Journal of Personality and Social Psychology
1987, Vol. 52, No. 6, 1161-1173

Copyright 1987 by the American Psychological Association, Inc.
0022-3514/87/$00.75

Temperature and Aggression: Effects on Quarterly, Yearly, and City Rates of Violent and Nonviolent Crime

Craig A. Anderson
Rice University

The hypothesized relation between uncomfortably hot temperatures and aggressive behavior was examined in two studies of violent and nonviolent crime. Data on rates of murder, rape, assault, robbery, burglary, larceny–theft, and motor vehicle theft were gathered from archival sources. The first three crimes listed are violent; the latter four are less violent (labeled *nonviolent*). On the basis of previous research and theory (Anderson & Anderson, 1984), it was predicted that violent crimes would be more prevalent in the hotter quarters of the year and in hotter years. Furthermore, it was predicted that this temperature–crime relation would be stronger for violent than for nonviolent crime. Study 1 confirmed both predictions. Also, differences among cities in violent crime were predicted to be related to the hotness of cities; this effect was expected to be stronger for violent than for nonviolent crimes. Study 2 confirmed both predictions, even when effects of a variety of social, demographic, and economic variables were statistically removed. Theoretical and practical implications are discussed.

Environmental factors affect a wide variety of aggression-related phenomena. For example, negative affect and interpersonal disliking are related to uncomfortably hot temperatures and to crowding (e.g., Bell, Garnand, & Heath, 1984; Griffitt, 1970; Griffitt & Veitch, 1971). Unpleasant odors influence physical aggression against others (Rotton, Frey, Barry, Milligan, & Fitzpatrick, 1979). The concentration of negative and positive ions in the air affects aggression and moods (Baron, Russell, & Arms, 1985; Charry & Hawkinshire, 1981). High ozone levels have been associated with increased family violence and assaults (Rotton & Frey, 1985). In sum, considerable evidence suggests that naturally occurring variations in our immediate environments exert powerful influences on social and antisocial affects and behaviors.

The most intensively studied relation, though, is that between temperature and aggressive behavior. Early theoretical thinking, as well as the prevailing folklore, postulated a positive linear (or at least monotonic) relation, with increasingly hot temperatures leading to increased aggressive behavior. Laboratory studies yielded mixed results, with the hot temperatures sometimes producing increased aggression and sometimes decreased aggression (e.g., Baron, 1972; Baron & Lawton, 1972). Subsequent laboratory studies suggested that negative affect mediated the temperature–aggression relation and that the relation was curvilinearly shaped in the form of an inverted U (Baron & Bell, 1976). (See Baron, 1979, for a review of this literature; see also Palamarek & Rule, 1979.) Up to moderate levels of negative affect, increases in negative affect (resulting from increasingly uncomfortable temperatures, for example) would produce increased aggression. At high levels of negative affect, though, further increases in negative affect (or hot temperatures) would increase attempts to escape from the situation. To the extent that such escape behaviors are incompatible with aggressive behaviors, the result would be decreased aggression at the highest levels of negative affect. For instance, the best way to reduce the negative affect produced by an argument with a neighbor in hot weather is to stop arguing and go inside your air-conditioned house.

There are, however, several interpretational and methodological problems with the curvilinear model and associated data (see Anderson & Anderson, 1984). Most revolve around the obviousness of temperature manipulations in the laboratory and possible subject reactions or strategies deriving from awareness of what is being tested. Field studies in which subjects do not know they are participating in a study avoid these problems.

Data from a variety of field studies examining the temperature–aggression relation have yielded primarily linear effects, with high temperatures producing the highest levels of aggression. For example, Carlsmith and Anderson (1979) found that between 1967 and 1971 the probability of a riot in the United States increased monotonically with ambient temperature. Anderson and Anderson (1984) examined daily frequencies of crimes in two major cities. In both cities, the frequency of violent crimes was positively linearly related to temperature; in neither case was there a quadratic (curvilinear) relation. Furthermore, when they adjusted for the level of nonviolent crimes, the predicted linear trend was still highly significant. In addition, the adjustments yielded a significant quadratic effect, but one that was precisely opposite in form to that predicted by the negative affect model derived from the laboratory studies discussed earlier. That is, increases in temperature at the high temperature range were associated with larger increases in violent crime than were corresponding increases in temperature at

I thank Morgan Slusher, Lynn Arnoult, David Lane, Constantine Tsedikides, Robert A. Baron, and Douglas T. Kenrick for their comments on an earlier version of this article.

Correspondence concerning this article should be addressed to Craig A. Anderson, Department of Psychology, P.O. Box 1892, Rice University, Houston, Texas 77251.

the moderate temperature range. Recently, Harries and Stadler (1983; Harries, Stadler, & Zdorkowski, 1984) showed similar linear effects on assaults in another major U.S. city.

Thus the field studies clearly show that even at very high temperatures (and presumably high negative affect) aggressive behavior increases with further increases in temperature. Two explanations for this contradiction of the laboratory studies seem particularly plausible. First, as suggested earlier (and in Anderson & Anderson, 1984), a variety of artifactual processes in the labs may result from subject awareness of temperature manipulations. That is, the inverted U model may be wrong, and the supportive data may be artifactual. Second, it may be that in those field settings that potentiate violent crimes, the perpetrators cannot readily escape the circumstances inducing the negative affect, whereas subjects in the lab can do so. That is, the inverted U model may be correct only in those limited circumstances where the person can escape the conditions that are producing the negative affect and where escape involves performing only nonaggressive behaviors. In the real world, of course, negative affect is often produced by circumstances we cannot control or avoid. Indeed, we sometimes cannot even identify the sources of our discontent.

Regardless of which explanation is true, it would appear that one should expect essentially linear relations between temperature and aggression in most real-world settings. The theoretical rationale for this prediction is as follows. Uncomfortably hot temperatures produce a generally negative level of arousal and negative affect. This negative affect is then transferred (cf. Zillmann, 1978) to a salient object in the person's immediate attention, an object that can be seen by the person as a reasonable source of the negative arousal. It may be, for instance, a spouse with whom one is arguing. In this way, negative arousal from a variety of sources (including temperature, ozone, ions, and lack of sleep) may be attributed to or focused on a ready target. If the negative arousal is sufficient, and if escape from the negative circumstances is not possible, aggressive behavior will be directed at the target. The exact process through which negative affect produces aggression has been the subject of much debate for many years (e.g., the frustration–aggression hypothesis, Miller, 1941). One may attack a perceived source of negative arousal as punishment for having created the arousal. At a less conscious level, negative arousal may automatically prime aggressive interpretational and behavioral schemata because of their semantic or associationistic similarity (cf. Berkowitz, 1984). Regardless of how one gets from negative affect to aggression, this model suggests that in most settings, increases in temperature will be associated with increases in aggressive behaviors even at very hot temperature levels.

Before accepting this pronouncement as true, though, note the interpretational problems with the field studies to date. The major problem is that they all are based on correlational data. Thus, causal statements are risky at best. For example, temperatures are highly related to seasonal events such as vacation time, students being out of school, and alcohol consumption, events that might influence crime rates.

One can control for this confounding to some extent in several ways. In the Anderson and the Harries studies, temperature effects were assessed after the effects of various time cycles (e.g., months, days of week) were partialed out. Anderson and Anderson (1984) also reasoned that violent and nonviolent crimes are probably related to many of the same confounded factors and that one should therefore correct for nonviolent crime rates when examining temperature effects on violent crime rates.

The best control for necessarily confounded (i.e., correlational) data is replication of hypothesized conceptual relations with the use of different measures in different contexts. This triangulation procedure works because the hidden or uncontrolled confounds present in a particular study will typically be absent in different studies of the same relation. If the hypothesized relation is obtained in such different studies, one can be more confident that postulated confounds do not account for the relation. To the extent that studies using a variety of measures of aggression in a variety of contexts all yield the same temperature–aggression relation, we can be confident that the relation is due to actual temperature effects rather than to uncontrolled artifacts.

Overview

The present pair of studies follows this triangulation rationale in extending previous work on the relation between temperature and aggression. Both studies examine variations in violent and nonviolent crime indexes as a function of temperature-related variables. Violent crimes were expected to be positively related to temperature. Nonviolent crimes may also be positively related to temperature, either because of confounds with variables related to temperature (e.g., alcohol consumption) or because of the aggressive component inherent in nonviolent crimes. In either case, violent crimes were expected to be more highly related to temperature than were nonviolent crimes because the behaviors involved are considerably more aggressive in nature. The first study examined crime rates in the United States over a 10-year period as a function of quarter of year (first, second, third, and fourth) and year (1971–1980). The second study examined crime rates in different cities as a function of a variety of social, economic, demographic, and environmental variables.

Study 1

In the United States, quarters of the year are closely related to temperature. In particular, the second and third quarters (April through September) have considerably more hot days than the first and fourth quarters. Therefore, one might expect violent crimes to be particularly prevalent in the second and third quarters. In addition, some years are notably hotter than others. Thus, one might also expect year effects that are related to temperature differences among years.

Method

Data were taken from the Federal Bureau of Investigation's (FBI's) *Uniform Crime Reports for the United States* (U.S. Department of Justice, 1981, 1982). For each quarter of the 10-year period of 1971 through 1980, a crime index was reported for each of seven crimes: murder, rape, aggravated assault, robbery, burglary, larceny–theft, and motor vehicle theft. The FBI crime index for each crime was created by setting the number of crimes reported in the first quarter of 1971 at 100. Changes in the number of crimes reported in subsequent quarters were reflected in proportional changes in the index. For instance, a murder index score of 200 meant that twice as many murders were reported in that quarter as were reported in the first quarter of 1971. A separate set of z scores was computed for each crime on the basis of the 40 data points for that crime. These seven crimes were then combined (z-score averages) into a violent crime index and a nonviolent crime index for each quarter of the 10-year period. The former consisted of murder, rape, and aggravated assault; the latter, of the remaining four crimes.[1]

The temperature–aggression model predicts a greater incidence of violent crime in the second and third quarters because those quarters are the hottest in the United States. The prediction for effect of years is less straightforward. First, an estimate of how hot in general the various years were must be created. To do this, data from the 1971 through 1980 issues of *Climatological Data* (U.S. Department of Commerce, 1983a) were examined. Specifically, for each of 240 reporting stations throughout the United States, the number of hot days that occurred in each year was recorded and averaged across stations. The 240 stations selected were all those stations that had reported this data for each of the 10 years. The definition of a hot day was that the maximum temperature recorded was ≥32.2 °C (90 °F). The yearly averages derived by this procedure were used to assess temperature effects on crime across years.

Results

I used analysis of variance (ANOVA) procedures to assess the effects of quarter and year in a 4 × 10 design, with one replication per cell. For each dependent variable, the quarter main effect ($df = 3$) was additionally partitioned into two pieces: a contrast testing the temperature–aggression hypothesis that the second and third quarters would yield the most crime, and the residual from that contrast. Year effects ($df = 9$) were similarly partitioned into several pieces. The temperature–year effect was assessed by using standard regression techniques on the hot day yearly averages discussed earlier. Essentially, the hot day averages become contrast weights in this procedure. Residual year effects (residual from the hot day "contrast") were also assessed. Finally, note that the Quarter × Year interaction was used as the error term because there was only one data point per cell (see Winer, 1971). A term incorporating Tukey's test for nonadditivity was included to see if the most likely (and most explainable) type of interaction existed. In none of the analyses that follow was this term significant, so it was dropped in the reported analyses.

Four dependent variables were assessed in this way. I examined violent crime and nonviolent crime measures first to see if temperature-related variables predicted either type of crime. The most stringent version of the temperature–aggression hypothesis, however, holds that the temperature–crime relation will be stronger for violent than for nonviolent crime. I created two other dependent variables to address this hypothesis more directly; they, too, were analyzed as outlined previously. First, a violent–nonviolent crime difference score was examined. Significant temperature effects on this variable would mean that temperature had a larger effect on one type of crime than the other. This is essentially a Temperature × Type of Crime interaction. Second, the effects of nonviolent crime were removed from violent crime rates via a covariance analysis. This was done because the two types of crime correlated very highly in this data set ($r = .77$), presumably because many of the variables affecting one (e.g., economic conditions, seasonal socialization patterns, and perhaps temperature) also affect the other. Temperature effects on this adjusted violent crime measure would thus be relatively free from unwanted confounds.

Violent Crime

Quarter of year proved to be a highly significant predictor of level of violent crime, $F(3, 27) = 87.43$, $p < .0001$. More important, the contrast testing the temperature–aggression hypothesis was also highly significant, $F(1, 27) = 137.28$, $p < .0001$. Violent crime was considerably higher in the second and third quarters ($M = 147.0$) than in the first and fourth ($M = 129.2$). The residual from this contrast was also highly significant, $F(2, 27) = 62.51$, $p < .0001$, apparently because violent crime was considerably higher in the third quarter ($M = 156.0$) than in the second ($M = 138.1$). This latter difference also was quite significant, $t(27) = 8.30$, $p < .0001$, and may be due to the fact that the third quarter (July, August, and September) is the hottest of all.

Year effects, in general, were very strong, $F(9, 27) = 40.20$, $p < .0001$. Temperature differences among years accounted for a highly significant portion of violent crime differences, $F(1, 27) = 105.16$, $p < .0001$. More violent crimes occurred in the hotter years than in the cooler years. The residual year effect (after accounting for temperature differences) was also very strong, $F(8, 27) = 32.09$, $p < .0001$. Inspection of the year means suggested that part of the residual year effect might have resulted from a general increase in violent crime over time. Further analysis revealed that this linear year effect was quite significant, $F(1, 27) = 210.03$, $p < .0001$. The new residual year effect (after accounting for both temperature differences and the linear year effect) was still significant, $F(7, 27) = 6.67$, $p < .0005$.

Nonviolent Crime

Quarter of year also yielded a significant effect on the level of nonviolent crime, $F(3, 27) = 10.18$, $p < .0001$. The contrast testing the difference between the average of the second and third quarters ($M = 113.6$) against the first and fourth quarters ($M = 110.7$) was also significant, although considerably less so than the corresponding contrast effect for violent crime, $F(1, 27) = 6.57$, $p < .02$. The residual from this contrast also was significant, $F(2, 27) = 59.86$, $p < .0001$. Apparently this resulted because the fourth quarter mean was higher than the temperature-based contrast would have it ($M = 117.4$) and because the second quarter mean was lower ($M = 108.15$). These results suggest that nonviolent crime is related to temperature somewhat, but not to the same extent as violent crime. As expected, the difference between violent and nonviolent crime rates was greater in the hottest quarters of the year, as shown in Figure 1.

The year effect on nonviolent crime was significant, $F(9, 27) = 22.84$, $p < .0001$. As in the violent crime analysis, a regression (contrast) analysis revealed that the temperature

[1] Note that the nonviolent crimes contain some aggression or violence. They are, however, considerably less violent than those summarized by the violent crime index. The label *nonviolent* is simply easier to use and think about than *violent-but-less-so-than-the-others*.

differences among years accounted for a significant portion of the year effect, $F(1, 27) = 15.08, p < .001$. Note that this is again considerably smaller than the comparable effect on violent crime. That is, the "hotness" of years seemed to have more impact on violent than on nonviolent crime, as shown in Figure 2.

The residual year effect on nonviolent crime was highly significant, $F(8, 27) = 23.81, p < .0001$. Nonviolent crime appeared to increase over the 10-year period. This linear year effect accounted for much of the residual year effect, $F(1, 27) = 76.89, p < .0001$. However, the new residual year effect (after accounting for temperature differences and linear year effects) was still significant, $F(7, 27) = 16.23, p < .0001$.

In sum, the analyses of violent and nonviolent crime showed both to be related to quarterly and yearly temperature differences. Also, as expected, the temperature effects appeared stronger for violent crime than for nonviolent crime.

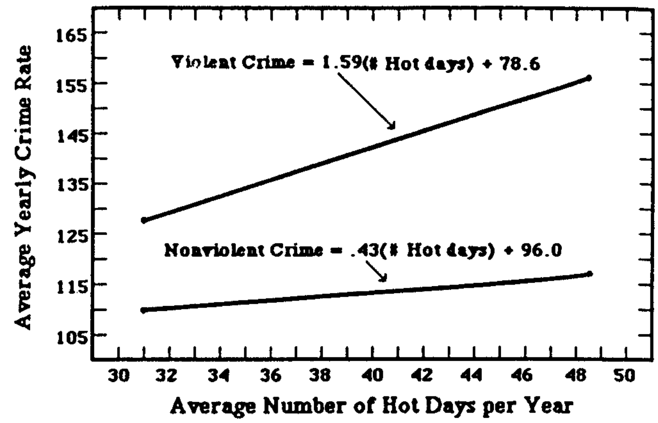

Figure 2. Effects of yearly differences in temperature on violent and nonviolent crime rates, United States, 1971–1980.

Violent–Nonviolent Crime

The aforementioned analyses do not directly test the most precise version of the temperature–aggression hypothesis. Specifically, they do not show that temperature affects violent crime rates significantly more than it affects nonviolent crime rates, although Figures 1 and 2 suggest that this interaction exists. The simplest and most direct way to test this hypothesis is to subtract nonviolent crime rates from the corresponding violent crime rates to see if the predicted temperature effects still obtain. Note that a repeated measures ANOVA, with type of crime as the repeated measure, yields essentially the same tests of the Type of Crime × Temperature (quarter and year) interactions.

The results of this analysis confirmed the reliability of the interactions suggested by Figures 1 and 2. First, the quarter effect was highly significant, $F(3, 27) = 45.00, p < .0001$, indicating that the quarter effects differed as a function of type of crime. More important, the predicted contrast was highly significant, $F(1, 27) = 119.80, p < .0001$. That is, the violent crime rates were considerably larger than nonviolent crime rates in the hotter second and third quarters ($M = 33.46$), but only moderately so in the cooler first and fourth quarters ($M = 18.48$).[2]

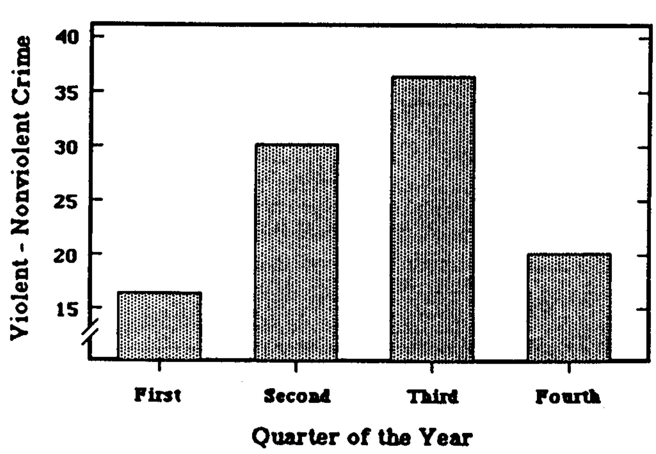

Figure 1. The difference between violent and nonviolent crime rates by quarter of the year, United States, 1971–1980.

The residual from the contrast was also significant, $F(2, 27) = 7.60, p < .01$. It resulted from the fact that violent crime was most elevated in the third quarter, relative to nonviolent crime, possibly because that is the hottest quarter. Indeed, the violent–nonviolent crime difference was significantly greater in the third quarter ($M = 36.97$) than in the second ($M = 29.95$), $F(1, 27) = 13.14, p < .0001$. The residual quarter effect, after removing the variance explained by these two contrasts, was not significant, $F(1, 27) = 2.06$.

As expected from the previous analyses and from Figure 2, the year effect was also significant, $F(9, 27) = 23.41, p < .0001$, indicating that the year effects differed for violent and nonviolent crime. The specific test of whether temperature differences among years were differentially related to violent and nonviolent crime rates was also significant, $F(1, 27) = 68.04, p < .0001$. In essence, this confirms that the slopes in Figure 2 are significantly different from each other; temperature differences among years were more strongly related to violent crime rates than to nonviolent crime rates.

The residual year effect was significant, $F(8, 27) = 17.83, p < .0001$. Inspection of the means by year suggested that violent crime increased more rapidly over years than did nonviolent crime. This linear year effect was highly significant, $F(1, 27) = 80.88, p < .0001$. However, the residual year effect was still significant even after removing both the temperature year and the linear year effects, $F(7, 27) = 8.82, p < .0001$.

Adjusted Violent Crime

Recall that the reason for comparing the temperature effects on violent and nonviolent crime is to control for confounded

[2] Recall that these are standardized indexes of crime equated at 100 in the first quarter of the 10-year period under investigation. Actual nonviolent crime rates are much higher than actual violent crime rates. Also note that an alternative analysis was carried out. Specifically, a violent crime ratio was computed by dividing violent crime rates by their corresponding nonviolent crime rates, as in Anderson & Anderson (1984). This analysis also revealed that temperature had a larger effect on violent than on nonviolent crime.

factors that correlate with temperature and crime (e.g., economic conditions). The difference analysis already described provides one way to do this. An alternative is to remove the effects of nonviolent crime (and presumably the confounded effects) from violent crime rates statistically and examine temperature effects (via quarter and year analyses) on the adjusted violent crime rates.

As previously reported, nonviolent crime was highly correlated with violent crime ($r = .77$), indicating that many of the same variables influence the different types of crime. The effect of nonviolent crime as a covariate in the ANOVA on violent crime was highly significant, $F(1, 26) = 354.64$, $p < .0001$. The effects of nonviolent crime were removed statistically, and the ANOVA was computed on the adjusted violent crime rates (with the loss of 1 degree of freedom).

The quarter effect on adjusted violent crime was still quite strong, $F(3, 26) = 26.38$, $p < .0001$. The crucial contrast between the hot second and third quarters (*M*s = 143.7 and 146.3, respectively) and the cool first and fourth quarters (*M*s = 132.6 and 129.9) was highly significant, $F(1, 26) = 76.43$, $p < .0001$. The residual from this contrast was not significant ($p > .25$).

Once again, the year effect was significant, $F(9, 26) = 16.00$, $p < .0001$. More important, the temperature differences among years accounted for a significant portion of the adjusted violent crime differences, $F(1, 26) = 36.28$, $p < .0001$. The residual year effect was also significant, $F(8, 26) = 13.46$, $p < .0001$. Inspection of the adjusted violent crime means revealed that violent crime increased more with time than did nonviolent crime. This linear year effect was highly significant, $F(1, 26) = 27.66$, $p < .0001$. The new residual year effect (after accounting for temperature differences and the linear year effect) was still significant, $F(7, 26) = 11.43$, $p < .0001$.[3]

Discussion

Study 1 provides strong support for the temperature–aggression hypothesis. Specifically, periods in which more hot days occurred were associated with increased violent crime. This occurred both within years, as shown by the quarter effects, and between years, as shown by the temperature–year effects. This occurred to a significantly greater extent for violent than for nonviolent crime. This occurred even when violent crime rates were statistically adjusted for level of concomitant nonviolent crime.

Although the statistical results clearly confirm the temperature–aggression hypothesis, they do not give us a good feel for the magnitude of the effect. To assess this, I used the regression results of the temperature–year analysis of adjusted violent crime to estimate the proportional change in violent crime to be expected from a 10-day change in the number of hot days experienced in a year. The result was that a year with 10 more hot days than normal produced about 7% more murders, rapes, and assaults. Thus, the effect of temperature seems both reliable and of a fairly large magnitude.

The importance of getting both quarter and year temperature effects should not be overlooked. Had only a quarter effect been observed, alternative explanations relying on a variety of seasonal differences would have been plausible. For instance, the second and third quarters have longer daylight hours, contain the traditional vacation times, are filled with more outdoor activities, are the focus of youth vacations from school and youth unemployment, and may be associated with increases in alcohol consumption. Thus, increases in violent crime rates may be due to increased opportunity, increased frustration, decreased inhibitions, and other seasonal effects rather than to temperature.

However, most such alternative explanations, for either quarter or year effects, cannot account for both. For instance, although the increased free time of youths out of school may be a plausible explanation for increased violence in the second and third quarters, it cannot explain the temperature effects of different years. Youths are out of school in the summer regardless of whether it is a hot or cool year. This is an example of triangulation within the same study. The same reasoning rules out a variety of alternative explanations, such as the seasonal unemployment rates of youths and amount of daylight hours.

Similarly, one should not overlook the importance of two additional findings: (a) quarter and year temperature effects were larger on violent crime than on nonviolent crime, and (b) even when nonviolent crime effects were partialed out, the quarter and year temperature variables were still related to violent crime. The high correlation between these two types of crimes ($r = .77$) suggests that they are influenced by many similar variables. But the temperature–aggression hypothesis states that hot temperatures should influence violent crimes the most. Thus, partialing out the effects of nonviolent crime should have removed most extraneous confounds with quarter and year temperature differences and left the pure temperature effects on violent crime relatively untouched. Similarly, the difference score analysis directly compared the size of temperature effects on violent and nonviolent crime. In sum, these results provide further internal triangulation evidence against many alternative explanations. Increases in free time and alcohol consumption, for instance, would be expected to influence both violent and nonviolent crimes. Yet the second and third quarters (associated with increased free time and alcohol consumption) showed increases primarily in violent crime.

Obviously, such internal triangulation and statistical procedures are not perfect solutions to the causality question in correlational data. But each additional data set supporting the basic temperature–aggression model should increase confidence in it. The case for the temperature–aggression hypothesis would be strengthened considerably if predictions derived from it were supported in a very different context (external triangulation). One such prediction concerns the crime rates in different cities. If hot temperatures do produce increases in violent crime, we should expect cities located in hot climates to have higher violent crime rates than cities in cooler climates. This should hold when the effects of correlated variables such as nonviolent

[3] An even more conservative test of the Type of Crime × Temperature–Year interaction is to remove linear year effects first. That is, one can test the unique variance of the temperature–year contrast for both the violent–nonviolent crime difference measure and for the adjusted violent crime measure. This assumes that all shared variance is actually due to the linear year effect. In both cases the interaction was still significant, $Fs(1, 27) \geq 6.55$, $ps < .02$.

crime, economic conditions, and social characteristics have been statistically removed. Study 2 examines this prediction.

Study 2

The basic unit of analysis in Study 2 was the Standard Metropolitan Statistical Area (SMSA) established by the Census Bureau. (These areas will be called cities throughout the rest of this article.) The goal of this study was to test the temperature–aggression hypothesis by seeing whether cities in hot climates had higher violent crime rates than cities in cooler climates. Although the basic idea is simple, testing it is complex. The most difficult problem concerns differences between cities that are confounded with temperature. Cities differ in many ways that are correlated with geographic location (hence, temperature) and with crime. These social variables include the economic characteristics, racial composition, age, and education of the residents, to mention just a few. Thus, any reasonable test of the temperature–aggression hypothesis requires that the effects of these social variables be controlled statistically.

Method

Data for this study were obtained from four archival sources. Crime rates for each of 260 cities were obtained from the 1980 FBI *Uniform Crime Reports of the United States.* (Several other SMSAs had incomplete crime data.) The reported crimes were the same as in Study 1. A violent crime index based on *z*-score averages of murder, rape, and aggravated assault rates was computed for each city. A similar nonviolent crime index, based on robbery, burglary, larceny-theft, and motor vehicle theft, was also computed.

Several climate variables were obtained from the 1980 volume of *Climatological Data: National Summary.* For each city, the following measures were obtained: number of hot days (≥32.2 °C, 90 °F), cooling degree days (amount of cooling needed to maintain a comfortable base temperature of 18.3 °C, 65 °F), average humidity, number of cloudy days (80 to 100% cloud cover), number of rainy days (≥.25 mm), number of cold days (≤0 °C, 32 °F), heating degree days (amount of heating needed to maintain a comfortable base temperature of 18.3 °C, 65 °F), and number of snowy days (≥25.4 mm). Preliminary analyses indicated that the snow, rain, and humidity variables did not contribute significant unique increments to the prediction of crime; they were dropped from all reported analyses.[4]

Social variables were obtained from two volumes of the 1980 census report: the *Census of the Population: General Population Characteristics* (U.S. Department of Commerce, 1983b), and the *Census of the Population: General Social and Economic Characteristics* (U.S. Department of Commerce, 1983c). The following variables were obtained: unemployment, per capita income, poverty rate, mobility (percentage living in a different home in 1975), high school education (percentage of the ≥25-year-old population that had graduated), college education (percentage of the ≥25-year-old population that had attended 4 or more years), population size, percentage Black, percentage Spanish,[5] percentage less than 18 years old, percentage 18 to 64 years old, percentage 65 and over, median age, number of law enforcement employees.

A derived variable, police, was computed by dividing the number of law enforcement employees by the population. Note that the law enforcement employee estimates were not reported by SMSA, but by city. To estimate these for each SMSA, the totals for cities falling in a given SMSA were computed. Data for several cities were missing, so the derived variable, police, also had several missing data points.

Several other variables had a few missing data points. Therefore, the degrees of freedom in the subsequent analyses vary as a function of which variables were used.

A second derived variable was computed by subtracting nonviolent crime rates from the corresponding violent crime rates. The reason for doing so was the same as in Study 1: to control for unmeasured correlated variables that influence crime rates in general and simultaneously to allow a test of the critical hypothesis that temperature influences violent crime more so than nonviolent crime. In essence, this difference variable provides tests of interactions involving type of crime (violent vs. nonviolent).

Also as in Study 1, the relation between violent and nonviolent crime rates was quite strong ($r = .72$), suggesting that many of the same extraneous variables influenced both types of crime in a similar way. Thus an adjusted violent crime index was computed in which the relation between violent and nonviolent crime was statistically removed via regression procedures. Again, the reason for doing so was to eliminate, as far as possible, confounding influences on the temperature–aggression relation under investigation. In sum, the analyses that follow were conducted on four crime variables: violent crime, nonviolent crime, violent crime minus nonviolent crime, and adjusted violent crime.

Results and Discussion

Data analysis consisted of two major steps. First, a social model of crime was derived for each of the four crime variables. To do this, I performed a number of regression analyses to test the various social variables (economic, demographic, etc.) listed earlier. The goal of this preliminary step was to identify those variables that contributed most to the prediction of crime so that their effects could be partialed out before the climate variables were tested. Fourteen social variables were measured. Thus, it was impossible to test a social model complete with all interactions. Such a model would contain 91 two-way, 364 three-way, 1001 4-way interactions, and so on, but there were only 216 data points without missing values. Therefore, two simplifying assumptions were made. First, I assumed that three-way and higher order interactions would be negligible, uninterpretable, and most likely the product of Type I errors. Second, I assumed that there would be no true crossover two-way interactions. The implication of this is that one need examine only the two-way interactions involving variables that have yielded some evidence of main effects.

On the basis of this reasoning, I performed regression analyses to identify social variables with significant main effects for each of the four crime variables. I then examined two-way interactions involving variables with significant main effects. For both sets of analyses (main effects and two-ways), the least significant predictor was dropped in successive runs until all variables kept in the model were significant at an alpha of .05. Note that all significance tests were conducted on the unique (unconfounded) variance.

---

[4] Because humidity contributes to perceptions of comfort, one might expect humidity effects. In naturally occurring variations in temperature and humidity, however, temperature variations contribute more to comfort than do humidity variations. Thus humidity typically fails to contribute significant unique increments (Kenrick & MacFarlane, 1984).

[5] This refers to people of Spanish-speaking origins (e.g., Hispanics or Mexican Americans). *Spanish* is the designation used by the Census Bureau.

Table 1
Social Model of Violent Crime

Variable	Main effects $F(1, 243)$	$r(251)$	Regression slope	Variable	Two-way interactions $F(1, 235)$	Regression slope
Black	109.68	.57	+	Black × High School	30.64	+
Moved	47.70	.36	+	Spanish × High School	25.26	+
College	42.79		−	Moved × Income	21.52	+
Spanish	23.13	.21	+	Income × College	15.79	−
Income	16.64		+	Black × College	13.92	−
Young	9.52		−	Black × Spanish	9.49	+
High school	4.96		+	Spanish × College	8.31	−
Poverty	4.57	.35	+	Black × Young	3.88	−
Population	4.53	.27	+			

Note. Black = percentage of Blacks in population; moved = percentage living in a different home in 1975; college = percentage of adults with a college education; Spanish = percentage of population of Spanish-speaking origin; income = per capita income; young = percentage under 18; high school = percentage of adults with a high school education; poverty = percentage living below poverty level; population = population size in thousands. Only effects significant at .05 are listed.

Once the social model of each type of crime was established, I performed the second major step in the analysis. This was to see to what extent the climate variables added significant unique increments to the prediction of crime.

Social Models

Violent crime. Differences among cities in violent crime rates were well predicted by 9 variables and 8 of their interactions. This does not mean that the 17 retained predictors (9 main effects, 8 interactions) should be interpreted as causal agents in violent crime, nor should one assume that deleted predictors are all causally unrelated to violent crime. Such inferences, which would require much more evidence than is available from one study (i.e., the need for triangulation), are beyond the scope of this article. However, the retained variables do account for an amazingly large portion of the violent crime variance ($R^2 = .75$). Thus, the model provides an excellent (albeit conservative) base for examining climate effects.[6]

The social model for violent crime is presented in Table 1. Included are the F values, the raw correlation with violent crime (where significant), and the direction of the slope estimate associated with the predictor. Note that the variables are listed in order of effect size and that each effect (reported by the F) is the unique increment of that predictor, controlling for all of the other variables listed in the table. (Of course, main effects are not tested with interactions in the model; Cohen & Cohen, 1975.) Although interpretation of these results is beyond the scope of this article, a description of several of the results may make it easier to understand the results in the table.

The largest main effect was for percentage of Blacks, $F(1, 243) = 109.68$, $p < .0001$. The simple correlation between violent crime and percentage of Blacks was .57 ($p < .0001$). The sign of the slope from the regression model was positive, as in the simple correlation, indicating that the larger the proportion of a city's population that was Black, the more violent crimes were reported.

The largest interaction was Black × High School, $F(1, 235) = 30.64$, $p < .0001$. The sign of the slope (positive) indicates that the relation between percentage of Blacks and violent crime became more positive as the percentage of adults in the city who were high school graduates increased.

The Income × College interaction had a negative slope. This indicates that the negative relation between the percentage of college graduates in a city and violent crime rate (the main effect of college) became more negative as average income level increased.

Nonviolent crime. The social model for nonviolent crime is presented in Table 2. Eight variables were retained as main effects; 10 interactions also were significant. The Black variable yielded the most significant unique variance to the prediction of nonviolent crime, $F(1, 224) = 39.25$, $p < .0001$. Examination of the simple correlations, though, revealed that population size (and several other variables) had higher correlations with nonviolent crime than did percentage of Blacks. This discrepancy is not at all unusual in regression analyses of this type, where the various predictors are themselves highly intercorrelated. It simply reflects the difference between testing the unique (i.e., unconfounded) relation versus the confounded one (i.e., the simple correlation). As was seen with violent crime, the social model of nonviolent crime also accounted for most of the variance among cities ($R^2 = .69$).

Violent–nonviolent crime. Differences between violent and nonviolent crime rates across cities were well predicted by the eight social variables listed as main effects and by the five interactions given in Table 3. The best predictor, in terms of both unique variance and simple correlation, was percentage of Blacks in the population. That is, cities with proportionally

[6] The tests are conservative in that the variance shared by the social model variables and the temperature variables is removed completely from the temperature variables. Note also that the cautions about interpreting the social models made earlier, and the claims for the use of these models as bases for testing the climate effects, hold for the nonviolent crime, the violent–nonviolent crime differences, and adjusted violent crime analyses to be reported later.

Table 2
Social Model of Nonviolent Crime

Main effects				Two-way interactions		
Variable	$F(1, 224)$	$r(231)$	Regression slope	Variable	$F(1, 214)$	Regression slope
Black	39.25	.26	+	Black × Spanish	13.52	+
Moved	36.05	.28	+	Age × Police Ratio	13.25	+
Spanish	31.02	.29	+	Moved × Spanish	12.71	−
Income	30.72	.38	+	Black × Police Ratio	10.37	−
Population	17.66	.47	+	Spanish × Police Ratio	9.65	−
Age	16.69		+	Income × Police Ratio	8.21	−
Police ratio	13.15	.37	+	Income × Population	7.58	−
Unemployed	7.48		+	Black × Income	7.00	+
				Age × Unemployed	6.97	+
				Black × Population	6.81	−

Note. Black = percentage of Blacks in population; moved = percentage living in a different home in 1975; Spanish = percentage of population of Spanish-speaking origin; income = per capita income; population = population size in thousands; age = median age; police ratio = number of law enforcement employees/population; unemployed = adult unemployment rate. Only effects significant at .05 are listed.

larger Black populations tended to have the largest preponderance of violent crime. The model accounted for most of the variation in violent–nonviolent crime rate differences ($R^2 = .56$).

Adjusted violent crime. When nonviolent crime was first removed from violent crime (via regression procedures), the social model of (adjusted) violent crime changed somewhat. Table 4 presents these results. Five variables yielded significant main effects; three interactions also were significant. This model accounted for 79% of the variance in violent crime.

Climate Effects

Violent crime. Each of the climate variables was added separately to the social model, and the unique contribution was assessed. For violent crime, each temperature variable added significantly, whereas the remaining climate variables did not. As expected, the number of hot days and the cooling degree-days measures were positively related to violent crime, whereas the number of cold days and the heating degree-days measures were negatively related to violent crime, $Fs(1, 234) \geq 7.21$, $ps < .01$. That is, even after accounting for and removing the effects of a variety of social variables, temperature was still strongly related to violent crime rates. Cities that had more hot days, required more cooling, had fewer cold days, and required less heating had significantly elevated rates of violent crime.

In subsequent analyses, the temperature measures were pitted against one another by including two at a time in the model and testing unique increments. Because these measures were highly intercorrelated, the unique increments of each decreased, as expected. For instance, when the number of hot days and the number of cold days were both in the model, the unique variance of cold days was not significant, but the unique variance of hot days was, $F(1, 233) = 5.43$, $p < .03$. The only finding of interest from these analyses was that number of cold days consistently contributed the least unique variance.

Nonviolent crime. The results of the climate variable analyses of nonviolent crime contrasted sharply with the violent crime

Table 3
Social Model of Violent–Nonviolent Crime Differences

Main effects				Two-way interactions		
Variable	$F(1, 217)$	$r(224)$	Regression slope	Variable	$F(1, 212)$	Regression slope
Black	46.42	.46	+	Unemployed × Police Ratio	25.05	−
Police ratio	20.42		−	Moved × College	17.39	+
College	14.26	−.22	−	College × Young	7.87	+
Moved	13.99		+	Young × Police Ratio	7.14	+
Young	7.33	.28	+	Unemployed × Young	5.54	+
Poverty	6.09	.41	+			
Unemployed	5.56		−			
Population	5.17	−.20	−			

Note. Black = percentage of Blacks in population; police ratio = number of law enforcement employees/population; college = percentage of adults with a college education; moved = percentage living in a different home in 1975; young = percentage under 18; poverty = percentage living below poverty level; unemployed = adult unemployment rate; population = population size in thousands. Only effects significant at .05 are listed.

Table 4
Social Model of Violent Crime With Nonviolent Crime Effects Partialed Out

	Main effects				Two-way interactions	
Variable	$F(1, 220)$	$r(224)$	Regression slope	Variable	$F(1, 217)$	Regression slope
Black	168.55	.57	+	College × Police Ratio	9.40	+
Moved	39.54	.20	+	Moved × Spanish	7.12	+
College	25.65	−.14	−	Moved × Police Ratio	6.70	+
Police ratio	16.41		−			
Spanish	15.65		+			

Note. Black = percentage of Blacks in population; moved = percentage living in a different home in 1975; college = percentage of adults with a college education; police ratio = number of law enforcement employees/population; Spanish = percentage of population of Spanish-speaking origin. Only effects significant at .05 are listed.

results. Briefly, none of the climate variables contributed significant unique variance in predicting nonviolent crime, $Fs(1, 213) \leq 2.46$, $ps > .12$. This result, in combination with the violent crime results already reported, strongly supports the hypothesized temperature–aggression relation. However, it does not directly test the hypothesis that temperature will have a significantly greater impact on violent than on nonviolent crime rates. The violent–nonviolent difference score analysis tests this interaction prediction.

Violent–nonviolent crime. Only one of the temperature measures was reliably related to differences between violent and nonviolent crime rates. The number of hot days experienced in the cities was positively related to the preponderance of violent crime, $F(1, 211) = 4.15$, $p < .05$. That is, number of hot days was more strongly related to violent crime than to nonviolent crime to a significant degree. None of the other climate variables was significant by itself.

One variable, however, did become significant when added to the model along with number of hot days. Specifically, the amount of cooling required to maintain a comfortable temperature became significantly (and positively) related to the difference between violent and nonviolent crime, $F(1, 210) = 5.38$, $p < .01$. In this model, number of hot days became somewhat more significant as well, $F(1, 210) = 9.48$, $p < .001$.

These results directly test and provide strong support for the temperature–aggression hypothesis. Even after controlling for a wide range of social variables, the hotness of a city was positively related to violent crime rates, but not to nonviolent crime rates. Furthermore, the difference in the temperature relations with these two types of crimes was statistically reliable.

Adjusted violent crime. Although all the temperature variables produced effects in the expected direction, once again only number of hot days yielded a significant unique increment in predicting violent crime adjusted for nonviolent crime. The number of hot days was strongly and positively related to adjusted violent crime, $F(1, 216) = 11.28$, $p < .001$. In addition, number of hot days remained highly significant ($p < .005$) regardless of which other climate variables were entered in the model with it. Thus it is clear that the temperature of a city, in particular the number of truly hot days, is strongly related to the rate of violent crime in that city.

None of the nontemperature climate variables was significant when added to the social model by itself. Interestingly, one variable became highly significant when added to the social model along with number of hot days. Number of cloudy days became a significant predictor of adjusted violent crime, $F(1, 198) = 12.07$, $p < .001$. The relation was positive, with more violent crime in cities with more cloudy days. This relation appeared only when number of hot days was in the model, probably because these two variables are themselves negatively related. That is, the positive relation between hot days and violent crime obscured the cloudy-day–violent-crime relation. This finding is consistent with previous work linking amount of sunshine (lack of cloud cover) to mood and helping behavior (Cunningham, 1979). It is important to note that number of hot days remained a highly significant predictor of violent crime even when number of cloudy days was in the model, $F(1, 198) = 22.55$, $p < .0001$.

These regression results were also used to estimate the magnitude of the temperature effects. Consider two hypothetical cities of moderate size (600,000), identical in all respects except climate. Assume that City A is 1 standard deviation hotter than City B (i.e., it has 42 more hot days per year). The present results suggest that City A will experience about 7% more violent crimes than City B. That is, City A will have (in each year) about 140 more murders, rapes, and assaults.

Finally, note that the same basic temperature–crime relations reported in the regression analyses also appear in the simple correlations. All of the significant climate and social variable correlations with crime, based on those cities having complete data, are reported in Table 5.[7]

General Discussion

Temperature–Aggression Relation

The results of these two studies provide powerful support for the temperature–aggression hypothesis. Considering all the published field studies on temperature and aggression, it becomes clear that increases in temperature lead to increases in

[7] Some pairs of variables had complete data on all 260 cities. The correlations based on varying samples did not differ in any appreciable way.

Table 5
Simple Correlations Between the Crime Variables and the Climate and Social Variables

Variable	Crime variable: Violent crime	Non-violent crime	Violent–nonviolent crime	Adjusted violent crime
Climate				
No. hot days	.52***	.20*	.46***	.55***
No. cold days	−.60***	−.36***	−.36***	−.49***
Heating degree days	−.65***	−.40***	−.38***	−.53***
Cooling degree days	.53***	.28***	.37***	.48***
Humidity				
Cloudy	−.36***	−.34***		−.18*
No. rainy days	−.37***	−.33***		−.20*
No. snowy days	−.48***	−.35***	−.22*	−.34***
Social				
% Black	.57***	.26**	.46***	.56***
% recently moved	.39***	.35***		.21*
% college		.28***	−.20*	
Police ratio	.23**	.33***		
% Spanish	.37***	.35***		
% unemployed				
Per capita income		.33***	−.36***	−.27**
Poverty rate	.48***		.44***	.52***
% high school graduates		.19*	−.34***	−.30***
Population	.29***	.40***		
% young (< 18 years)			.29***	.25**
% adult (18 to 64 years)				
% elderly (≥65 years)				
Median age				

Note. $N = 206$. Only correlations significant at .01 are listed.
* $p < .01$.
** $p < .001$.
*** $p < .0001$.

aggression. The relation has been shown in a variety of ways with a variety of measures of aggression at a variety of levels of analysis. Carlsmith and Anderson (1979) showed that the conditional probability of a riot is linearly (or monotonically) related to temperature. Anderson and Anderson (1984) found that the number of daily violent crimes increased directly as a function of temperature, in two different cities. They also showed that this effect did not occur for nonviolent crimes and that adjusting for nonviolent crimes did not eliminate the violent crime–temperature relation. Study 1 of the present article revealed temperature effects on overall U.S. violent crime as a function of quarter of the year and among years. Finally, Study 2 showed that temperature differences could account for a significant portion of differences in violent crime rates between U.S. cities.

A common reaction to data of this type is to attempt to discover potential confounds that may explain the results. This is scientifically healthy, as correlational data are risky bases for causal analysis, thus the need for the process I have labeled *triangulation*. A brief look at the most obvious possible confounds is warranted, for if they cannot be dismissed, the present results become much less important.

The major problem in these data is that temperature is correlated with time of year and with various social and behavioral factors. A variety of seasonal effects, including adults' vacations, school vacations, hours of daylight, youth unemployment, and free time, may be dismissed for a variety of reasons. Specifically, temperature-related year effects (Study 1) as well as temperature-related city effects (Study 2) occurred despite the irrelevance of the seasonal variables just listed. And as previously mentioned, in the earlier Anderson and Harries studies the effects of various time cycles (months, days of week) were partialed out, yet temperature–aggression effects were still obtained. Thus the obtained effects cannot be accounted for by the seasonal variables.

More potential alternative explanations can be created, of course. Space limitations preclude a listing (and rebuttal) of all that I have created or encountered. Thus I leave it to the reader to consider additional ones and to test their applicability across the wide range of studies on the temperature–aggression relation. Barring some new, robust alternative, it seems safe to conclude that temperature effects on aggression are real, fairly strong, and certainly important.

Linear (Monotonic) Versus Curvilinear Effects

Present Studies

Study 1 does not provide a good opportunity to test the curvilinear model with any degree of precision. One could examine the various violent crime measures for curvilinear (quadratic) effects of yearly differences in temperature, but their nonsignificance would tell us little. This is because hotter years will have more moderately warm days than cooler years, not just more hot days. Thus both the linear and the curvilinear models are consistent with an essentially linear temperature effect in these aggregate data. Such tests were conducted, however, because a significant negative quadratic component (i.e., an inverted U) would be somewhat difficult for the monotonic position to explain.

The only finding of interest from these analyses was a significant positive quadratic component on the violent–nonviolent difference score, $F(1, 27) = 4.75$, $p < .05$. That is, not only did hotter years tend to produce significant linear increases in violent crime rates (relative to nonviolent rates), but this positive relation was accelerated in the relatively hottest years, a result most consistent with the monotonic model (cf. Anderson & Anderson, 1984).

Study 2 does not allow a simple, conclusive test of the monotonic (linear) versus curvilinear positions either, but it does allow several indirect tests. First, if aggression does in fact decrease at high temperatures (defined as above 85 °F by previous scholars), we should expect the variable *number of hot days* (defined as being above 90 °F) to be unrelated (or only marginally related) to violent crime. What relation there is should result from some correlation between number of hot days and number of moderately hot days. Thus cities with large numbers of hot days should experience fewer violent crimes on those days, canceling out the increased violence experienced on moderately hot days. This assumes, of course, that number of moderately hot (e.g., 81–85 °F) and number of hot days (e.g., >90 °F) is less than perfectly correlated across cities. Inspection of temperature distributions for 89 cities analyzed by Carlsmith and Anderson (1979) revealed that some cities had more hot than moderately hot days (primarily in the South and Southwest), whereas most cities had more moderately hot than hot days, confirming this assumption. The fact that number of hot days was the best climatological predictor of violent crime speaks strongly against the curvilinear hypothesis.

Second, the curvilinear model suggests that if we can remove general temperature effects but leave the hot days effects intact, we should see a negative relation between number of hot days and violence. The various measures of temperature do tap into slightly different aspects of temperature, and number of hot days certainly is more sensitive to extremely hot days than are the other measures. Nonetheless, in no case did the number of hot days–violence relation become negative when hot days was entered into models along with other temperature variables. Indeed, the other temperature variables (number of cold days, heating degree days, and cooling degree days) tended to lose their significance when the effects of number of hot days were removed.

The only exception to this pattern occurred with the violent–nonviolent crime rate differences. There, amount of cooling necessary to maintain a comfortable temperature became significant only when number of hot days was in the model (the F for cooling changed from 0.13 to 5.38). This confirms that these temperature measures assess different aspects of the temperature characteristics of a city. Most important, though, was the finding that even when the effects of this other temperature variable were removed, the effect of number of hot days still predicted the relative increase in violent crime at hotter temperatures.

Third, a quadratic temperature term (number of hot days squared) was included to see if it contributed significantly (beyond the linear effect) to the prediction of violent crime, violent–nonviolent crime rate differences, and adjusted violent crime. Basically, this term tests the curvilinear prediction that cities with many hot days would have violent crime rates lower than or equal to cities with a moderate number of hot days. The tests were nonsignificant (Fs < 1).[8]

Other Interpretational Difficulties

One difficulty in examining the linear–curvilinear hypotheses in many field studies is that crimes (such as murders, rapes, and riots) do not all take place at the hottest time of day. In addition, the affect–aggression models cannot specify how long a time negative affect can last. Presumably, if one gets in a foul mood for a variety of reasons, including being uncomfortably hot, this mood may translate into negative assessments of others that may persist long after the transient (but causal) factors such as temperature are no longer present. Thus the high frequency of violent actions on hot days (as in the Anderson & Anderson, 1984, violent crime studies, or the Carlsmith & Anderson, 1979, riot study) may be either linearly caused by negative affect, malevolent intentions, and aggressive actions; created by the hot temperatures; or curvilinearly caused by aggressive tendencies created by an increase in occurrence of moderate temperatures in the night (on hot days) and during the day.

A recent field study by Kenrick and MacFarlane (1984) provides triangulation evidence that is not amenable to the time-of-day defense of the curvilinear model. The important feature of this study was that aggression and temperature were assessed at the same time of day. These researchers examined the relation between temperature and car horn honking at an experimenter whose car blocked the subject's car at the exit from a residential tract. The major result was that aggression (horn honking) was linearly related to temperature. Furthermore, the effect was more pronounced for subjects in cars with windows rolled down (not air conditioned).

Another defense of the curvilinear position is that the inflection point, where aggression should decrease with further increases in temperature, is seldom reached in the field and then for only limited periods of time in a given hot day. This criticism may be partially valid for the present studies. Certainly, only a small portion of the person–days in the United States have temperatures above 90 °F. Again, triangulation from other studies makes this alternative untenable. For example, in Anderson and Anderson's (1984) study of violent crime, one of the target cities was Houston, Texas (Study 2). In Houston, a large portion of the days have very hot temperatures, bad traffic problems, air pollution, and other features known to increase levels of negative affect, presumably beyond the inflection point. Similarly, the Kenrick and MacFarlane (1984) study was conducted in the spring and summer in Phoenix, Arizona, with temperatures well above the theoretical inflection point.

One final defense of the curvilinear hypothesis involves consideration of the broader context in which hot temperatures are experienced. As temperature increases, people may take action to reduce their negative affect. They may get out of the sun, enter air-conditioned buildings, or take cold showers. If the curvilinear model is correct, these actions may reduce negative affect to the most aggressive (midrange) level. Aggressive actions under these conditions would show up on hot days, however, resulting in a misleading linear or monotonic pattern.

Although this alternative explanation seems plausible, there are several reasons to doubt it. First, this position predicts that those who are moderately successful at reducing temperature-induced negative affect should show the largest increase in aggression in hot weather. However, Harries et al. (1984) showed that the hot summer effects on aggressive crime rates are most pronounced in neighborhoods where air conditioning is scarce.

Second, riots typically begin and take place in locales (i.e., outdoors in lower income neighborhoods) where the means to reduce negative affect do not exist. Thus this alternative suggests that the probability of a riot should decrease at hot temperatures. Carlsmith and Anderson (1979), however, showed increases in riot probabilities at high temperatures.

Finally, consider the subjects in the Kenrick and MacFarlane (1984) horn-honking experiment in Phoenix. On hot days, those with air conditioning should have had a moderate level of negative affect while waiting for the experimenter's car to move out of the way and, therefore, should have been maximally aggressive according to the curvilinear model. On cooler days, the air-conditioned subjects should have had low levels of negative affect and low levels of aggression. Thus this alternative curvi-

[8] It is possible, as discussed earlier, that the curvilinear model was not supported because it holds only when escape from aversive circumstances is easy and because violent crimes occur primarily in negative circumstances that are impossible to escape.

linear model predicts a positive relation between temperature and horn honking for those with air conditioning. For those without air conditioning, though, hot days should produce high levels and cooler days should produce moderate levels of negative affect and thus a negative temperature–aggression relation. This is because hot days would be extremely uncomfortable and cooler days (in the spring and summer in Phoenix) would be only mildly uncomfortable. The results, as already mentioned, contradicted this curvilinear model quite strongly; there was a strong positive relation for those without air conditioning and a weak positive relation for those with air conditioning. This is exactly what the linear model predicts.

Of course, all the aforementioned field studies are correlational in nature, making causal statements risky. (Actually, the Kenrick & MacFarlane study is more accurately viewed as a quasi-experiment.) But the widely divergent procedures used in them makes artifactual explanations of the results implausible. Each study had a different set of potential confounds, but each produced the same results. On the whole, it seems reasonable to conclude that the relation between temperature and aggression in natural settings is a positive one, either linear or monotonic.

Theoretical and Practical Implications

Although there is considerable evidence for the hypothesized temperature–aggression relation, the processes underlying this relation are not clear. The best theoretical model at the moment is that uncomfortably hot temperatures produce negative arousal. Negative arousal is fairly general and spills over or gets attached to social objects that are salient, especially those that are generating negative arousal themselves. When the annoyance or anger level gets high enough, aggressive behavior is emitted. This model clearly requires extensive refinement and further testing.

Practical implications for controlling or reducing aggression depend on the underlying processes producing aggression. Obviously there are many aggression factors unrelated to temperature. Just as obviously, there is not much one can do about the weather. However, much of our time is spent in environs that can be air conditioned. Indeed, as noted earlier, Harries et al. (1984) reported data suggesting that some portion of summer violence is due to lack of air conditioning in low-income neighborhoods. I am not suggesting that we should air condition the ghettos; the amount of money involved could probably be spent more effectively on providing the same people with nutritional, educational, and job assistance. But there may be situations in which the most effective use of available resources would be to improve the immediate climate. For instance, in a variety of institutional settings, such as in prisons and factories, violence and productivity problems may be reduced by cooling the environment and modifying other environmental factors that influence aggression (cf. Baron et al., 1985; Charry & Hawkinshire, 1981; Rotton & Frey, 1985).

A second implication derives from the earlier discussion of why the field studies never show the downturn in aggression at very hot temperatures. Recall that one possibility mentioned was that the downturn may occur only if the individual can escape the circumstances giving rise to negative affect by performing some nonaggressive behavior. Removing environmentally induced negative affect (as mentioned earlier) does not eliminate all negative affect, but probably only a small fraction in most cases. Providing ready avenues of escape from the major frustrations may reduce violence in general as well as the negative effects of hot temperatures. The problems associated with unemployment, for instance, are likely a major source of negative arousal that cannot easily be avoided. Job training programs may provide one escape route.

Finally, the temperature–aggression model suggests that people typically misattribute negative arousal arising from uncomfortable temperatures to readily available social targets. That is, we blame other people for upsetting us, even when much of our negative arousal is actually due to temperature. Perhaps making people aware of how much impact hot temperatures have on mood state and on aggressive tendencies will allow them to identify times when this is occurring and to combat the process. Indeed, this reattribution process may be what happens in the laboratory studies that find occasional downturns in aggression at high temperatures.

Studies designed to investigate the utility of these practical implications will also inform us about the validity of the underlying process assumptions. Particularly rich directions for future research would seem to include investigations of the cognitive, attributional, and physiological components of temperature-induced negative affect and aggression.

References

Anderson, C. A., & Anderson, D. C. (1984). Ambient temperature and violent crime: Tests of the linear and curvilinear hypotheses. *Journal of Personality and Social Psychology, 46,* 91–97.

Baron, R. A. (1972). Aggression as a function of ambient temperature and prior anger arousal. *Journal of Personality and Social Psychology, 21,* 183–189.

Baron, R. A. (1979). Aggression and heat: The "long hot summer" revisited. In A. Baum, J. E. Singer, & S. Valins (Eds.), *Advances in environmental psychology* (pp. 57–84). Hillsdale, NJ: Erlbaum.

Baron, R. A., & Bell, P. A. (1976). Aggression and heat: The influence of ambient temperature, negative affect, and a cooling drink on physical aggression. *Journal of Personality and Social Psychology, 33,* 245–255.

Baron, R. A., & Lawton, S. F. (1972). Environmental influences on aggression: The facilitation of modeling effects by high ambient temperatures. *Psychonomic Science, 26,* 80–82.

Baron, R. A., Russell, G. W., & Arms, R. L. (1985). Negative ions and behavior: Impact on mood, memory, and aggression among Type A and Type B persons. *Journal of Personality and Social Psychology, 48,* 746–754.

Bell, P. A., Garnand, D. B., & Heath, D. (1984). Effects of ambient temperature and seating arrangement on personal and environmental evaluations. *Journal of General Psychology, 110,* 197–200.

Berkowitz, L. (1984). Some effects of thoughts on anti- and prosocial influences of media events: A cognitive-neoassociation analysis. *Psychological Bulletin, 95,* 410–427.

Carlsmith, J. M., & Anderson, C. A. (1979). Ambient temperature and the occurrence of collective violence: A new analysis. *Journal of Personality and Social Psychology, 37,* 337–344.

Charry, J. M., & Hawkinshire, F. B. W. (1981). Effects of atmospheric electricity on some substrates of disordered social behavior. *Journal of Personality and Social Psychology, 41,* 185–197.

Cohen, J., & Cohen, P. (1975). *Applied multiple regression/correlation analysis for the behavioral sciences.* New York: Wiley.

Cunningham, M. R. (1979). Weather, mood, and helping behavior: Quasi experiments with the sunshine Samaritan. *Journal of Personality and Social Psychology, 37,* 1947–1956.

Griffitt, W. (1970). Environmental effects on interpersonal affective behavior: Ambient effective temperature and attraction. *Journal of Personality and Social Psychology, 15,* 240–244.

Griffitt, W., & Veitch, R. (1971). Hot and crowded: Influences of population density and temperature on interpersonal affective behavior. *Journal of Personality and Social Psychology, 17,* 92–98.

Harries, K. D., & Stadler, S. J. (1983). Determinism revisited: Assault and heat stress in Dallas, 1980. *Environment and Behavior, 15,* 235–256.

Harries, K. D., Stadler, S. J., & Zdorkowski, R. T. (1984). Seasonality and assault: Explorations in inter-neighborhood variation, Dallas 1980. *Annals of the Association of American Geographers, 74,* 590–604.

Kenrick, D. T., & MacFarlane, S. W. (1984). Ambient temperature and horn-honking: A field study of the heat/aggression relationship. *Environment and Behavior, 18,* 179–191.

Miller, N. (1941). The frustration–aggression hypothesis. *Psychological Review, 48,* 337–342.

Palamarek, D. L., & Rule, B. G. (1979). The effects of ambient temperature and insult on the motivation to retaliate or escape. *Motivation and Emotion, 3,* 83–92.

Rotton, J., & Frey, J. (1985). Air pollution, weather, and violent crimes: Concomitant time-series analysis of archival data. *Journal of Personality and Social Psychology, 49,* 1207–1220.

Rotton, J., Frey, J., Barry, T., Milligan, M., & Fitzpatrick, M. (1979). The air pollution experience and physical aggression. *Journal of Applied Social Psychology, 9,* 397–412.

U.S. Department of Commerce. (1983a). *1971–1980 climatological data: National summary.* Washington, DC: U.S. Government Printing Office.

U.S. Department of Commerce. (1983b). *1980 census of the population: General population characteristics* (PC80-1-B1). Washington, DC: U.S. Government Printing Office.

U.S. Department of Commerce. (1983c). *1980 census of the population: General social and economic characteristics* (PC80-1-C1). Washington, DC: U.S. Government Printing Office.

U.S. Department of Justice. (1981). *1980 uniform crime reports for the United States.* Washington, DC: U.S. Government Printing Office.

U.S. Department of Justice. (1982). *1981 uniform crime reports for the United States.* Washington, DC: U.S. Government Printing Office.

Winer, B. J. (1971). *Statistical principles in experimental design.* New York: McGraw-Hill.

Zillmann, D. (1978). Attribution and misattribution of excitatory reactions. In J. Harvey, W. Ickes, & R. Kidd (Eds.), *New directions in attribution research* (Vol. 2, pp. 335–368). Hillsdale, NJ: Erlbaum.

Received September 19, 1986
Revision received January 15, 1987
Accepted January 18, 1987 ■