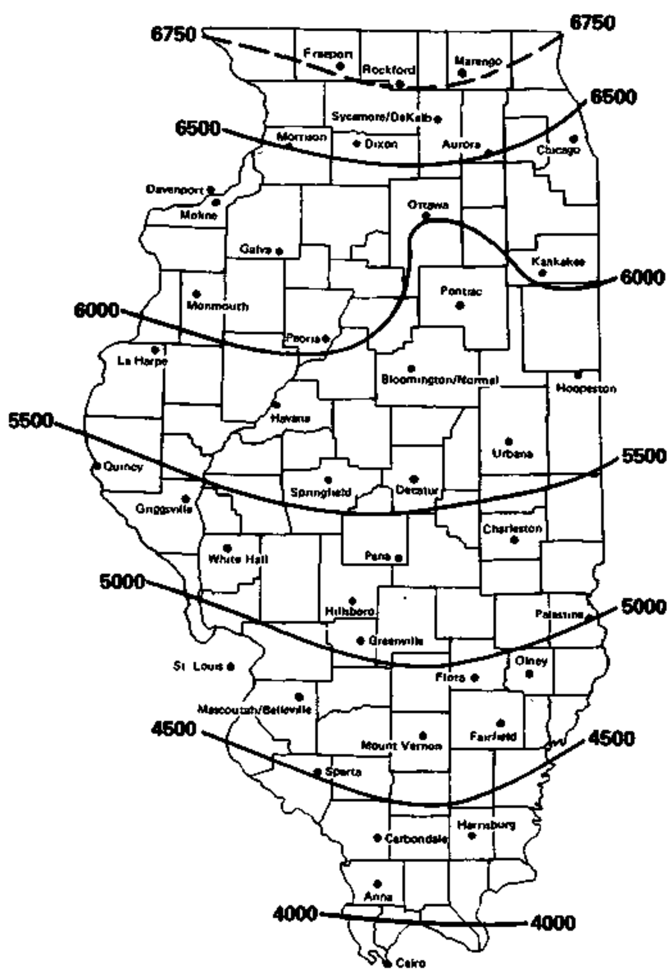

Figure 4. Mean annual HDDs, 1901-1986 (the stations used are indicated)

Table 2. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means for Predicting Annual HDDs (RMSE Evaluation Method)

Rank	*1st year ahead*	*2nd year ahead*	*3rd year ahead*	*4th year ahead*	*5th year ahead*	*5-year average*
1 (Best)	11	19	18	17	16	18
2	12	18	17	19	18	19
3	10	21	20	16	15	17
4	20	20	19	18	17	20
5	13	11	10	20	19	16
6	19	10	16	15	14	21
7	18	17	9	9	8	10
8	9	22	21	8	20	15
9	22	9	8	21	13	11
10	21	16	15	14	21	9
11	14	23	22	23	22	22
12	17	12	24	22	7	14
13	23	15	23	24	23	12
14	16	25	14	13	12	13
15	15	24	25	11	10	23
16	24	26	11	10	11	8
17	8	13	12	7	9	24
18	25	14	13	12	24	25
19	26	27	26	25	25	26
20	27	8	7	26	30	7
21	7	28	27	30	29	27
22	28	29	28	27	26	28
23	29	30	30	29	28	29
24	30	7	29	28	27	30
25	5	6	6	6	6	6
26	4	4	5	5	5	5
27	6	5	NWS	4	4	4
28	3	3	4	NWS	NWS	3
29	2	2	3	3	3	NWS
30	1	NWS	2	2	2	2
31 (Worst)	NWS	1	1	1	1	1

Table 3. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means for Predicting Annual HDDs (MSE Evaluation Method)

Rank	*1st year ahead*	*2nd year ahead*	*3rd year ahead*	*4th year ahead*	*5th year ahead*	*5-year average*
1 (Best)	**11**	**19**	**18**	**17**	**16**	**18**
2	**12**	**18**	**17**	**19**	**18**	**19**
3	**10**	**21**	**20**	**16**	**15**	**17**
4	**13**	**20**	**19**	**18**	**17**	**20**
5	**19**	**11**	**10**	**20**	**19**	**16**
6	**20**	**17**	**16**	**15**	**14**	**21**
7	**18**	**10**	**9**	**9**	**20**	**10**
8	**9**	**22**	**21**	**21**	**8**	**15**
9	**21**	**9**	**8**	**8**	**13**	**11**
10	**22**	**16**	**15**	**14**	**21**	**9**
11	**14**	**23**	**22**	**23**	**22**	**22**
12	**17**	**12**	**24**	**22**	**23**	**14**
13	**23**	**15**	**23**	**24**	**7**	**13**
14	**16**	**24**	**14**	**13**	**12**	**12**
15	**15**	**25**	**25**	**11**	**10**	**23**
16	**8**	**13**	**11**	**10**	**11**	**8**
17	**24**	**26**	**12**	**12**	**9**	**24**
18	**25**	**14**	**13**	**7**	**24**	**25**
19	**26**	**27**	**26**	**25**	**25**	**26**
20	**27**	**8**	**7**	**26**	**30**	**7**
21	**7**	**28**	**27**	**30**	**29**	**27**
22	**28**	**29**	**28**	**27**	**26**	**28**
23	**29**	**30**	**30**	**29**	**28**	**29**
24	**30**	**7**	**29**	**28**	**27**	**30**
25	**5**	**6**	**6**	**6**	**6**	**6**
26	**4**	**4**	**5**	**5**	**5**	**5**
27	**6**	**5**	**4**	**4**	**4**	**4**
28	**3**	**3**	**3**	**NWS**	**3**	**3**
29	**2**	**2**	**NWS**	**3**	**NWS**	**2**
30	**1**	**NWS**	**2**	**2**	**2**	**NWS**
31 (Worst)	**NWS**	**1**	**1**	**1**	**1**	**1**

Table 4. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means for Predicting Annual HDDs (MAE Evaluation Method)

Rank	*1st year ahead*	*2nd year ahead*	*3rd year ahead*	*4th year ahead*	*5th year ahead*	*5-year average*
1 (Best)	11	11	9	17	16	19
2	12	10	10	19	18	18
3	10	19	18	8	15	10
4	9	18	8	16	19	8
5	8	9	17	9	17	9
6	13	21	20	18	8	17
7	20	20	19	20	21	20
8	14	17	16	15	7	11
9	19	13	21	22	20	16
10	15	22	7	23	22	21
11	18	12	23	21	14	15
12	22	14	12	24	23	22
13	17	16	11	14	24	12
14	21	24	13	11	13	14
15	7	25	15	7	10	13
16	16	8	24	25	11	23
17	23	23	22	10	9	7
18	25	26	25	12	30	24
19	25	15	14	13	29	25
20	26	27	26	26	25	26
21	27	7	27	30	12	27
22	28	28	6	29	28	28
23	4	29	30	27	26	29
24	29	30	28	28	6	30
25	5	6	29	6	27	6
26	30	4	5	5	5	5
27	6	3	3	4	4	4
28	3	5	4	NWS	3	3
29	2	2	NWS	2	NWS	NWS
30	1	NWS	2	3	2	2
31 (Worst)	NWS	1	1	1	1	1

Table 5. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means for Predicting Annual HDDs (WINS Evaluation Method)

Rank	*1st year ahead*	*2nd year ahead*	*3rd year ahead*	*4th year ahead*	*5th year ahead*	*5-year average*
1 (Best)	11	11	18	19	18	19
2	12	19	17	17	16	18
3	10	18	20	16	15	17
4	9	10	10	20	19	20
5	8	21	9	18	21	16
6	20	17	16	22	20	21
7	19	20	19	23	17	15
8	13	16	23	15	22	22
9	14	22	15	21	14	8
10	15	9	21	9	23	9
11	18	24	24	8	8	11
12	22	15	14	14	7	10
13	17	25	13	24	13	14
14	16	14	8	13	NWS	23
15	21	8	7	25	24	12
16	23	13	22	12	11	13
17	25	12	25	NWS	12	24
18	4	26	12	11	30	25
19	26	23	6	7	10	7
20	24	7	11	10	6	26
21	7	27	26	26	25	NWS
22	27	NWS	NWS	5	29	27
23	5	28	27	6	9	6
24	28	29	30	30	28	28
25	3	30	28	29	26	30
26	NWS	6	29	27	5	29
27	29	3	5	28	4	5
28	30	4	2	4	27	4
29	2	5	3	2	3	3
30	6	2	4	1	1	2
31 (Worst)	1	1	1	3	2	1

Predicting Annual Heating Degree Day Totals 1 to 5 Years Ahead

Table 6 is a summary of the ranks (from best to worst) of 1-year predictions of annual HDDs averaged over all 41 sites, according to the four methods. For all four methods, the three top-ranked prediction-averaging periods are the 11-, 12-, and 10-year means, respectively. The next 10 prediction means in rank generally center around the 20-year mean. Note that the NWS prediction mean is ranked lowest according to three of the four methods.

Table 7 is a similar summary of means for all of Illinois, ranked by accuracy in predicting the 5-year mean annual total HDDs. In this case, the means ranging between 15 and 20 years in length are the best predictors of HDDs averaged over the subsequent 5 years. The next-best set of prediction means are those around 10 years in length. Extreme long- and short-length prediction means do relatively poorly.

As shown in tables 8 through 11, there is a tendency for 20-year means to be best for predicting the second, third, fourth, and fifth individual years in advance. Again, the means with extremely long and short lengths consistently predict poorly.

Table 12 is a summary of the prediction means that were ranked first for each prediction period according to each of the four evaluation methods. It proves difficult to distinguish the best prediction mean or means objectively, so the top-ranked prediction mean for each period is chosen as best. The 11-year prediction mean is best for one year in advance, but it gradually gives way to the longer means as the predictions extend further into the future.

It can be concluded from these tables that a mean of 11 years is best for predicting the annual HDD totals for the next year over all of Illinois. For 2,3,4, and 5 years in advance, a prediction mean of between 17 and 19 years is most appropriate. For predicting mean annual HDD totals for the next 5-year period, a mean of 18 or 19 years is best.

Predicting Winter, Extended Winter, and Monthly Heating Degree Day Totals 1 to 5 Years Ahead

We now focus on specific portions of the year, including the winter season (defined two ways) and each individual month of the year. The best predictor of winter HDD totals (December-February) one year in advance centers around 21 years (table 13). This is true for the 2- through 5-year predictions and the total 5-year period as well.

Aside from these shifts away from the 11-year mean, the winter season results are in general agreement with the results for the annual total HDDs discussed previously. The results for the extended winter season (October-April) (table 14) are also very similar to the annual results. The 11-year running mean is best for the 1-year predictions, while the 18- to 20-year means are best for predictions made 2, 3, 4, and 5 years in advance. The 19-year running mean is best for the entire 5-year period.

For individual months, the means that are best for predicting one year ahead are longest for March and shortest for July (table 15). It must be kept in mind that the HDD numbers for June, July, and August are normally quite small, and virtually no heating is needed in Illinois during this time of the year. The lengths of monthly means that are best for predicting the entire 5-year monthly average period, divided by month, do not exhibit a clear pattern (table 16).

The best prediction means for any given month are more likely to approach 30 years for predicting the subsequent 5-year averages than for predicting 1 year in advance. The longer prediction means for March HDD totals imply that they are persistent interannually. The shorter means for October indicate less persistence.

Features of the NWS 30-Year Means

A feature that clearly emerges from these analyses is the consistently poor predictive performance of the NWS 30-year mean, regardless of season, month, or year(s) for which predictions are made. Given the prominent use of the NWS mean in previous weather normalizations (see Gillan, 1984), as well as its use as a reference for evaluating recent weather, it is important to examine more closely how well the NWS mean has related to interannual HDD variations in Illinois.

Some of the most compelling evidence in support of using shorter means than the NWS 30-year base is shown by superimposing the 30-year means onto various long-term trends (figure 5). Included in this figure are the smoothed, annual HDD totals averaged over the entire state for each year from 1901 to 1984 (solid line); the 19-year running mean (which performed best overall) for the original, unsmoothed data (dashed line); and 30-year means as calculated by the NWS method (line segments).

Table 6. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means in Predicting an Individual Year 1 Year Ahead, According to the Four Evaluation Methods

Rank	*RMSE*	*MSE*	*MAE*	*WINS*
1 (Best)	11	11	11	11
2	12	12	12	12
3	10	10	10	10
4	20	13	9	9
5	13	19	8	8
6	19	20	13	20
7	18	18	20	19
8	9	9	14	13
9	22	21	19	14
10	21	22	15	15
11	14	14	18	18
12	17	17	22	22
13	23	23	17	17
14	16	16	21	16
15	15	15	7	21
16	24	8	16	23
17	8	24	23	25
18	25	25	25	4
19	26	26	24	26
20	27	27	26	24
21	7	7	27	7
22	28	28	28	27
23	29	29	4	5
24	30	30	29	28
25	5	5	5	3
26	4	4	30	NWS
27	6	6	6	29
28	3	3	3	30
29	2	2	2	2
30	1	1	1	6
31 (Worst)	NWS	NWS	NWS	1

Table 7. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means in Predicting an Individual Year 5 Years Ahead, According to the Four Evaluation Methods

Rank	*RMSE*	*MSE*	*MAE*	*WINS*
1 (Best)	18	18	19	19
2	19	19	18	18
3	17	17	10	17
4	20	20	8	20
5	16	16	9	16
6	21	21	17	21
7	10	10	20	15
8	15	15	11	22
9	11	11	16	8
10	9	9	21	9
11	22	22	15	11
12	14	14	22	10
13	12	13	12	14
14	13	12	14	23
15	23	23	13	12
16	8	8	23	13
17	24	24	7	24
18	25	25	24	25
19	26	26	25	7
20	7	7	26	26
21	27	27	27	NWS
22	28	28	28	27
23	29	29	29	6
24	30	30	30	28
25	6	6	6	30
26	5	5	5	29
27	4	4	4	5
28	3	3	3	4
29	NWS	2	NWS	3
30	2	NWS	2	2
31 (Worst)	1	1	1	1

Table 8. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means in Predicting an Individual Year 2 Years Ahead, According to the Four Evaluation Methods

Rank	*RMSE*	*MSE*	*MAE*	*WINS*
1 (Best)	19	19	11	11
2	18	18	10	19
3	21	21	19	18
4	20	20	18	10
5	11	11	9	21
6	10	17	21	17
7	17	10	20	20
8	22	22	17	16
9	9	9	13	22
10	16	16	22	9
11	23	23	12	24
12	12	12	14	15
13	15	15	16 ,	25
14	25	24	24	14
15	24	25	25	8
16	26	13	8	13
17	13	26	23	12
18	14	14	26	26
19	27	27	15	23
20	8	8	27	7
21	28	28	7	27
22	29	29	28	NWS
23	30	30	29	28
24	7	7	30	29
25	6	6	6	30
26	4	4	4	6
27	5	5	3	3
28	3	3	5	4
29	2	2	2	5
30	NWS	NWS	NWS	2
31 (Worst)	1	1	1	1

Table 9. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means in Predicting an Individual Year 3 Years Ahead, According to the Four Evaluation Methods

Rank	*RMSE*	*MSE*	*MAE*	*WINS*
1 (Best)	18	18	9	18
2	17	17	10	17
3	20	20	18	20
4	19	19	8	10
5	10	10	17	9
6	16	16	20	16
7	9	9	19	19
8	21	21	16	23
9	8	8	21	15
10	15	15	7	21
11	22	22	23	24
12	24	24	12	14
13	23	23	11	13
14	14	14	13	8
15	25	25	15	7
16	11	11	24	22
17	12	12	22	25
18	13	13	25	12
19	26	26	14	6
20	7	7	26	11
21	27	27	27	26
22	28	28	6	NWS
23	30	30	30	27
24	29	29	28	30
25	6	6	29	28
26	5	5	5	29
27	NWS	4	3	5
28	4	3	4	2
29	3	NWS	NWS	3
30	2	2	2	4
31 (Worst)	1	1	1	1

Table 10. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means in Predicting an Individual Year 4 Years Ahead, According to the Four Evaluation Methods

Rank	*RMSE*	*MSE*	*MAE*	*WINS*
1 (Best)	17	17	17	19
2	19	19	19	17
3	16	16	8	16
4	18	18	16	20
5	20	20	9	18
6	15	15	18	22
7	9	9	20	23
8	8	21	15	15
9	21	8	22	21
10	14	14	23	9
11	23	23	21	8
12	22	22	24	14
13	24	24	14	24
14	13	13	11	13
15	11	11	7	25
16	10	10	25	12
17	7	12	10	NWS
18	12	7	12	11
19	25	25	13	7
20	26	26	26	10
21	30	30	30	26
22	27	27	29	5
23	29	29	27	6
24	28	28	28	30
25	6	6	6	29
26	5	5	5	27
27	4	4	4	28
28	NWS	NWS	NWS	4
29	3	3	2	2
30	2	2	3	1
31 (Worst)	1	1	1	3

Table 11. Best-to-Worst Rankings of 1- to 30-Year Running Means and NWS 30-Year Means in Predicting an Individual Year 5 Years Ahead, According to the Four Evaluation Methods

Rank	*RMSE*	*MSE*	*MAE*	*WINS*
1 (Best)	16	16	16	18
2	18	18	18	16
3	15	15	15	15
4	17	17	19	19
5	19	19	17	21
6	14	14	8	20
7	8	20	21	17
8	20	8	7	22
9	13	13	20	14
10	21	21	22	23
11	22	22	14	8
12	7	23	23	7
13	23	7	24	13
14	12	12	13	NWS
15	10	10	10	24
16	11	11	11	11
17	9	9	9	12
18	24	24	30	30
19	25	25	29	10
20	30	30	25	6
21	29	29	12	25
22	26	26	28	29
23	28	28	26	9
24	27	27	6	28
25	6	6	27	26
26	5	5	5	5
27	4	4	4	4
28	NWS	3	3	27
29	3	NWS	NWS	3
30	2	2	2	1
31 (Worst)	1	1	1	2

Table 12. Prediction Means That Were Ranked First for Predicting 1 through 5 Years in Advance and the Entire 5-Year Period, According to the Four Evaluation Methods

Year	*RMSE*	*MSE*	*MAE*	*WINS*
1	11	11	11	11
2	19	19	11	11
3	18	18	9	18
4	17	17	17	19
5	16	16	16	18
5-year period	18	18	19	19

Table 13. Prediction Means That Were Ranked First for Predicting 1 through 5 Years in Advance and the Entire 5-Year Period for the Traditional Winter (December-February), According to the Four Evaluation Methods

Year	*RMSE*	*MSE*	*MAE*	*WINS*
1	20	20	23	23
2	22	22	22	22
3	21	21	21	21
4	20	20	20	20
5	19	19	19	19
5-year period	19	19	20	19

Table 14. Prediction Means That Were Ranked First for Predicting 1 through 5 Years in Advance and the Entire 5-Year Period for the Extended Winter (October-April), According to the Four Evaluation Methods

Year	*RMSE*	*MSE*	*MAE*	*WINS*
1	11	11	11	11
2	19	19	19	19
3	20	20	18	20
4	19	19	19	19
5	18	18	18	18
5-year period	19	19	19	19

Table 15. Prediction Means That Were Ranked First for Predicting Individual Months 1 Year Ahead, According to the Four Evaluation Methods

Month	*RMSE*	*MSE*	*MAE*	*WINS*
January	23	23	21	21
February	24	24	24	24
March	28	28	28	NWS
April	23	23	23	23
May	23	23	23	23
June	19	19	19	19
July	5	5	5	4
August	23	23	23	2
September	25	25	25	25
October	12	12	12	12
November	22	22	22	22
December	20	20	18	18
Mean	20.58	20.58	20.25	18.67

Table 16. Prediction Means That Were Ranked First for Predicting Individual Months for the 5-Year Period, According to the Four Evaluation Methods

Month	*RMSE*	*MSE*	*MAE*	*WINS*
January	18	18	18	19
February	30	30	28	28
March	28	28	28	NWS
April	28	28	22	22
May	28	28	22	22
June	19	19	18	18
July	23	21	21	3
August	20	21	19	30
September	25	30	24	24
October	12	12	12	12
November	22	22	30	30
December	18	18	18	18
Mean	22.58	22.92	21.67	21.42

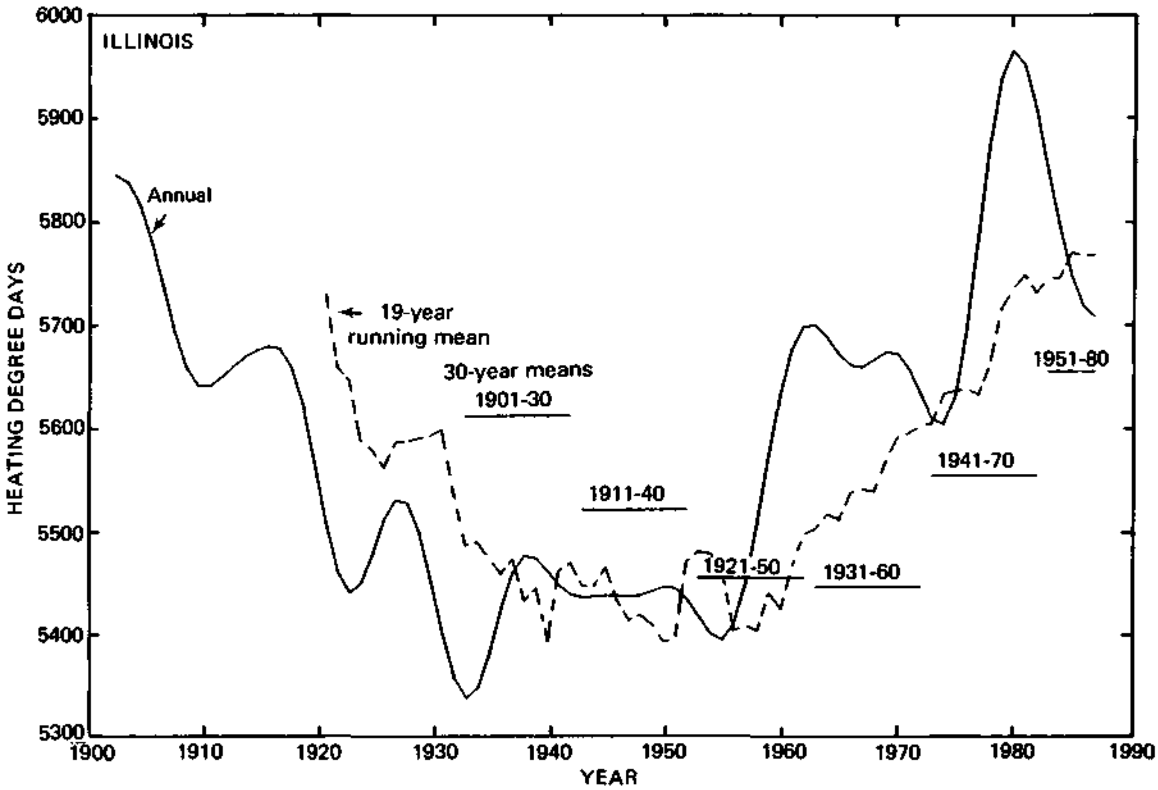

Figure 5. Overlay of smoothed, spatially averaged annual HDDs (solid line), 19-year running mean (dashed line), and NWS 30-year means (line segments) for the 41 stations in Illinois

The data shown by the solid line in figure 5 were passed through a 3-point smoother with weights of 0.25, 0.5, and 0.25 to suppress the high-frequency noise while leaving the general trends (Panofsky and Brier, 1968).

Note the high interannual variability of HDDs occurring within each of the standard 30-year averaging periods. Moreover, recall that it is standard practice when using these means in rate-case decisions to use a given 30-year mean for up to 10 years after its calculation. In fact, if one is attempting to predict up to five years in advance, it is possible to apply NWS means up to 15 or 16 years after they have been calculated.

Note that the NWS means do poorly under fluctuating climate and perform well only at the inflection points on the curve or during periods of homogeneous climate. For example, the NWS mean for 1941 to 1970 describes a period of fluctuating climate and thus could be expected to be a poor predictor for subsequent years in that same period of climate.

In figures 6 through 9, the NWS means, as defined in table 1, and their standard deviations are plotted over time for four sites chosen to form a south-to-north transect of Illinois. (The plots for the remaining 37 sites are available upon request.) The left-hand axis shows the average HDDs for each 30-year period, while the right-hand axis shows their standard deviations.

Means tend to vary by 250 to 350 HDDs for the six overlapping periods. At the same time, the standard deviations vary by 150 to 300 HDDs. These plots help to demonstrate that the NWS 30-year means can change dramatically through time and can rapidly lose predictive capability.

Spatial Variability of Predictive Means across Illinois

With regard to the spatial variability of the best predictive means, there is evidence of a recent shift southward of the HDD contours. This is supported by comparing the 19-year period 1968-1986 with the 87-year period 1901-1986 for Illinois (figure 10). The

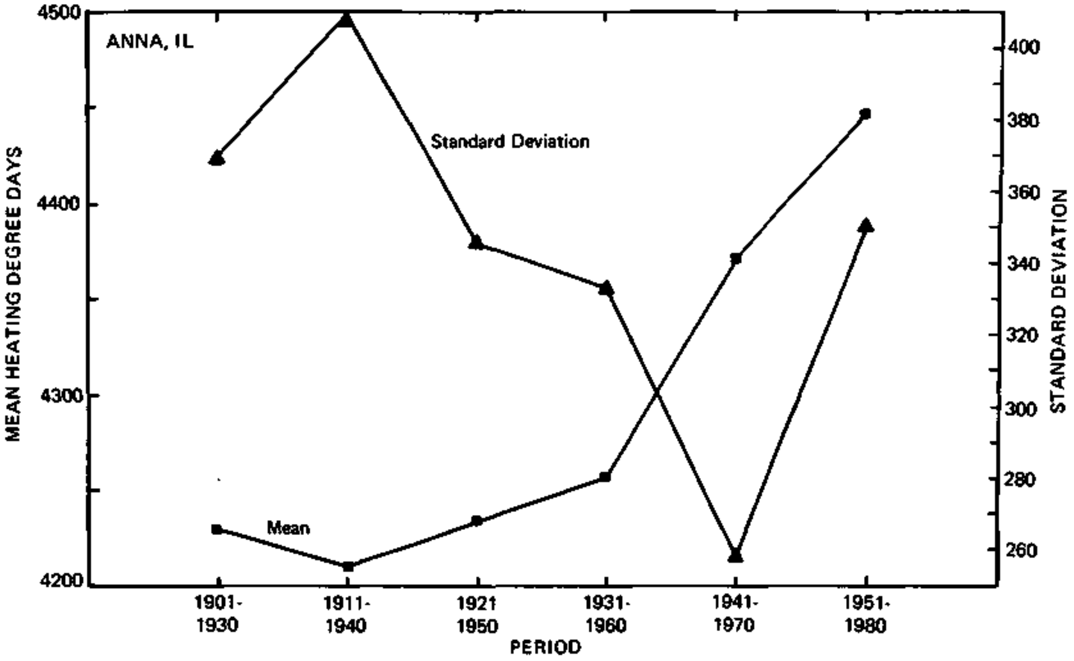

Figure 6. Time series of NWS 30-year means and standard deviations
for Anna, Illinois

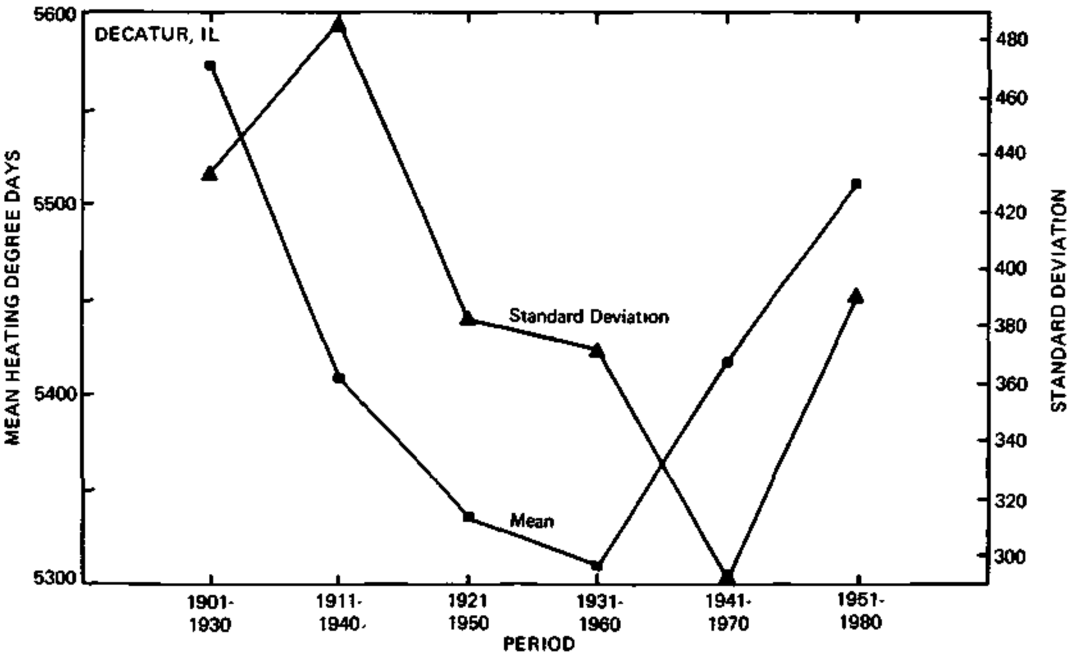

Figure 7. Time series of NWS 30-year means and standard deviations
for Decatur, Illinois

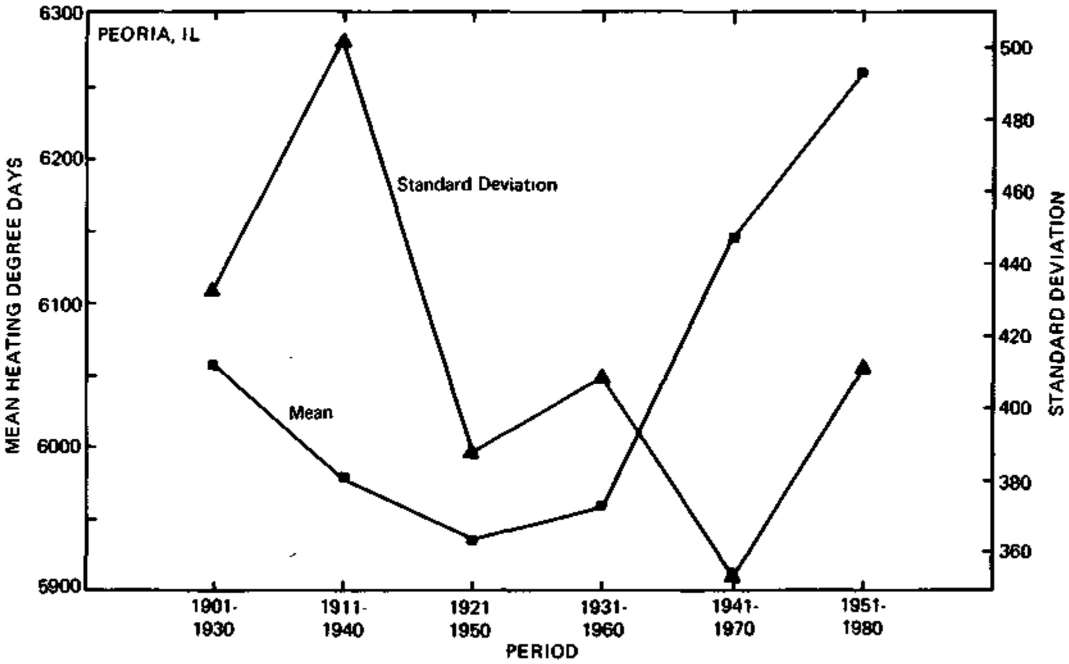

Figure 8. Time series of NWS 30-year means and standard deviations for Peoria, Illinois

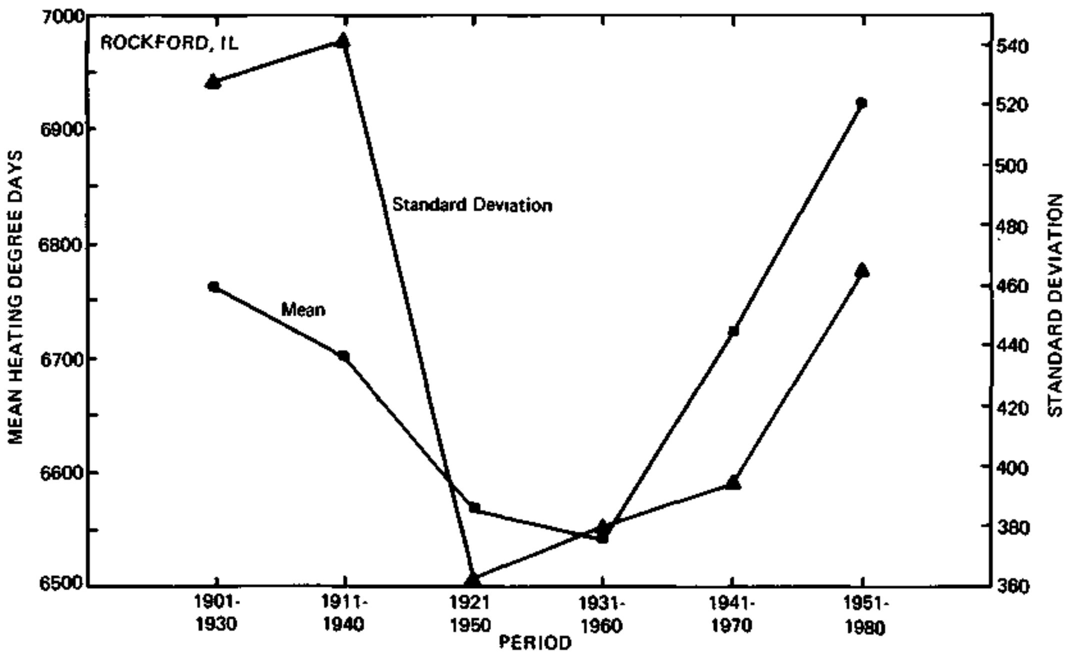

Figure 9. Time series of NWS 30-year means and standard deviations for Rockford, Illinois

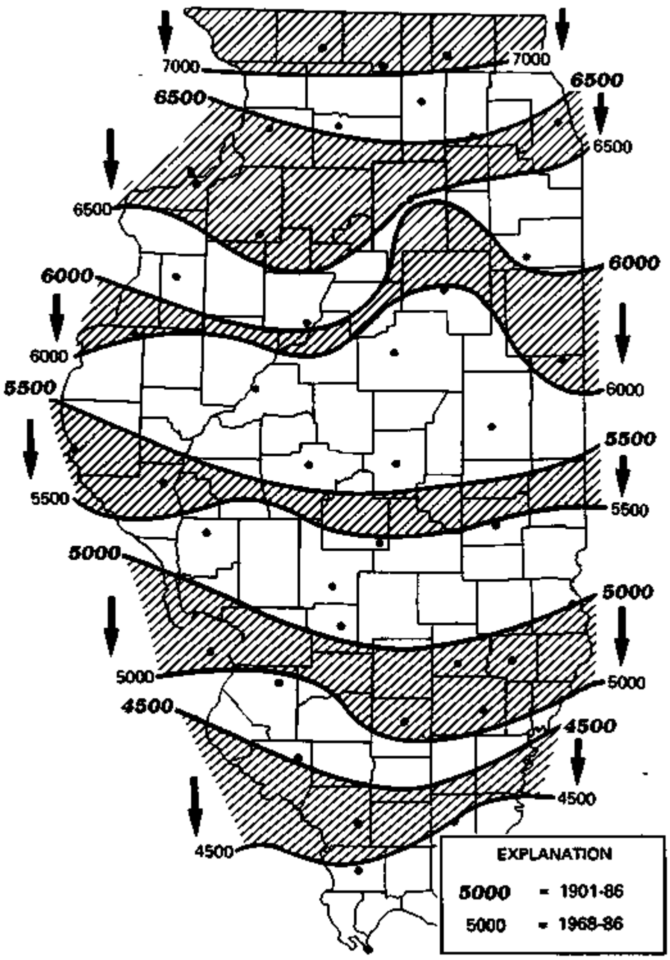

Figure 10. 1968-1986 19-year average annual HDD pattern and 1901-1986 87-year average pattern, showing the shift southward over the last two decades

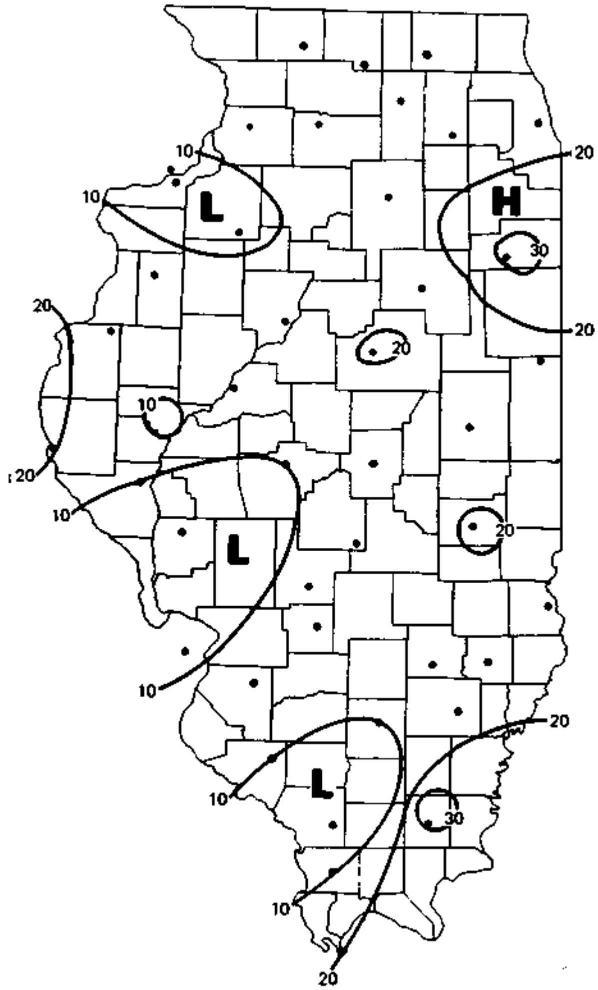

Figure 11. Distribution of the first-ranked annual HDD averaging periods (based on the RMSE method) for the 5-year average prediction period

19-year period is used because it is the averaging period of optimal prediction for more than one year ahead. This comparison suggests that the optimal means may vary spatially somewhat over time.

As figure 11 shows, however, there is minimal spatial variability in the best predictive mean across Illinois at any given time. These patterns are also reflected in the predictions for 1, 2, 3, 4, and 5 years ahead. Exceptions occur just north of St. Louis, around Moline, and in southwestern Illinois, where 8- to 10-year averaging periods do well. The NWS 30-year mean does best only at Kankakee and Harrisburg. These patterns are somewhat consistent for all four methods, but they do change with the length of the prediction.

A map for the extended winter (October-April) (figure 12) shows less organization than noted above. The cluster of shorter means in the St. Louis area disappears, and Chicago and Havana are added to the list of sites where the NWS 30-year mean does well. However, even with the larger number of stations used in this study than in previous studies, the results show homogeneity over the entire state. This implies that irregularities such as in observation times and instrument exposures do not play a strong role in determining the best averaging period because such irregularities would affect each station differently.

Because the 19-year mean is the best predictor overall for the subsequent five years, a map of mean annual HDDs is included for the 19-year period, 1968-1986 (figure 13). This map represents the optimal projection of annual HDDs for 1987 through 1991.

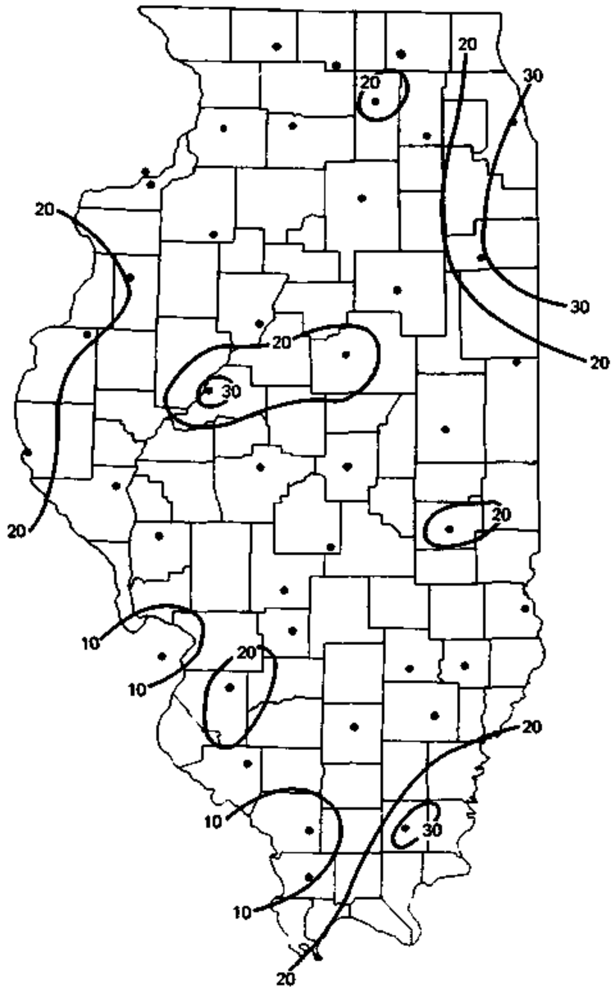

Figure 12. Distribution of the first-ranked averaging periods (based on the RMSE method) over the extended winter (October-April) for the 5-year average prediction period

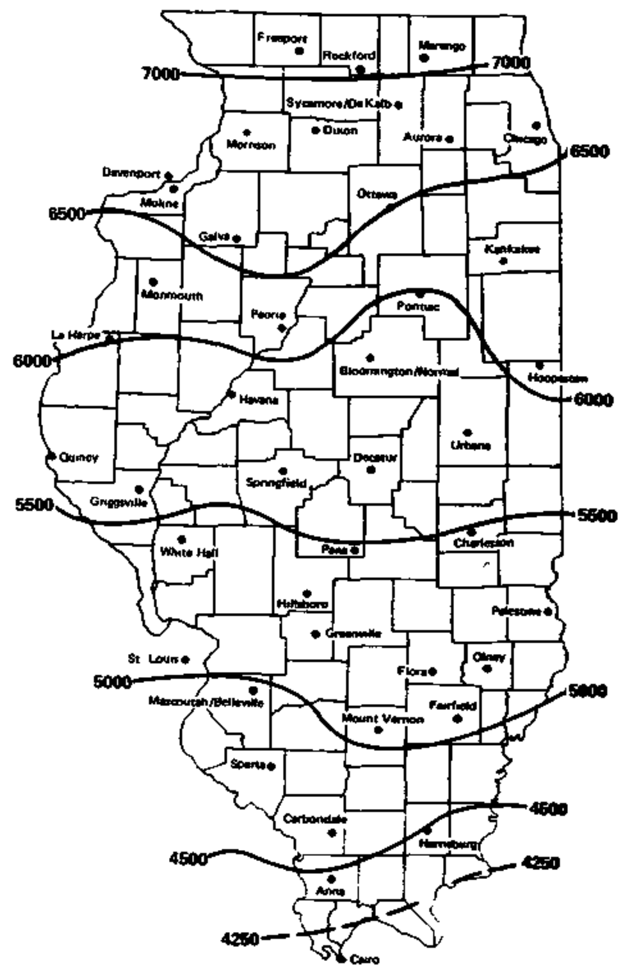

Figure 13. Mean annual HDDs, 1968-1986

Recall that there are small pockets in the state (approximately one-third of the state) where the optimal mean period is not 19 years, and thus the values in figure 13 might not all be optimal. However, it is possible to obtain the appropriate averaging periods for these few small pockets from information in figure 11.

Summary

Daily temperature data from 41 long-term stations in Illinois were used to calculate daily HDD amounts. From these data, monthly, seasonal, and annual HDD totals were calculated, and an analysis was undertaken to seek optimal predictive HDD means. Running means from 1 to 30 years in length and the NWS 30-year mean were used to predict HDDs 1, 2, 3, 4, and 5 years in advance (and for the 5-year average prediction period). Minimization of the difference between the actual and predicted amounts (the predictive error) was the basis for determining the best mean. Four methods previously used in the literature were applied to analyze these predictive errors.

On the basis of the results obtained from the four methods, the means were ranked from best to worst in terms of predictive capability. *An examination of the top-ranked means across Illinois shows that the 11-year mean performed best for predicting 1 year into the future. However, the 19-year mean proved to be the best predictor of individual years 2,3, 4, and 5 years in advance and was also the best overall predictor of the entire 1- through 5-year period.* At the same time, the NWS 30-year mean generally did not perform as well as the other means.

We also addressed four specific issues noted from earlier studies. First, most publications deal with 1-year predictions, which may not always be adequate for applications such as setting gas rates. In this study, predictions were extended from 1 to 5 years in advance to accommodate rate-setting procedures. Differences were found between the best 1-year predictor and the best predictors for the other years.

Second, all four methods (RMSE, MSE, MAE, and WINS) produced nearly the same rankings of the means. While the MAE, MSE, and RMSE methods stressed different aspects of the performance of each mean, the final results between methods were statistically the same. This suggests that the findings reported here are not artifacts of the technique used.

Third, all means from 1 to 30 years in length were used, as opposed to a select few. Consideration of all possible means quite likely explains why our results differ from those obtained by Lamb and Changnon (1981). Although Lamb and Changnon used four of the same stations used here, as well as the same testing technique (WINS), they used only the 5-, 10-, 15-, 20-, 25-, and 30-year means.

Fourth, this study obtains good spatial coverage by including 41 stations across Illinois. This large number also diminishes the influence of single stations for which there may be poor-quality data. The homogeneity of the results across Illinois suggests that choosing optimal means is more closely related to prediction period than to spatial location. There is evidence, however, that spatial distributions of optimal means vary over time, thus requiring consistent updating.

The next section discusses a generalized weather-normalization model that was developed for Illinois. Results of the foregoing analysis were entered in this model to demonstrate, in economic terms, the consequences of using different HDD means.

DEVELOPMENT AND MANIPULATION OF A GENERALIZED WEATHER-NORMALIZATION MODEL FOR ILLINOIS

To provide perspective on the magnitude of impacts on revenues resulting from choice of climatic data for weather normalization, a generalized weather-normalization model was developed. Averaging periods based on analyses from the previous section were inserted into this model. The model described here is run with historical climate data. Its parameters are actual revenue data obtained from an Illinois natural gas company.

Development of the Weather-Normalization Model

Sales of natural gas are related directly and linearly to daily weather conditions as expressed in HDDs (Herbert, 1986; Peoples Gas, Light and Coke Co. [PGL&CC], 1982). Using a linear regression model, Herbert showed that 95 percent of the variability in monthly sales of natural gas to residential customers is explained by the variation in monthly HDDs.

In a document prepared for the Illinois Commerce Commission, Peoples Gas, Light and Coke Company stated that 96 to 97 percent of their daily sales of natural gas to residential, commercial, and light-industrial customers is explained by daily variation in HDDs. Figure 14 shows the relationship between HDDs and volume of gas sold.

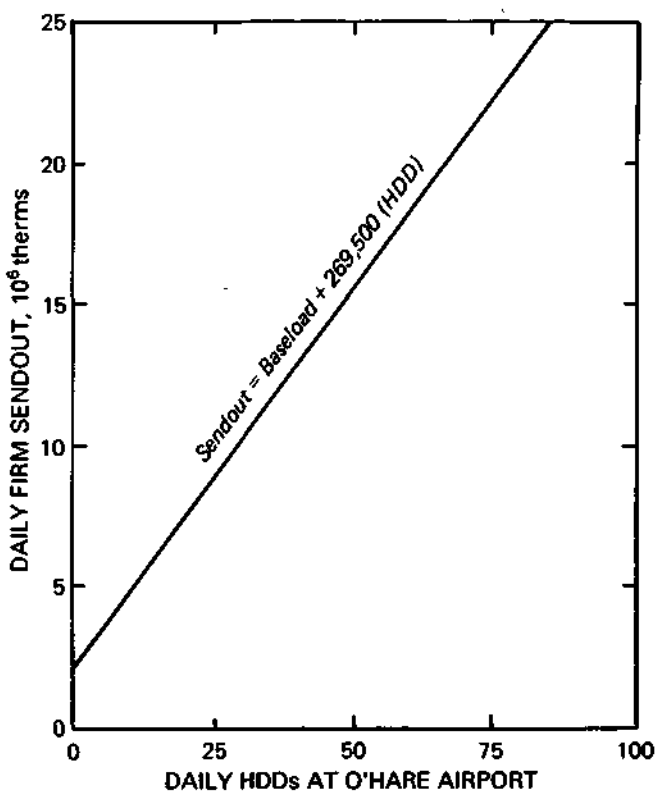

Figure 14. Relationship between daily HDDs and volume of gas sold

Because the data from PGL&CC are readily available and a matter of public record, they form the heart of the weather-normalization methodology used here. Equation 3 is a linear equation derived from the line of best fit shown in figure 14. The equation can be used to predict the volume of gas sold, on the basis of knowledge of daily totals of HDDs.

$$\text{Sendout} = \text{Baseload} + 269{,}500.0\ (\text{HDD}) \qquad (3)$$

In equation 3, sendout is the daily amount of gas sold in therms (a therm equals 100,000 BTU, if a cubic foot of gas is assumed to contain the equivalent of 1,000 BTU), and HDD represents the daily total of HDDs. In this equation, the baseload (the volume of gas sold to satisfy non-space-heating requirements) is equal to 2,000,000.0 therms.

For this study, the actual form of the relationship, that is, its linearity, is more important than the actual numbers that represent the slope and the baseload (i.e., intercept). This linearity, which is argued to exist for all gas utilities, suggests that a relationship like the one shown above could be developed empirically for every gas service area in the state, as well as for different time periods. Equations adapted to specific utilities would have different slopes and baseloads, but all the equations would be linear.

Equation 3 is based on data from the Chicago metropolitan area. Specifically, this equation is based on the volume of gas sold between May 1, 1981, and April 30, 1982, and the HDD values are those computed from O'Hare Airport data for the same period. Although the actual regression coefficients would vary from one region to the next across Illinois or from one time period to the next, the functional form of the relationship (linearity) would not vary.

Therefore, because our objective is to show the relative differences associated with choosing different averaging periods, it is acceptable to use the relationship derived above as a typical expression of the form of the relationship between HDDs and gas volume sold statewide over the period of the study (obviously, actual values in this relationship will vary from location to location or period to period). In reality, a company would use the latest data to reestimate a model such as this each time there is cause to normalize sales (such as for a rate change request or simply for routine annual reporting to the ICC).

The next step in the process was to attach dollar figures to the predicted volumes of gas sales. For this, 1986 gas prices were obtained from an actual mid-state utility as illustrative for the state. The monthly charges that customers are assessed (in this case, customers in the residential rate class) include a monthly facilities charge, a charge related to customers' actual gas consumption, and an adjustment reflecting the current market price of gas.

These data were combined with the sales volume predicted on the basis of daily HDDs, giving sales in 1986 dollars. Of course, by using the appropriate price index, these figures could be adjusted to reflect any year.

The preceding methodology can be used to calculate the relative effects of different averaging periods on sales. Figure 15 details the procedures embodied in a computer program developed to automate the above model.

Input Data Provided to the Model, and Functional Model Elements

Two sets of input data were provided to the model for case runs. The first set included predictive HDD values averaged over optimal averaging periods as discussed previously. These values are assumed to predict the HDD values for a hypothetical test-year case.

The second set included actual HDD values from the test year being predicted. Thus the procedure followed was to compare adjusted revenues produced by predictive HDDs with revenues produced by the actual HDDs in any illustrative test year.

This represents a departure from what is considered an ideal model application. The optimal means used here were developed from the analyses presented previously, which focus on HDD values integrated over months, seasons, and years. The HDD values used in the models, however, are daily totals. So, in essence, HDD means that are optimized on one-time integrations (months, seasons, years) are applied to HDD values of a different integration (daily).

For example, for the test-year case developed for 1970, an 11-year (1959-1969) averaging period was

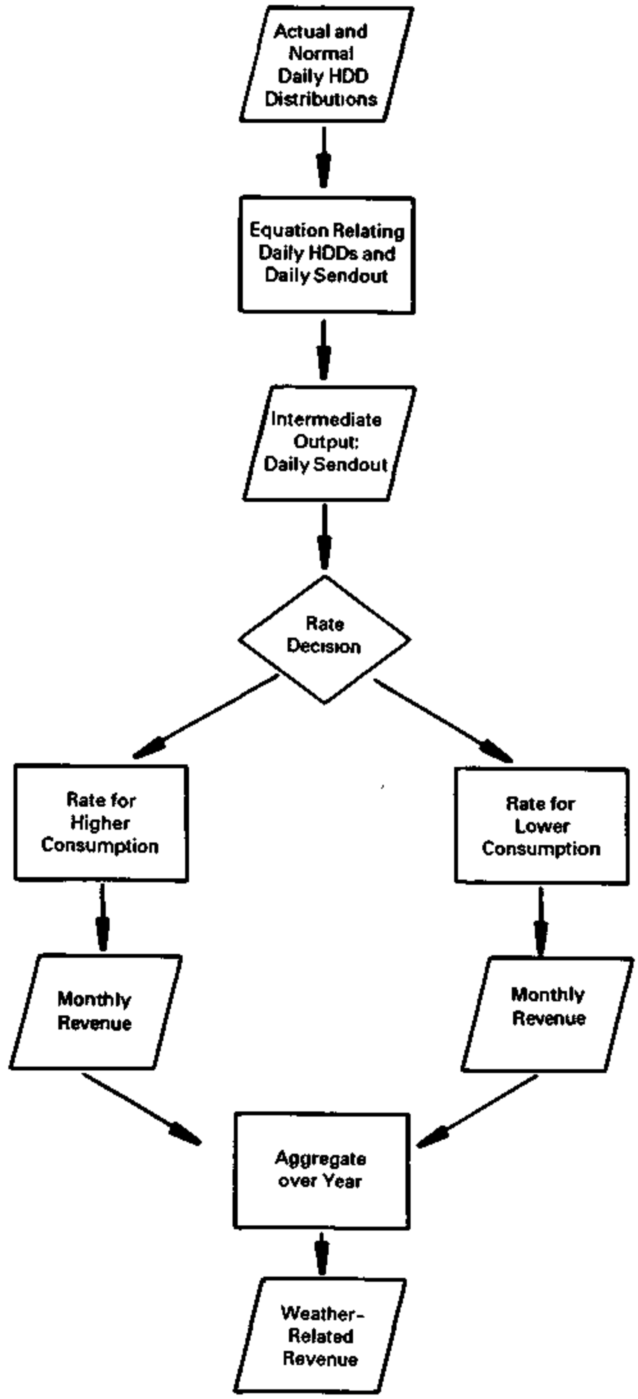

Figure 15. Flow chart of the weather-normalization model

chosen to predict each HDD daily total for the test year. That is, the daily HDD totals were averaged over the 1959-1969 period, resulting in 365 average daily HDD totals.

These HDD totals were all entered sequentially into the model to perform one run of the test-year case revenues adjustment. Then daily HDD totals averaged over the NWS 30-year period (1931-1960) were likewise entered into the model to derive another set of adjusted revenues. The two adjusted revenue sets can then be compared to examine the absolute magnitude of the difference produced by the two averaging periods.

The preceding disparity reflects a compromise between the commonly accepted practice of normalizing with larger time integrations of HDDs (usually annual HDD totals) and the theoretically more correct method of using smaller (daily) HDD time integrations. Smaller time integrations are considered better than integrations longer than a month because of standard billing procedures (discussed below). Wendland (1983) suggests that the use of longer-than-daily time integrations of HDDs does not result in substantive loss of information.

Natural gas utilities use a "block rate" billing structure within a basic billing period (usually a month). Rate blocks are simply different prices per unit (therm) of gas sold. For example, the first units of gas sold to a customer during a month may come from an initial block priced at $5 per unit of gas, whereas the remaining units of gas may come from the next block priced at $3 per unit.

As Gillan (1984) argues, it may be inappropriate to integrate HDDs over time periods longer than a month because consumption may span more than one rate block, thus forming a discontinuous relationship between HDDs, gas consumption, and revenues. To further illustrate, a winter with evenly distributed monthly totals of HDDs and corresponding consumption levels (say, consumption is never high enough to jump to the next block) will reflect different revenues from a winter with the same seasonal HDD totals but with much internal variability, wherein one or more months of extreme cold or warmth will cause consumption to span more than one block.

Although the preceding must be acknowledged, we do not feel that use of daily HDDs poses a significant problem for this study because 1) as long as the integrations are consistent among model runs, comparative evaluations can be made of the degree to which choice of averaging period is reflected in adjusted sales; and 2) to make a comparative evaluation, it is not necessary, nor is it our intention, to develop and demonstrate an absolutely optimal normalization routine.

The primary advantage of setting up the model to accommodate daily HDD averaging periods is that it permits more precise simulation of company revenues than the use of other time integrations. Further research beyond the scope of the present study is needed to determine whether or not use of daily HDDs in weather normalization will require that optimal HDD averaging periods be calculated for each day of the year. It is not clear that sufficient additional information to justify the added complexity would be gained from use of individual daily averaging periods.

The model has two basic functional elements: the price schedule and the relationship between HDDs per day and consumption. The facts that the above relationship is clearly linear (Herbert, 1986; PGL&CC, 1979, 1982), and that this is reflected in the PGL&CC relationship, are sufficient justification for using equation 3 to form the functional core of the model. The choice of the price schedule is constrained by what was obtainable in communications with various companies in Illinois. However, reasonably complete price schedules have been obtained from at least one company and are assumed to be typical for the state.

The assumptions inherent in the model are: 1) the relationship between consumption and weather is linear (justified previously); 2) the hypothetical company serves 880,000 residential customers; and 3) these customers are subject to the price schedule noted below:

Price schedule:

a) Facilities charge = $8.50 per month

b) Commodity charge:
First 90 therms per month = 13.87¢ per therm
Over 90 therms per month = 5.180¢ per therm above 90

c) Adjustment reflecting current market price of gas = 35.00¢ per therm

This price schedule is an approximation of the 1986 residential service classification for the company from which the price schedule was obtained. It was assumed that all customers of this hypothetical company fall in the residential class. Adding in other rate classes would have introduced unneeded complexity, although this could easily be done from a modeling standpoint.

Model Application

In applying the model, the fundamental question addressed was, How would adjusted revenues (in 1986 dollars) be affected if climate normals were the only factors in the normalization model that were allowed to vary?

To address this question, three years in the historic climate record (1942, 1956, and 1978) were selected to serve as hypothetical test years. These years were chosen to represent a period following declines in HDDs (1942), a period with stable HDDs (1956), and a period of increasing HDDs (1978) (see figure 3). Eleven climate stations (figure 1) were chosen (as a subset of the 41 original stations) to give the state balanced spatial representation.

Independent model runs were made by using four categories of HDD values:

1) Daily HDD values from each of the 11 stations for each test year, 1942, 1956, and 1978. (An additional run was carried out to obtain mean annual adjusted revenues for the five-year periods beginning with each of the hypothetical test years.)

2) 11-year means of each daily HDD value, constructed from the 11 years before a test year.

3) 19-year means of each daily HDD value, constructed from the 19 years before a test year.

4) The most recently constructed NWS 30-year daily HDD mean for the test years.

These inputs were based on work described in the first major section of this report. The runs were intended to indicate what hypothetical normalizations would have resembled in 1986 dollars if such historical climatic conditions had been experienced in 1986.

The model outputs are hypothetical gas sales revenues (in 1986 dollars) that would accrue to a company under different assumptions of normal climate. We make no pretense that these outputs perfectly characterize any given company at any given point in time. Furthermore, these figures are not adjusted to reflect operating costs incurred in providing the gas for sales.

However, the model outputs are useful as a means of evaluating, in economic terms, the relative impact on weather normalization produced by different climate means over large gas distribution areas (i.e., those that range in size up to that of Illinois).

Model Results

The model results were used to address three related issues: 1) spatial variation of adjusted revenues in a given hypothetical test year; 2) temporal variation of adjusted revenues between the hypothetical test years; and 3) differences in a given year in adjusted revenues produced by different climatic means. Accordingly, model outputs are displayed in three general forms.

First, for each of the 11 stations and for each of the three hypothetical test years (1942, 1956, and 1978), weather-adjusted revenues were produced based on 1) daily HDD values in a given test year, and 2) daily HDD values averaged over the 5-year period beginning with the test year. The resulting revenues represent the actual weather-adjusted revenues against which to compare predicted adjusted revenues obtained with the predictive average HDDs. Weather-adjusted revenues were then predicted for each test year (and associated 5-year average period) by using 1) the 11-year average HDDs, 2) the 19-year average HDDs, and 3) the NWS 30-year average HDDs (table 17).

Second, absolute intertemporal differences between test-year adjusted revenues were obtained for the means over all stations for each of the five categories described in the previous paragraph (table 18). For example, 11-year adjusted revenues for 1942 were subtracted from 11-year adjusted revenues for 1956. Third, for each station and hypothetical test year, differences were tabulated between revenues adjusted with the NWS 30-year mean and revenues adjusted with the 11- and 19-year means (table 19).

Spatial Variation

The strong and directly linear relationship between degree days and revenues in the model assures a spatial distribution of adjusted revenues that is similar to the HDD distributions discussed previously (table 17). To restate, there is a clear and consistent HDD gradient from a high in the north to a low in the south. Likewise, adjusted revenues show a high in northern areas and a low in the south.

In building a hypothetical test-year case for 1942 across Illinois by using 11-year HDD averaging periods (table 17a), adjusted revenues would range from $1,164,636,000 in Rockford to $879,920,000 in Cairo, a difference of $284,716,000. Moreover, the mean adjusted revenue over the 11 sites (taken as the statewide mean) is $1,042,447,000.

Rockford had an absolute difference of $122,189,000 from this mean, and Cairo had an absolute difference of $162,527,000 from this mean (table 17a). This pattern holds for each of the other averaging periods (19-year and NWS 30-year periods), as well as for the other hypothetical test years (1956 and 1978).

Table 17. Actual and Predicted Adjusted Revenues for Three Hypothetical Test Years: 1942, 1956, and 1978

(In thousands of dollars)

a) 1942

Station	*1942*	*5 years ahead (1942-1946)*	*11-year mean (1931-1941)*	*19-year mean (1923-1941)*	*NWS mean (1911-1940)*
Aurora	1,104,375	1,169,262	1,151,739	1,169,207	1,177,530
Cairo	868,332	871,341	879,920	885,237	890,386
Charleston	976,658	1,021,353	1,018,245	1,028,295	1,035,416
LaHarpe	1,030,107	1,078,254	1,080,853	1,092,186	1,098,196
Morrison	1,085,684	1,137,706	1,133,458	1,145,827	1,157,123
Mt. Vernon	923,361	950,536	951,715	959,507	970,326
Peoria	1,043,894	1,110,357	1,088,526	1,102,314	1,111,087
Rockford	1,099,787	1,163,494	1,164,636	1,177,882	1,190,112
Sparta	891,803	912,831	924,782	929,457	939,982
Urbana	1,017,824	1,064,408	1,065,062	1,079,444	1,088,164
White Hall	972,795	1,002,154	1,007,989	1,022,838	1,029,698
Mean	1,001,329	1,043,790	1,042,447	1,053,835	1,062,547

b) 1956

Station	*1956*	*5 years ahead (1956-1960)*	*11-year mean (1945-1955)*	*19-year mean (1937-1955)*	*NWS mean (1921-1950)*
Aurora	1,176,326	1,181,717	1,172,093	1,165,770	1,163,560
Cairo	892,668	895,413	862,923	872,247	877,018
Charleston	1,088,244	1,074,370	1,021,236	1,023,627	1,020,289
LaHarpe	1,125,088	1,122,541	1,079,071	1,083,197	1,082,867
Morrison	1,164,110	1,161,887	1,143,619	1,141,803	1,140,480
Mt. Vernon	981,332	979,882	956,728	956,078	954,559
Peoria	1,128,389	1,131,802	1,105,310	1,102,343	1,099,689
Rockford	1,191,515	1,201,526	1,161,737	1,163,708	1,169,025
Sparta	944,954	952,702	916,508	921,252	923,440
Urbana	1,091,733	1,091,522	1,051,916	1,058,854	1,068,597
White Hall	1,030,271	1,025,197	996,682	1,004,203	1,011,147
Mean	1,074,057	1,074,414	1,042,529	1,044,825	1,046,424

c) 1978

Station	*1978*	*5 years ahead (1978-1982)*	*11-year mean (1967-1977)*	*19-year mean (1959-1977)*	*NWS mean (1941-1970)*
Aurora	1,263,932	1,221,506	1,177,334	1,184,026	1,178,516
Cairo	965,097	918,787	887,812	891,434	882,318
Charleston	1,146,138	1,091,193	1,033,932	1,039,680	1,036,663
La Harpe	1,225,725	1,148,624	1,114,147	1,113,890	1,097,188
Morrison	1,313,140	1,249,207	1,162,814	1,166,310	1,153,174
Mt. Vernon	1,074,173	1,047,900	980,115	978,821	967,234
Peoria	1,238,854	1,176,916	1,139,696	1,145,960	1,124,897
Rockford	1,322,321	1,272,914	1,218,046	1,219,526	1,189,035
Sparta	1,049,229	992,863	953,867	954,834	938,810
Urbana	1,193,231	1,142,708	1,088,402	1,091,847	1,075,155
White Hall	1,123,036	1,068,091	1,033,352	1,036,026	1,020,058
Mean	1,174,052	1,023,971	1,071,774	1,074,759	1,060,277

Table 18. Intertemporal Absolute Differences between Mean Adjusted Revenues for the Eleven Climate Stations Used in the Model Analysis

(In thousands of dollars)

a) Single test-year actual adjusted revenues

	1942	*1956*
1942	**0**	**0**
1956	**72,728**	**0**
1978	**172,723**	**99,995**

b) 5-year mean actual adjusted revenues

	1942-1946	*1956-1966*
1942-1946	**0**	**0**
1956-1960	**30,624**	**0**
1978-1982	**50,443**	**19,819**

c) 11-year mean adjusted revenues

	1931-1941	*1945-1955*
1931-1941	**0**	**0**
1945-1955	**82**	**0**
1967-1977	**29,327**	**29,245**

d) 19-year mean adjusted revenues

	1923-1941	*1937-1955*
1923-1941	**0**	**0**
1937-1955	**9,010**	**0**
1959-1977	**20,924**	**29,934**

e) 30-year NWS mean adjusted revenues

	1911-1940	*1921-1950*
1911-1940	**0**	**0**
1921-1950	**16,123**	**0**
1941-1970	**2,270**	**13,853**

Table 19. Absolute Differences in Normalized Revenues for 1942, 1956, and 1978 Resulting from Use of Different HDD Means

(In thousands of dollars)

a) 1942

Station	*NWS mean (1911-1940) minus 11-year mean*	*NWS mean minus 19-year mean*
Aurora	**25,791**	**8,323**
Cairo	**10,466**	**5,149**
Charleston	**17,171**	**7,121**
La Harpe	**17,343**	**6,010**
Morrison	**23,665**	**11,296**
Mt. Vernon	**18,611**	**10,819**
Peoria	**22,561**	**8,773**
Rockford	**25,476**	**12,230**
Sparta	**15,200**	**10,525**
Urbana	**23,102**	**8,720**
White Hall	**21,709**	**6,860**
Mean	**20,099**	**8,711**

b) 1956

Station	*NWS mean (1921-1950) minus 11-year mean*	*NWS mean minus 19-year mean*
Aurora	**-8,533**	**-2,21**
Cairo	**14,095**	**4,771**
Charleston	**-947**	**-3,338**
La Harpe	**3,796**	**-330**
Morrison	**-3,139**	**-1,323**
Mt. Vernon	**-2,169**	**-1,519**
Peoria	**-5,621**	**-2,654**
Rockford	**7,288**	**5,317**
Sparta	**6,932**	**2,188**
Urbana	**16,681**	**9,743**
White Hall	**14,465**	**6,944**
Mean	**7,606**	**3,667**

c) 1978

Station	*NWS mean (1941-1970) minus: 11-year mean*	*NWS mean minus 19-year mean*
Aurora	**1,182**	**-5,510**
Cairo	**-5,494**	**-9,116**
Charleston	**2,731**	**-3,017**
LaHarpe	**-16,959**	**-16,702**
Morrison	**-9,640**	**-13,136**
Mt. Vernon	**-12,881**	**-11,587**
Peoria	**-14,799**	**-21,063**
Rockford	**-29,011**	**-30,491**
Sparta	**-15,057**	**-16,024**
Urbana	**-13,247**	**-16,692**
White Hall	**-13,294**	**-15,968**
Mean	**12,208**	**14,482**
Overall mean	**13,304**	**8,953**

Note: Means were calculated by using absolute values.

These results support the conclusion that location in Illinois influences the magnitude of normalization adjustments to revenues. Adjusted revenues based on a single climate mean for the entire state can differ from adjusted revenues based on climate means for specific locations within the state by as much as hundreds of millions of dollars. It is instructive to view these differences as a form of the costs of using location-inappropriate climate means in the normalization of revenues rather than using climate data reflective of the distribution areas of gas companies.

Therefore, it is recommended that climate stations from which HDD means are drawn for making revenue adjustments be reflective of the distribution area of a given company. Moreover, in cases where distribution areas are large or are split into multiple locations, it is desirable to use more than one climate station in the normalization.

Temporal Variation

Intertemporal differences in adjusted revenues are considerable between the hypothetical test years (table 18). To continue with the example of revenues adjusted by using 11-year climatic means, differences (areally averaged over the 11 stations) range from a low of $82,000 between 1942 and 1956 to a high of $29,327,000 between 1942 and 1978 (table 18c). The mean difference over the three hypothetical test years is $19,551,000.

These intertemporal differences were apparent for other climate averaging periods as well (tables 18d and 18e). The average intertemporal differences in adjusted revenues using 19-year means (m = $19,956,000) are similar to those for the 11-year means and are substantially larger than the same figure for the NWS 30-year mean (m = $10,748,000).

These results make two broad generalizations possible. First, although intertemporal differences in adjusted revenues attributed to climatic means are considerable (approximately tens of millions of dollars), they tend to be less important than the differences in revenue adjustments resulting from spatial variability of climatic means. This difference (space versus time) can be as much as one order of magnitude in some instances.

For example, recall that for 1942 the difference in adjusted revenues between Rockford and the statewide mean, based on an 11-year averaging period, is more than $122,000,000. However, statewide mean intertemporal differences (between 1942 and 1956) in adjusted revenues based on an 11-year averaging period are only $82,000.

Second, the fact that there is substantial variability in adjusted revenues when climatic means are calculated for different time periods, all things being equal, demonstrates the potential economic effect of climatic variability on normalizations. Clearly, Illinois experiences persistent periods of climate that differ considerably from that of periods immediately prior or subsequent. Such periods may span the lifetimes of several rate decisions.

Unfortunately, the variation in mean intertemporal differences based on the different averaging periods (tables 18c through 18e) raises many questions. For example, if the goal of weather normalization is to adjust revenues by using climate means that minimize climatic variability over long periods of time — for example, decades or longer — then the longer the averaging period of the mean, the better. This is supported by the relatively small intertemporal differences in adjusted revenues produced by the NWS 30-year means. In contrast, the differences produced by the 11- and 19-year means seem quite large.

There is an important pitfall to avoid with respect to this last point. It may be tempting to assume that smaller intertemporal differences in adjusted revenues (obtained with longer averaging periods) are more stable, more reliable, or otherwise better than larger intertemporal differences. Returning to Court's (1968) suggestion that "normal" is what best predicts the future (the future in this case being a test year or test five years), it is not surprising, and should be considered a positive attribute, that these differences in adjusted revenues between test years are relatively large when using shorter averaging periods (11- and 19-year means). These differences occur because the conditions of normalcy (according to Court) are themselves highly changeable.

Put in terms of relevance to a gas utility, these larger intertemporal differences indicate that shorter averaging periods more accurately portray what is normal within the context of the average lifetime of a particular rate decision (five years or less).

Revenue Variation Resulting from Choice of Climate Normal

We finally turn to the question of the relative effect on revenue adjustments, in a year, that is produced by different averaging periods (table 19). To focus the discussion, we concentrate on the individual differences between the 11- and 19-year means and the NWS 30-year mean.

We chose 11- and 19-year means because our previous analysis suggests that they are most effective in predicting HDDs for 1 and 5 years in advance, respectively, and we compared them with the NWS 30-year mean because of its inferior predictive capabilities and because it remains widely used.

As with the intertemporal variations in adjusted revenues, we propose that differences in adjusted revenues between an optimal averaging period and any other averaging period for a given hypothetical test year can be thought of as the economic costs of using inappropriate climatic information.

Table 19 shows large apparent revenue differences between the NWS 30-year mean and both the 11- and 19-year means. For example, in 1942, the absolute difference in adjusted revenues between use of an 11-year mean and the NWS 30-year mean totaled more than $25 million for Rockford. These differences remain large for all stations and all years. This demonstrates that choice of averaging period does make a significant difference in the magnitude of a revenue adjustment.

These results point to a potentially significant conclusion. In Illinois, some level of revenue adjustment disparity exists between the commonly accepted method of normalization (using NWS 30-year means) and a climatically optimal normalization (as defined in this study). This is based on Court's (1968) premise of "normal" climate (discussed previously and adhered to in this study), and on acceptance that the means found in this study to best capture this definition of normal are in fact optimal.

In accordance with these premises, it is also possible to conclude implicitly that there are costs associated with using the less-than-optimal NWS 30-year means to adjust revenues. These costs are borne either by the utility (as when overestimating warm-weather effects on revenues by using too low an HDD normal), or by the utility's customers (as when overestimating cold-weather effects on revenues by using too high an HDD normal).

Summary

This section presented a generalized revenues normalization model developed for this study. The model is based on a documented linear and direct relationship between HDDs and gas sales revenues. The model was calibrated with 1986 dollars and applied uniformly across Illinois, allowing only climatic inputs to vary in any given application.

The model was run for three different hypothetical test years (1942, 1956, and 1978) at 11 sites across Illinois. Variable inputs, as mentioned previously, were restricted to the differently defined climatic normals (11-year, 19-year, and NWS 30-year means) plus HDD values for each test year, and were averaged for the five years beginning with each test year.

The findings of this exercise include:

1) Location within Illinois accounts for large differences in revenue normalizations because of normal spatial variations in HDDs. Revenues adjusted by using a single average climate mean for the entire state can differ from revenues adjusted by using climatic means from specific locations within Illinois by hundreds of millions of dollars.

This points to the importance of the climate data used being reflective of climatic conditions within gas distribution areas. For larger gas distribution areas, more than one station should be integrated into the normalization for the area.

2) Intertemporal differences in revenue adjustments for any site are considerable (tens of millions of dollars) and suggest that natural temporal variability in climate means (within periods of 30 years or less) should be accounted for when establishing standards for performing normalizations. Larger temporal variations in revenue adjustments between test years are produced by shorter means (11- and 19-year means) than by the longer NWS 30-year mean. This shows that shorter-term means perform better and more precisely than the longer means in capturing what is normal in a given period — a finding supported by the climate analysis of the first section of the report.

3) Choice of climate mean at a given location and time can produce differences in revenue adjustments that approximate tens of millions of 1986 dollars. The average differences over the 11 sites in adjusted revenues based on 11-year means and revenues based on the NWS 30-year means were $20,099,000 for 1942, $7,606,000 for 1956, and $12,208,000 for 1978.

The differences between adjustments using 19-year means and those using the NWS 30-year means were $8,711,000 for 1942, $3,667,000 for 1956, and $14,482,000 for 1978.

The normalization model developed here, and the dollar figures produced from it, do not presume to capture all of the intricacies of an actual normalization precisely. However, this model is instructive in illustrating relative impacts on revenue adjustments produced by climate data. Moreover, on the basis of this model, we conclude that differences in revenue adjustments produced by optimal climate means from those produced by other climate means represent costs (either to a utility or to its customers) of using inappropriate climate information.

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