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Does Life Seem Better on a Sunny Day? Examining the Association between Daily Weather Conditions and Life Satisfaction Judgments

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Abstract

Weather conditions have been shown to affect a broad range of thoughts, feelings, and behaviors. The current study examines whether these effects extend to life satisfaction judgments. We examine the association between daily weather conditions and life satisfaction in a representative sample of over 1 million Americans from all 50 states who were assessed (in a cross-sectional design) over a 5-year period. Most daily weather conditions were unrelated to life satisfaction judgments, and those effects that were significant reflect very small effects that were only detectable because of the extremely high power of these analyses. These results show that weather does not reliably affect judgments of life satisfaction.

One of the most salient features of people's daily environment is the weather to which they are exposed. Weather conditions, including precipitation, sunshine, temperature, and humidity, can have potentially large effects on people's behaviors. Some of these effects are unsurprising and mundane, including the effects of weather on the clothes that people wear, the mode of transportation that people may take to work, and the specific recreational activities in which people engage (few people choose to picnic in the rain). Yet in recent years, social scientists have documented an increasingly diverse set of research findings that show more surprising links between weather conditions and more complex psychological phenomena. For instance, Simonsohn (2010) showed that people are more likely to enroll in an academically rigorous college if they visited that college on a cloudy day as compared to a sunny day. Other research shows that people behave more altruistically on sunny days than cloudy days (Cunningham, 1979) and even that stock market returns are higher on sunny days than on cloudy days (Hirshleifer & Shumway, 2003). Still other studies show that extreme heat can be linked with higher levels of aggressive behavior (Anderson, 1989). Taken together, these studies show that weather can have a powerful effect on people's thoughts, feelings, and behavior. The goal of the current paper is to examine whether the effects of weather conditions extend to judgments about one's life as a whole. In other words, we seek to determine whether life seems better when the weather is good.

The Processes Underlying Well-Being Judgments

To understand why weather might affect well-being judgments, it is first necessary to understand the processes that underlie the judgments themselves. Subjective well-being (SWB) reflects an overarching evaluation of the quality of a person's life from his or her own perspective (Diener, Suh, Lucas, & Smith, 1999). Traditionally, psychologists have

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used SWB measures to examine the characteristics of happy and unhappy people. By studying the causes, correlates, and outcomes of SWB, psychologists can identify resources and life circumstances that are necessary for people to thrive. This can inform theories about basic needs, while simultaneously providing practical guidance to individuals who may want to improve the quality of their lives. Psychologists and economists have also called for the use of SWB measures as guides for policy decisions (e.g., Diener & Seligman, 2004; Diener, Lucas, Schimmack, & Helliwell, 2009; Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004). The rationale behind this recommendation is that (a) existing indicators (which are primarily economic in nature) provide an incomplete view of quality of life; (b) different people may define quality of life differently and subjective measures let people weight various factors in different ways; and (c) well-being surveys are relatively inexpensive and easy to administer, which means that large amounts of data can be acquired relatively easily. Of course, well-being measures will only be useful in these applied and theoretical settings if the scores that are obtained from these measures are reliable and valid. If well-being judgments can be influenced by irrelevant factors such as the weather at the time of the judgment, then this could negatively impact the reliability, validity, and utility of these measures.

An intuitive model of how someone might construct a life satisfaction judgment is that the respondent would examine the various aspects of his or her life and then average across these domains (perhaps weighting by importance) to derive an overall evaluation (Schimmack, Diener, & Oishi, 2002). According to this model, important life circumstances should predict satisfaction judgments. In addition, because most important life circumstances do not change much over the short-term, life satisfaction ratings should be expected to be relatively stable and to change only when these external factors change. Life satisfaction judgments that changed dramatically from one day to the next would not be consistent with ideas about the nature of the underlying construct. Similarly, life satisfaction judgments that were impervious to the effects of major changes in life circumstances might be suspect.

Considerable evidence shows that self-report measures of subjective well-being do behave in ways that are consistent with these intuitive models. For instance, there are now many studies that have examined the short- and long-term stability of life satisfaction measures, and these studies consistently show that life satisfaction judgments are quite stable over the short-term but that stability slowly declines over longer periods of time (Lucas & Donnellan, 2007, 2012; Fujita & Diener, 2005; Schimmack & Oishi, 2005). In other words, stability is high across periods of time in which major changes in life circumstances are unlikely to occur and much lower over longer periods of time. In addition, the measures are sensitive to cross-sectional differences in life circumstances and responsive to changes in such circumstances (Diener et al., 1999, 2009; Lucas, 2007a). For instance, Lucas (2007b) showed that across two national panel studies, the onset of a severe disability was associated with a substantial drop in life satisfaction and that levels of satisfaction never returned to their baseline levels, even after a period of many years. Together with studies showing that self-reported well-being judgments correlate reasonably well with scores obtained from alternative measurement techniques (Schneider & Schimmack, 2009; Lucas, Diener, & Larsen, 2009; Diener et al., 1999; Lucas, Diener, & Suh, 1996), this research suggests that intuitive models of well-being judgments provide an adequate description of how such judgments are made.

Yet despite the substantial evidence for the validity of well-being measures, concerns have been raised about additional processes that might impact the judgments that people make, at least in certain circumstances. According to judgment models, the task of constructing such judgments is cognitively demanding and therefore, respondents may not want or be able to conduct a thorough search of all relevant information. Thus, they may rely on simple heuristics, some of which may result in biased and even nonsensical responses (Schwarz & Strack, 1999). For instance, rather than exhaustively searching their memory for all relevant life experiences and circumstances, participants may simply focus on the first few domains that come to mind when considering the quality of their lives. If the specific domains that happen to come to mind change from one moment to the next or can be easily manipulated, then well-being measures would be unreliable and subject to severe context effects.

Similarly, it is possible that mood at the time of judgment may affect the well-being reports that participants provide. For instance, mood may affect life satisfaction judgments through mood-congruent recall—people in a good mood may be more likely than people in a bad mood to recall pleasant life circumstances or events (Rusting, 1998). These memory effects could lead to an overly positive evaluation when in a good mood. Alternatively, when constructing well-being judgments, people may simply rely on their current mood as a quick and easily calculated proxy for how they feel about their lives as a whole (Schwarz & Strack, 1999). Rather than carefully searching their memory for explicit events and characteristics that might inform their judgment of how their lives are going, people may simply consider whether they are currently feeling good or bad and then use that information as input into their overall evaluation. Regardless of the process by which current mood affects these judgments, if these effects exist, then any factor that subtly affects current mood might also affect broader well-being judgments in undesirable ways. Indeed, Schwarz and Strack (1999) reviewed evidence that suggests that many transient factors do in fact impact the life satisfaction judgments that people make, often in very powerful ways.

Of course, one must ask how these two sets of findings can co-exist. If context effects are so large and pervasive, how can the psychometric characteristics of well-being measures be so strong? Wouldn't the impressive reliability, stability, and validity of well-being measures suggest that context effects are weak enough not to be important or that their effects wash out across a sample of participants who vary in their mood or who vary in the specific domains that are on their mind? Unfortunately, despite the strong psychometric evidence, context effects could still pose problems for well-being measures if researchers are not careful about study design. If researchers are not careful during the process of questionnaire construction or if they fail to consider additional contextual effects that may affect the response process at the time of the survey, systematic biases could emerge and affect results in a powerful way. Thus, if well-being judgments have some amount of validity, but contextual effects have the potential to affect the information that is obtained, then an important question for applied and theoretical researchers concerns the size and robustness of these context effects. The goal of the current study is to determine whether life satisfaction judgments fluctuate with the weather and then to evaluate the size and robustness of this effect.

The Association between Weather and Life Satisfaction Judgments

Studies that examine the links between weather and psychological phenomena usually start with the assumption—an assumption that is often not tested directly—that weather affects mood. The mood state that the weather conditions create is then thought to affect the phenomenon of interest. For instance, Simonsohn (2010) found that people were more likely to enroll in an academically rigorous college if they had visited the college on a cloudy day than if they had visited on a sunny day. He suggested that this effect is due to the links between cloudiness, mood, and the value that people place on academic activities. Cloudiness is thought to be associated with negative moods, and these sad moods "[make] mellow activities like reading or studying more appealing" (p. 272). Furthermore, because people use their current utility to predict their future utility, they are more likely to enroll in a particular college if current conditions increase the perceived utility of the college at that moment. Thus, at least for academically rigorous institutions, visits on cloudy days should increase the appeal of the academic activities that lay ahead. Similarly, Cunningham (1979) noted that nice weather could affect mood through symbolic associations. In other words, nice weather "could increase mood by stimulating thoughts of swimming, picnics, and other outings, whereas cloudy days could be associated with the disappointment of canceled plans and the annoyance of rain and snow" (p. 1954). The mood that is induced could then carry over and affect other behavior like altruistic acts. If the weather does affect mood, which can then create a relatively rosy view of the world, then it might also be possible for weather to have effects on people's broader judgments of their lives as a whole through the processes specified by the judgment model (or alternatives like the mood-congruent-recall model).

Again, the presumed mechanism underlying the association between weather and life satisfaction is that pleasant weather conditions lead to more positive mood states, which in turn affect life satisfaction judgments. Thus, in addition to studies that focus on weather and life satisfaction, studies that focus on weather and mood provide evidence about the plausibility of the more complicated life satisfaction effect. However, many studies that examine the effects of weather on psychological phenomena simply assume that mood effects exist and do not directly test the mediating effect of mood. In fact, few of these studies provide thorough reviews of studies that actually test this assumption. Therefore, before discussing previous literature on weather and life satisfaction, we also review studies linking weather and mood along with the more explicitly relevant studies on weather and life satisfaction. It is important to note that our own study can only address the latter association.

Studies Focused on Weather and Mood

We identified ten studies that have examined the association between weather and current mood without assessing life satisfaction. In one study, Parrott and Sabini (1990) approached 65 students on sunny days or cloudy days and asked them to complete a single-item mood measure. Consistent with predictions, participants reported more positive mood on sunny days than on cloudy days.

Most other studies that have examined weather and mood have followed participants over time using diary methodology. In the earliest of these, Goldstein (1972) examined the associations in a sample of seven students assessed over eleven days. Very few details were reported in this one-page report, and indeed, it is not entirely clear what analyses were conducted with this nested design, as only single correlations were reported for each weather variable (and sometimes it appears that the correlations that are reported are for individual participants). However, Goldstein found that mood was higher when humidity was low, barometric pressure was high, and the temperature was not cooler than normal. Neither cloud cover ("clearness" in Goldstein's terms) nor absolute temperature were related to mood, and precipitation was not investigated.

Howarth and Hoffman (1984) looked at the associations between weather and mood in a sample of 24 participants assessed over 11 days. Again, it is not clear how the data were analyzed, as correlations as small as .10 were reported to be significant even in this small sample; but Howarth and Hoffman found 14 significant effects among the 70 correlations they examined (10 different mood variables and 7 different weather conditions were examined). For instance, sunshine was negatively correlated with "anxiety" ($r = -.13$) and "skepticism" ($r = -.11$), precipitation was positively correlated with "anxiety" ($r = .12$) and "potency" ($r = .11$), and temperature was negatively correlated with "anxiety" ($r = -.13$) and "potency" ($r = -.11$), but positively correlated with "sleepiness" ($r = .13$). However, given the sparse set of small correlations, strong conclusions about the associations with weather are difficult to draw from this study.

Using a similar design, Sanders and Brizzolara (1982) examined the links between three weather variables (relative humidity, temperature, and barometric pressure) and mood in a sample of 30 participants who were followed for 25 days. Few details were reported in this brief report, but the authors did note that in univariate analyses, none of the weather variables predicted mood. However, they also conducted a canonical correlation analysis and found an association between humidity and the combination of various mood ratings.

Because these studies have extremely small sample sizes and because few details about the analyses are provided, interpretation of these mixed results is difficult. More recent studies have used larger sample sizes (or longer periods of assessment) and have described their procedures in more detail. Again, however, mixed results have emerged. For instance, in two separate studies Clark and Watson (1988) and Watson (2000) found no associations between weather and mood in samples of students followed for up to 90 days. Denissen, Butalid, Penke, and van Aken (2008) surveyed 1,200 participants over a two-year period and found few weather effects. Specifically, no weather variable was significantly associated with positive affect. For negative affect, results were a bit more complicated. In univariate analyses (i.e., when each weather variable was entered on its own as a predictor of affect), weather was unrelated to negative affect. However, when multiple weather conditions were entered simultaneously, temperature was positively associated with negative affect, whereas both windspeed and the amount of sunlight were negatively associated with negative affect. Overall, Denissen et al. concluded that weather effects were relatively small. Similarly, Klimstra et al. (2011) examined the association between mood and weather in a sample of over 400 adolescents and their mothers who reported on their moods multiple times over a 30-day period. Consistent with Dennissen et al., Klimstra found only weak associations between specific weather conditions and mood, with absolute values of correlations ranging from 0.00 (between precipitation and both happiness and anxiety) to 0.06 (between temperature and happiness). Again, however, Klimstra et al. dismissed these effects as being small and focused instead on individual differences in these effects.

More recently, Kööts, Realo, and Allik (2011) used an experience sampling design (in contrast to the more common daily-diary study, which focuses on average mood over the course of a day) to examine the association between weather and mood at a single moment. Over 100 participants were assessed up to 7 times a day for up to 14 days. Importantly, the study was run on two separate occasions, one in the fall/early winter (in Estonia) and one in the late winter/spring. Kööts et al. (2011) found that negative affect was *positively* associated with temperature (which runs counter to expectations) and negatively associated with humidity. Positive affect was also positively associated with temperature and negatively associated with humidity. In addition, positive affect was positively associated with luminance. Fatigue was negatively associated with temperature and luminance. Kööts et al. (2011) noted, however, that all effects were quite small. In addition, it appears that the authors did not control for time of day, which has clear associations both with the weather variables that were included in the model and with mood (Watson, 2000).

In perhaps the strongest set of studies that has actually found consistent mood effects, Keller et al. (2005) identified a potentially important moderator of the weather/mood association. They conducted three studies examining the links between weather and mood, and they found that although weather had no main effect on mood, associations differed depending on the extent to which people spent time outdoors on the day they were assessed. For those who spent a lot of time outside, temperature and barometric pressure were positively associated with mood; for those who spent little time outdoors, the associations were in the opposite direction. No other weather variables were assessed. Thus, across all these studies, some associations between weather and mood have been found, but the precise weather conditions that appear to be most important vary across studies, and some studies (including some large studies) have found no effects at all.

Studies Focused on Weather and Life Satisfaction

Although the effect of weather on mood is a precondition for effects on life satisfaction (at least according to the most plausible explanations of the processes that underlie this effect), it is possible to study more direct effects of weather on life satisfaction, just as studies that link weather to behavior typically do not assess mood itself. We found two published and two unpublished studies that attempted to answer this question (though some of these studies also had measures of affect and/or current mood).

The oldest and most frequently cited of these papers is one by Schwarz and Clore (1983). In this study, experimenters contacted participants by phone on either sunny days or rainy days. Importantly, the sunny days that were chosen were some of the first sunny days of the spring (in a relatively cold climate), and the rainy days were those that followed soon after. In one condition, participants were simply asked to report on their life satisfaction. In two other conditions, the weather was made salient by first asking participants about the weather and then having them make life satisfaction judgments. The purpose of this manipulation was to alert participants to the potential effect of the weather on their mood, which might lead them to discount its effects when making life satisfaction judgments. Consistent with their predictions, people reported higher life satisfaction on sunny days than on rainy days, but only when the weather was not made salient. Thus, it appeared that weather affected life satisfaction judgments, unless the potential biasing effect of the weather was made salient to participants.

Although the Schwarz and Clore (1983) study has played an influential role in research on mood effects on life satisfaction, it is important to note that the sample size was relatively small. Indeed, although the total sample size was 84, the use of a 2 X 3 design meant that there were just 14 participants per cell. Importantly, the significant interaction was driven just by one of these 14-person cells—all five other cells were nonsignificantly different from one another. Thus, it is important to consider additional studies that have tested this effect.

Two of the three papers we found used much larger samples, and all three additional studies employed representative sampling strategies. First, Barrington-Leigh (2008) looked at life satisfaction and weather in two Canadian samples with sample sizes ranging from 4,000 to 20,000 respondents. Importantly, in these very large samples, no effects of daily weather on either a happiness measure or a life satisfaction measure emerged. Cloudiness over the past seven days was negatively associated with life satisfaction (but not happiness), but cloudiness on the day of the survey was not. This aggregate measure of cloudiness likely reflects a seasonal effect rather than a current weather effect. No other weather variable was associated with happiness or life satisfaction in these samples.

Second, Pray (2011) examined weather effects in a sample of approximately 4,000 adults who had completed a life satisfaction measure in addition to a day-reconstruction-based time-use measure in which they reported on their affect for various activities throughout the previous day. Pray found that weather was only associated with life satisfaction among women, with significant negative effects for rain and for high temperatures. Interestingly, affect in the daily-report measures was not affected by precipitation, even though there was an effect for life satisfaction (though again, this effect only held for women). This lack of correspondence between affect/weather associations and satisfaction/weather associations is not consistent with a judgment-model explanation.

Most recently, Kämpfer and Mutz (in press) examined the association between weather and well-being in three large-scale studies in Europe. Unfortunately, because the city of residence was not recorded in the survey itself, the authors needed to infer from other information where the respondent lived, and this was only possible for a small percentage of respondents. Thus, although the parent studies are large, the sample sizes for each of the three studies were less than 200. Importantly, rather than relying on raw weather data, Kämpfer and Mutz created a dichotomous variable that was coded as 1 only if there was more than four hours of sun and no precipitation on the day of the survey. Between 13% and 24% of respondents provided a well-being judgment on such sunny days, which further reduces power to detect an effect. Although the authors interpreted the results as being supportive of the prediction that weather affects satisfaction, results were quite mixed. For instance, the only effects that were significant by traditional standards were in Study 1 (and even in this study, one-tailed tests were used), where sunny days were associated with higher ratings of fulfillment in private and professional life. The effects in Studies 2 and 3 (where more traditional life satisfaction and general happiness questions were included) were nonsignificant, though in the expected direction. Again, the small sample sizes and low power make these mixed findings difficult to interpret.

Summary of Previous Research on Weather

What is most notable about these studies is that with the exception of the two papers by Watson and Clark (Clark & Watson, 1988; Watson, 2000), all of the above studies have found some effect of weather, either on mood, or less frequently on life satisfaction. Thus, a cursory review might conclude that weather effects are robust and replicable. Indeed, most studies that discuss potential effects of weather on mood or life satisfaction conclude that weather affects well-being judgments. However, a close look shows that many different weather effects are examined in most of the studies that have been conducted, and even with mood as an outcome, few if any of these specific effects replicate. Thus, it is critically important to determine the extent to which weather can really affect the judgments that people make.

The Current Study

Existing studies examining the links between weather conditions and life satisfaction have resulted in inconsistent findings. The inconsistencies themselves are problematic, as they lead to questions about the robustness of the effect. However, the divergent findings might result from differences in the design of the original studies. Notably, Schwarz and Clore (1983), who conducted a study that found an effect of weather, chose days that should maximize mood effects. Specifically, they chose a sunny day that was one of the first sunny days of the spring in a cold climate. It is possible that discrepant results have been due to differences in the climate or time of year in which the study took place. The current study re-examines the weather effect using a very large, nationally representative sample of participants from the United States. Importantly, participants were recruited from all 50 states and they were assessed throughout the year over a five year period. This allows us to test complex interactions between daily weather conditions at the time of the survey and broader climatological averages for the region and time of year. This design, combined with the extremely high power of this study, should maximize the possibility of finding weather effects. Furthermore, the very large sample size should allow us to estimate the size of these effects with very high precision.

Method

The goal of these analyses is to determine whether daily weather conditions are associated with life satisfaction scores. To accomplish this goal, we link each person's responses to historical weather data from the location and date on which the survey took place. Multilevel modeling strategies are then used to isolate daily weather effects from seasonal or regional effects.

Participants

The Behavioral Risk Factor Surveillance System (BRFSS) is a set of state-level surveys organized by the U.S. Centers for Disease Control and Prevention (Centers for Disease Control and Prevention (CDC), 2005–2009). The goal of these surveys is to track health conditions in the United States. Although the surveys have been conducted since 1984, life satisfaction was only assessed starting in 2005. For this reason, only the waves from 2005 to 2009 are included in this analysis. Over 1.9 million respondents participated in the survey during these five years (the data are cross-sectional, and thus, each respondent only participated once).

Two pieces of information about the location of these respondents was provided by the BRFSS. First, information about the respondent's county was provided. Second, a large sub-sample of participants (about 1 million) were grouped into one of 265 metro areas. As described below, we used two sources of weather data, one that could be linked by county and one that could be linked by metro area. However, the data source for the metro areas included a wider range of weather variables than did the source for counties, and thus, we relied on this source of data (and the somewhat smaller sample size, N = 1,071,290) for our primary analyses. All analyses were repeated with the more limited weather variables in the second source of county-based data, and results were quite similar. Tables from these additional unreported analyses are included as online supplemental material.

Measures

Life satisfaction was assessed using a single item that read "In general, how satisfied are you with your life." Participants responded using a 4-point scale with the options "Very Satisfied," "Satisfied," "Dissatisfied," or "Very Dissatisfied" (responses were scored such that higher scores reflect higher satisfaction). Although single-item measures are not ideal, existing research shows that such measures often perform quite well. For instance, Lucas and Donnellan (2012) used longitudinal data from four large-scale, nationally representative panel studies to estimate the reliability of widely-used single-item life satisfaction measures. They showed that reliability estimates tended to exceed .70 for these measures. Other research shows that these measures correlate with other indicators (including non-self-report measures) and with relevant life circumstance variables (see Diener et al., 2009).

Weather data were initially collected from two sources. First, the National Climactic Data Center's Climate Data Online website (http://www7.ncdc.noaa.gov/CDO/cdo) provides historical weather data from thousands of weather stations across the United States. Information about the county in which these stations are located is provided, which allows us to link this information with the data from the BRFSS. Although a variety of weather-related variables are available, most stations only report total amount of all precipitation, amount of snowfall, minimum temperature, and maximum temperature for the day. A smaller but still substantial number of stations report humidity levels, windspeed, and barometric pressure (approximately 650,000 participants were available for analyses using these additional variables). Unfortunately, little information about cloud cover—a potentially important predictor—was included at these sites.

The website Weather Underground (www.weatherunderground.com) also provides historical weather data for a large number of locations. Variables recorded in this historical data include mean temperature, precipitation, mean cloud cover, mean barometric pressure at sea level, mean wind speed, and mean humidity. Because the available data were more complete, we used the Weather Undergound data for our primary analyses, though we also report results from the NOAA in supplemental on-line tables, and we reference these when evaluating the robustness of effects. We used the names of the cities included in the BRFSS metro area locations to identify relevant weather stations for those areas. If more than one city was listed by the BRFSS as being within the metro area, we aggregated across weather stations for those areas on a particular day.

Analytic Procedure

To examine the association between daily weather conditions and life satisfaction, a multilevel modeling strategy was used (implemented using the **lme4** package in the R statistics program (R Development Core Team, 2010)). The goal of this analysis is to determine whether day-to-day changes in weather are associated with well-being scores. However, because this is a national sample that was assessed over a five-year period, regional differences in weather and life satisfaction need to be considered. Specifically, if an uncentered daily weather variable is entered as a predictor of individual-level life satisfaction, then daily and regional effects are confounded: the estimated effect for that predictor would reflect a mix of between-region and within-region associations (Enders & Tofighi, 2007). For instance, when testing the associations with daily precipitation, the coefficient for precipitation could be significantly different from zero simply because areas with higher levels of average precipitation are less satisfied than areas with less precipitation, even though respondents within any given area are no less happy on rainy days than on sunny days. Therefore, it is important to carefully consider how to center the weather variables when including them as predictors.

In addition, the effect of absolute levels of any weather variable may vary depending on when in the year the weather occurred. A 50 °F day may contribute to positive mood (and hence higher life satisfaction) if it occurred in the middle of winter in a cold climate, whereas this same absolute temperature might contribute to a negative mood (and hence lower life satisfaction) if it occurred in the middle of summer in a warm climate. Thus, seasonal differences must be considered when examining the effects of weather.

To isolate daily weather effects from seasonal differences and regional differences, we used a three-step centering procedure. First, for each weather variable, we calculated the five-year monthly average within each metro area, for all areas in the dataset. We then centered each daily weather variable around this monthly average, so that daily weather reflects deviations from seasonal averages. Second, we centered the monthly average around the regional average. Finally, we centered each region’s average around the grand mean across all regions. This last step simply makes the intercept from the model more interpretable because it now reflects the average life satisfaction for an area with an average level of whichever weather variable is being investigated.

Once the weather variables were constructed, we tested each in separate multilevel models. In each model, life satisfaction was the outcome variable, daily and monthly weather were within-group (or Level-1) predictors, regional average weather was a between-group (or Level-2) predictor, and all interactions were included. Thus, the model can test whether a particularly hot day in a summer month in a hot climate has a different effect than a particularly hot day in a winter month in a cold climate. Metro-area was included as the grouping factor, and a random intercept was modeled. All other effects were treated as fixed. A full model with all variables was not included. However, targeted tests of interactions between variables were included. Specifically, we included temperature and precipitation in a single model and temperature and cloud cover in a single model. These models included all terms from the single-variable models (including all interactions), plus the interaction between the two weather variables. The p-value for all analyses was set at .05, and thus, significant estimates are those where the estimate is at least twice the size of the standard error. It is important to note that with a sample size this large, we have a great deal of power to detect even very small effects. Thus a critical consideration will be how large an effect needs to be before it is practically important.

In addition to testing the effects of daily weather conditions, we also tested whether extreme weather conditions were associated with differences in life satisfaction ratings. It is possible that normal variations in weather conditions do not affect judgments but that extreme events do. Therefore, for each of the weather conditions, we constructed dichotomous "extreme" weather variables that were coded as "1" if some threshold was reached (and "0" otherwise). We then replaced the daily weather variable with this dichotomous "extreme weather" variable in each of the models. Specifically, for temperature, we coded days that were at least 10 degrees Fahrenheit above the monthly average as being "extremely warm" and days that were at least 10 degrees lower than the monthly average as being "extremely cold." Both variables were tested in separate models. The Extreme Precipitation variable was coded as "1" if at least a half an inch of precipitation fell on the day of the response. Cloud cover was recorded on a 0–8 scale, and we recoded values of 0 or 1 to represent "Extreme Sun" and values of 7 or 8 to represent "Extreme Cloudiness." For barometric pressure, values that were at least .30 inches above normal were counted as "Extremely High Pressure" and values that were at least .30 inches below normal were counted as "Extremely Low Pressure." For humidity, levels of 95% humidity or above were counted as "Extremely High Humidity" and levels of 50% humidity or below were counted as "Extremely Low Humidity." Finally, for windspeed, average speeds of 15 MPH or greater were counted as "Extremely Windy."

In our final models, we tested whether change in weather from the previous day was associated with higher or lower levels of life satisfaction. It is possible that it is not the absolute weather conditions that matter, but the extent to which these conditions deviate from recent conditions. In other words, people's mood (and hence their life satisfaction) may improve when there is a large and noticeable change from a less desirable weather condition to a more desirable one or from a more desirable condition to a less desirable one. Therefore, for each weather variable, we calculated the change in that variable from the previous day and added that variable (and all interactions) into the basic daily-weather-condition models described above.

Finally, it is important to note that the estimated coefficients for these analyses were often very small when the original weather units were used. Therefore before any centering occurred, we transformed the variables in such a way as to avoid the need for many decimal points. Specifically, we divided the original units for Precipitation by 10, Temperature by 100, Cloud Cover (which was originally on a 0 to 8 scale) by 10, Wind Speed by 100, and Humidity by 100. This means that one unit of the precipitation variable now reflects 10 inches, one unit of the temperature variables reflects 100 degrees Fahrenheit, one unit of Wind Speed reflects 100 miles per hour, one unit of humidity reflects 100 percentage points. Barometric pressure was kept in its original metric, which reflects one inch of mercury. Obviously, these transformations only affect the number of decimal points that are reported in the tables, but not any substantive results or significance values.

Results

Across the full sample, the mean level of life satisfaction was 3.39. The between-person standard deviation was .63, the between-county standard deviation was .09, and the between-metro-area standard deviation was .04. Estimated weather effects can be compared to these standard deviations to determine how big they are relative to the variance that exists in this sample. However, it is important to note that although regions do vary in meaningful ways (see, e.g., Lawless & Lucas, 2011; Oswald & Wu, 2010), the amount of absolute variance across metro areas is very small relative to variance across individuals (just 6% of the size). Thus, using this standard deviation will make most effects look large.

Our analyses proceed one variable at a time, focusing on each of the three models that we tested (the basic model with daily weather conditions, one or more models with extreme weather indicators, and a final model that tests change from the previous day). The first column of Table 1 shows the basic model, which tests the association between temperature and life satisfaction. As can be seen in this table, there is a significant effect of the average temperature of the metro-area, with participants in warmer areas reporting higher average life satisfaction. However, there is no effect of monthly temperature, and more importantly, no effect of daily temperature. As rows 5 through 8 of this column show, there were also no significant interactions, which means that the effect of daily temperature does not vary significantly across seasons, metro-areas, or seasons within metro-areas. Given the extremely high power to detect effects in this sample, these results strongly suggest that daily variations in temperature do not affect life satisfaction ratings in this sample.

Columns 2 and 3 of Table 1 show estimated coefficients for the dichotomous Extreme Warmth and Extreme Cold variables (in these models, the centered “Daily” variable is replaced with the dichotomous indicator). For extreme cold, no significant effects emerged. For extreme warmth, there was a significant interaction between extreme warmth and average monthly temperature. The precise pattern of this effect, however, does not match intuitions about how weather should affect life satisfaction ratings. The coefficient is positive, which means that extremely warm temperatures are especially likely to be associated with higher levels of life satisfaction in warm months, whereas extremely warm temperatures are especially likely to be associated with low life satisfaction in cold months. For instance, in a month that was 20 degrees above average, life satisfaction would be predicted to be 3.39 on a non-extreme day versus 3.41 on an extremely warm day. In contrast, in a month that was 20 degrees below average, life satisfaction would be predicted to be 3.39 on a non-extreme day versus 3.38 on an extremely warm day. This contradicts the intuition that warm weather would be especially desirable in cold months and less desirable in warm months. In addition, the effect size is extremely small, reflecting just a .03 standard deviation difference for the larger of the two comparisons. Finally, this effect was not replicated in the county-level analyses reported in the supplemental material. Thus, this does not appear to be a robust or practically important effect.

The final column of Table 1 shows the estimated coefficients for the models testing change from the previous day’s weather. Again, the effect of regional weather is significant, and a negative interaction between monthly temperature and regional temperature that sometimes approached significance in the other three models is now significant in this one. Neither of these effects is relevant, however, for understanding the role of current weather on life satisfaction. Again, daily temperature is not associated with life satisfaction, and change in temperature from the previous day is also unrelated. However, there is a significant negative interaction between daily temperature and change in temperature. As with the interaction between extreme warmth and monthly temperature, however, the effect is very small, and the precise pattern does not match with intuition or with the effect found in previous studies like Schwarz and Clore (1983). Specifically, according to these estimates, life satisfaction is higher on a warm day that occurs after a decline in temperatures than on a warm day that occurs after an increase in temperatures. In addition, life satisfaction should be higher on a cold day that follows an increase in temperature than a cold day that occurs after a decrease in temperature. Although one could construct a plausible explanation of such effects that involved relief from extreme temperatures, one would also expect this to be moderated by seasonal effects (e.g., a decline might be especially desirable in extremely hot months but less so in the winter).

It is important to note that this interaction term is also significant in the county-level analyses (see supplemental material). However, the precise pattern differs a bit. In the county-level analyses, there is also a three-way interaction with month. In addition, the effect only emerges on warmer than average days—life satisfaction is higher on warmer than average days that occur after a larger than average drop in temperature from the previous day than on warm days that occur after a larger than average increase in temperature from the previous day, but this effect only emerges in warmer than average months. There are no effects for change from the previous day on colder than average days or in colder than average months. Thus, the inconsistency in this effect, combined with its small size, should lead to caution when interpreting this effect.

Table 2 shows the results for precipitation. A quick glance shows that none of the effects was significant across the three models tested. Thus, although the rain is one of the weather variables emphasized in at least some previous studies, these results show that the amount of precipitation that occurred on the day of the life satisfaction report is unrelated to life satisfaction judgments.

Results for cloud cover are presented in Table 3. As with temperature, there is a consistent regional effect: Metro areas with lower average cloud cover tend to report higher levels of life satisfaction. However, daily cloud cover, whether analyzed as absolute levels, extreme levels, or change from the previous day, is unrelated to life satisfaction judgments. Of the many interactions tested, one significant interaction did emerge, that between daily cloud cover and change in cloud cover from the previous day. However, this effect again does not fit with intuition and is even smaller than the effects for temperature reported above. For instance, the model predicts life satisfaction on a perfectly sunny day to be unaffected by the cloud cover on the day before—predicted life satisfaction is 3.39 regardless of whether the day followed a perfectly sunny day or a completely cloudy day. In contrast, the model predicts life satisfaction on a very cloudy day to be higher when it follows a sunny day (3.40) than when it follows a cloudy day. The robustness of this effect could not be tested in the county-level data, as the cloud cover variable was not available, but given the extremely small size of this effect ($d = .02$) and its counterintuitive direction, this appears not to be a practically important effect.

Tables 4, 5, and 6 show the results for barometric pressure, wind speed, and humidity. Low barometric pressure is typically associated with clear, calm weather, and Keller et al. (2005) found that this was the primary factor predicting mood in their study. Table 4 shows that none of the effects for barometric pressure were significant in this sample. Similarly, Table 5 shows that none of the effects for wind speed were significant. Finally, Table 6 shows that of the humidity effects tested, only one emerged as being significantly different than zero: the effect for change from the previous day. In this case, regardless of when in the year it occurred and what the absolute humidity was, an increase in humidity was associated with higher levels of life satisfaction. Again, this effect did not replicate in the county-level analyses, and its relative size is extremely small. Even an implausibly large increase in humidity of 100% would be associated with just 2/100ths of a standard deviation increase in life satisfaction.

Although we focused on the analyses at the metro-area level (because weather data were more complete for metro areas than for counties), we did conduct all analyses at the county level as well, using the NOAA data. As noted above, only one of the effects that emerged at the metro-area level was significant at the county level. One additional effect emerged at the county level that did not replicate at the metro-area level; we mention it here and refer the reader to the supplemental material for additional details. In the county-level analyses, barometric pressure was positively associated with life satisfaction, especially in months with higher than average pressure, but the effect was very small ($d = .06$ for one of the largest comparisons).

As a final test of the weather hypothesis, we examined the interaction between temperature and precipitation and between temperature and cloud cover. The idea behind this analysis is that a cold, rainy day might have an interactive effect on life satisfaction that exceeds the additive effect of either factor considered on its own. The first model included all terms from the first column of Tables 1 and 2, with the addition of an interaction between daily temperature and daily precipitation. The second model included all terms from the first column of Tables 1 and 3, with the addition of an interaction between daily temperature and daily cloud cover. Because the results mostly replicate those from Tables 1 and 2, details are not presented. However, the important new finding from this analysis is that the interactions between daily temperature and daily precipitation are small and not significant ($B = −0.276$, $SE = 0.254$). Similarly, the interaction between daily temperature and daily cloud cover was small and not significant ($B = −0.007$, $SE = 0.032$). Thus, even when meaningful combinations of weather conditions are examined, no associations with daily weather are observed.

Each of the analyses described above look solely at the links between weather conditions and life satisfaction judgments. However, Pray (2011) found evidence that such weather effects may vary by gender. Specifically, she found that weather effects on life satisfaction and affect (specifically high temperature and precipitation) were significant for women but not men. To address this possibility, we reran the models from the first columns of Tables 1 through 6, this time including main and interactive effects with gender (details of these analyses are included in the supplemental tables). Two significant interactions emerged, though neither was large and their interpretation is not clear. First, there was a significant positive interaction between gender and daily precipitation and regional precipitation ($B = 20.68$, $SE = 8.75$). However, because the interaction between daily and regional precipitation is negative among men, this means that the effect is reduced among women. Second, there is a three-way interaction between gender, daily wind speed, and regional wind speed ($B = −4.78$, $SE = 2.01$). Again, here the interaction is positive for men, which means that the interaction is reduced among women. Given the size of these effects, the unreliability of interactions, and the fact that these do not replicate with the county data, these interactions do not appear to reflect important qualifications of the weather findings described above.

General Discussion

Psychologists and other social scientists have made great strides in understanding the causes and correlates of self-reported subjective well-being. Indeed, the large body of research from within psychology is encouraging enough that the field is on the verge of making important new contributions to policy decisions. In addition to the growing body of academic well-being research that has direct policy relevance (see Diener et al., 2009, for a review), more and more government agencies are proposing to collect well-being measurements on a regular basis, and some governments have made a focus on well-being a priority (e.g., Stiglitz, Sen, & Fitoussi, 2009; Stratton, 2010). However, if SWB judgments are to provide useful information in any of these areas of investigation, it is essential that researchers address concerns about potentially problematic psychometric properties.

One concern about these measures is that the task of constructing a well-being judgment is potentially a cognitively demanding one (Schwarz & Strack, 1999). As a result, respondents may rely on heuristics that allow them to come up with a response very quickly but that may reduce reliability. For instance, Schwarz and Strack suggested that contextual effects like the weather effect that is the focus of this study can move scores around in powerful but undesirable ways. As a result, well-being scores may not accurately reflect a stable underlying sense of quality of a person's life.

In contrast to this view, other researchers have posited not only that well-being judgments result from a combination of chronically and temporarily accessible sources of information, but that chronically accessible sources account for most of the variance in these judgments (Eid & Diener, 2004; Schimmack et al., 2002; Schimmack & Oishi, 2005). Because the information that is chronically accessible should theoretically reflect aspects of a person's life that are particularly important to that person, respondents should be able to quickly generate a valid life satisfaction judgment simply by considering the information that is most accessible. If so, then the important question is not whether temporarily accessible (and potentially irrelevant) information *can* influence life satisfaction, but how strong the effect of this information is relative to more relevant criteria for judging the quality of one's life.

In the current study, we examined the extent to which judgments of life satisfaction fluctuate with the weather. Previous research has shown that diverse social behaviors can be affected by the weather, and the presumed mechanism that underlies many of these effects is that weather affects mood and mood in turn affects behavior. Thus, it is not unreasonable to assume that the weather can affect life satisfaction judgments through the same process. Although a small number of studies have examined the links between weather and life satisfaction, the precise effects that have emerged have been quite inconsistent. Indeed, even the more basic links between weather and mood are not robust across studies. However, the effect of weather on mood or life satisfaction may vary by context, and many existing studies were conducted within limited geographical areas or during a relatively narrow time of the year. Thus, if the effect of weather varies by season or region, important weather effects might have been missed.

To address these questions, we linked weather data from a five-year period to life satisfaction judgments from over 1 million respondents from around the U.S. Even though this study had enough power to detect extremely small associations, no main effects of daily weather effects emerged, and only a few small interaction effects were identified. Notably, only one of the interactions that could be tested using an alternative source of weather data (and a larger sample) replicated even though much of the data overlapped, and the precise pattern of this interaction differed across the two analyses. Thus, in this very large sample, no interpretable or practically significant effects of weather emerged. It is important to note that the methods used in this study reflect the type of survey that would actually be used as input to policy decisions. Indeed, the set of surveys from which these data were drawn (the BRFSS) is often used to provide official statistics regarding rates of diseases around the country. Thus, if weather effects do not have an effect in this real-world scenario, then it means that they are likely not a problem in other policy-relevant data-collection situations.

Limitations

The current study is the largest investigation of weather effects on life satisfaction judgments to date. Indeed, the size and diversity of the sample, combined with the fact that respondents were recruited from many different regions and assessed on different days throughout the year means that a broad range of weather conditions could be tested. Therefore, the data from the BRFSS provides an ideal way to test the associations between daily weather conditions and life satisfaction judgments. Yet despite these strengths, our study has some limitations.

Most notably, some of the more recent studies that have examined weather effects have suggested that moderator variables may affect the extent to which weather matters for life satisfaction judgments. For instance, Keller et al. (2005) suggested that the extent (and even the direction) of weather effects on mood is dependent on whether a person has spent a considerable amount of time outdoors on the day of the assessment. Indeed, it is possible that the student participants in the early Schwarz and Clore (1983) paper spent more time outdoors than do older adults, which could be responsible for the large effects that emerged in that study. Similarly, Pray (2011) found gender differences in the links between weather and life satisfaction, and she explained these differences by referring to time-use variables that vary by gender. Finally, Denissen et al. (2008) noted that although on average, weather had small effects on mood, there were individual differences in the size of these effects (also see Klimstra et al., 2011). Although we were able to assess gender (and this variable had few meaningful moderating effects on the associations that we examined), no other potentially useful moderating variables were assessed. Therefore, we cannot rule out the possibility that weather does have larger effects in meaningful subgroups within our sample.

In addition, although our study shows that no weather effects emerged in this particular widely used data set, this does not mean that weather effects on life satisfaction judgments *cannot* occur, and it does not rule out the broader principles identified by judgment-model researchers. It is possible that some other feature of this specific research design prevented the effects of weather and/or current mood from occurring. A different design might have identified these effects. For instance, in the BRFSS, the life satisfaction question came after many other questions about stable conditions in people's lives (e.g., their health, employment status, disability status, and income), and it is possible that the information made salient by these additional questions wiped out any potential weather effect. However, if that is the case, this leads to questions about how robust such weather effects are and how easy they are to counteract. The BRFSS survey organizers did not report any special procedures to counteract weather effects. Thus, given the lack of effects in this relatively standard design, it would be important for researchers to identify which characteristics are likely to elicit such effects, if they do exist.

Finally, we cannot rule out the possibility that the people who were available to participate in this survey differ in important ways depending on the weather.[1] For instance, outgoing, active, and generally happy people may be more likely to be outside of the home (and thus unavailable for a telephone-based survey) on warm, sunny days than on cold, rainy days. This could potentially create the appearance of weather effects when none exist, or it could wipe out actual weather effects if the selection biases go in the opposite direction to naturally occurring weather effects. Importantly, this criticism holds not only for our study, but for almost all other between-person studies reviewed in this paper. Only Keller et al. (2005) experimentally manipulated exposure to weather to rule out such effects. In any case, given the lack of weather effects in this very large sample, either the bias would need to be very large, or the weather effects that do exist would need to be very small for such effects to be canceled out in this way.

In addition to these limitations in the methodology, we also wanted to note one boundary on the conclusions that readers should draw from this work. The goal of our analyses was to assess the effect of daily weather conditions on life satisfaction judgments. Although the details of our analyses also have some implications for seasonal and regional differences,

[1]Thanks to Robert Metcalfe for this suggestion.

these effects are more difficult to interpret. Indeed, some of the analyses did suggest that seasonal and regional effects exist, but it is not always clear that these can be directly linked to weather as opposed to some other systematic feature that varies with season or region. Thus, future research would need to look further at additional confounding variables to provide stronger interpretations of these effects.

Conclusion

Few would argue that self-reported well-being measures like the one used in the BRFSS provide a flawless picture of a person's (or a region's) quality of life. Indeed, important questions remain about the reliability and validity of these measures, and it is not clear whether self-reported subjective well-being really can be useful in policy settings. However, to improve these measures (or to determine whether they should be abandoned in favor of dramatically different alternatives), it is critically important to know precisely which problems affect the measures and how bad these problems really are in terms of their effects on reliability and validity. The current study examined this issue by testing whether life satisfaction judgments fluctuate with the weather. Although our study cannot rule out the possibility that weather effects *can* influence life satisfaction judgments, it does show that the effects are usually not detectable in a sample of over 1 million respondents assessed over a period in which realistic variations in weather occurred.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

Estimates for Temperature Models.

	Centered		Extreme Heat		Extreme Cold		Difference	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	3.389 *	0.003	3.390 *	0.003	3.390 *	0.003	3.390 *	0.003
Daily (D)	−0.009	0.009	0.005	0.004	−0.004	0.003	−0.004	0.010
Monthly (M)	−0.005	0.004	−0.007	0.004	−0.005	0.004	−0.005	0.005
Area (A)	0.074 *	0.028	0.072 *	0.028	0.071 *	0.028	0.076 *	0.028
D:M	0.038	0.063	0.065 *	0.024	−0.008	0.021	0.033	0.068
D:A	0.174	0.133	0.100	0.053	−0.000	0.048	0.153	0.143
M:A	−0.106	0.062	−0.113	0.065	−0.085	0.065	−0.132 *	0.065
D:M:A	1.636	0.892	0.666	0.352	−0.299	0.315	1.090	0.968
Difference (Dif)							−0.021	0.013
D:Dif							−0.380 *	0.169
Dif:M							−0.030	0.091
Dif:A							0.006	0.193
D:Dif:M							−0.739	1.048
D:Dif:A							−2.209	2.402
Dif:M:A							1.287	1.311
D:Dif:M:A							4.729	12.927

Note.

* = p<.05. In the Centered model, daily temperature is centered around the monthly mean. In the Extreme Heat and Extreme Cold models, daily temperature is a dichotomous variable that indicates whether the temperature on that day exceeded the 10 degrees above or below the typical temperature for that month. The Difference model includes centered daily temperature and the difference between the current day's temperature and the previous day's temperature.

Table 2

Estimates for Precipitation Models.

	Centered		Extreme		Difference	
	Estimate	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
Intercept	3.390*	0.003	3.390*	0.003	3.390*	0.003
Daily (D)	0.003	0.024	−0.002	0.003	−0.030	0.036
Monthly (M)	−0.036	0.166	−0.021	0.166	−0.085	0.170
Area (A)	−0.560	0.553	−0.480	0.547	−0.593	0.555
D:M	−1.785	2.699	0.340	0.672	−1.796	4.834
D:A	4.772	4.315	−0.079	0.630	3.659	6.062
M:A	−2.775	22.402	−7.513	23.447	−4.295	23.249
D:M:A	48.939	300.065	−20.558	63.926	−6.586	429.464
Difference (Dif)					0.042	0.025
D:Dif					−0.010	0.076
Dif:M					−4.694	2.885
Dif:A					−4.717	4.572
D:Dif:M					2.480	4.730
D:Dif:A					16.897	11.084
Dif:M:A					311.188	344.238
D:Dif:M:A					−624.657	664.652

Note.

* = p<.05. In the Centered model, daily precipitation is centered around the monthly mean. In the Extreme model, daily precipitation is a dichotomous variable that indicates whether the precipitation on that day exceeded .25 inches. The Difference model includes centered daily precipitation and the difference between the current day's precipitation and the previous day's precipitation.

Table 3

Estimates for Cloud Cover Models.

	Centered		Extreme Sun		Extreme Clouds		Difference	
	Estimate	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
Intercept	3.388*	0.003	3.388*	0.003	3.388*	0.003	3.387*	0.003
Daily (D)	0.001	0.003	0.000	0.002	0.002	0.002	0.001	0.003
Monthly (M)	0.002	0.009	0.002	0.012	0.009	0.011	0.000	0.011
Area (A)	−0.083*	0.026	−0.085*	0.027	−0.089*	0.026	−0.089*	0.026
D:M	−0.053	0.041	−0.001	0.024	−0.044	0.027	−0.077	0.050
D:A	−0.002	0.030	0.004	0.018	0.029	0.021	0.024	0.036
M:A	−0.017	0.107	0.028	0.138	0.016	0.121	0.003	0.118
D:M:A	0.327	0.477	−0.125	0.252	−0.157	0.308	0.318	0.566
Difference (Dif)							0.001	0.003
D:Dif							0.032*	0.010
Dif:M							0.074	0.046
Dif:A							−0.027	0.034
D:Dif:M							0.009	0.157
D:Dif:A							0.221	0.121
Dif:M:A							0.266	0.539
D:Dif:M:A							−0.613	1.848

Note.

* = $p<.05$. In the Centered model, daily cloud cover is centered around the monthly mean. In the Extreme Sun and Extreme Clouds models, daily cloud cover is a dichotomous variable that indicates whether the cloud cover on that day is less than 2 or greater than 6. The Difference model includes centered daily cloud cover and the difference between the current day's cloud cover and the previous day's cloud cover.

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Table 4

Estimates for Barometric Pressure Models.

	Centered		Extreme Low		Extreme High		Difference	
	Estimate	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
Intercept	3.390*	0.003	3.391*	0.003	3.390*	0.003	3.390*	0.003
Daily (D)	0.005	0.003	−0.002	0.003	0.004	0.003	0.004	0.004
Monthly (M)	−0.001	0.011	0.003	0.011	−0.004	0.011	−0.001	0.011
Area (A)	0.008	0.064	0.007	0.064	0.003	0.064	0.004	0.064
D:M	0.056	0.055	−0.050	0.050	0.040	0.050	0.082	0.061
D:A	0.091	0.089	0.003	0.084	0.078	0.084	0.040	0.098
M:A	−0.345	0.225	−0.303	0.230	−0.298	0.229	−0.270	0.232
D:M:A	0.202	1.126	−0.693	1.054	−1.231	1.128	0.218	1.227
Difference (Dif)							0.003	0.004
D:Dif							0.005	0.014
Dif:M							−0.075	0.069
Dif:A							0.175	0.119
D:Dif:M							−0.067	0.233
D:Dif:A							0.290	0.391
Dif:M:A							−0.421	1.561
D:Dif:M:A							−7.030	4.763

Note.

* = p<.05. In the Centered model, daily barometric pressure is centered around the monthly mean. In the Extreme High and Extreme Low models, daily pressure is a dichotomous variable that indicates whether the pressure on that day is .30 inches less than or greater than the monthly average. The Difference model includes centered daily pressure and the difference between the current day's pressure and the previous day's pressure.

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Table 5

Estimates for Wind Speed Models.

	Centered		Extreme		Difference	
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	3.390 *	0.003	3.390 *	0.003	3.390 *	0.003
Daily (D)	0.003	0.020	−0.000	0.005	0.002	0.025
Monthly (M)	0.060	0.058	0.060	0.060	0.070	0.063
Area (A−)	0.054	0.129	0.055	0.129	0.037	0.129
D:M	0.404	1.890	0.215	0.405	0.427	2.421
D:A	−0.960	0.981	0.085	0.172	−0.622	1.219
M:A	2.991	2.972	4.646	3.253	2.320	3.188
D:M:A	81.596	87.079	−17.263	13.057	140.583	108.811
Difference (Dif)					−0.009	0.021
D:Dif					0.372	0.396
Dif:M					0.800	2.017
Dif:A					−0.831	1.070
D:Dif:M					−27.370	37.918
D:Dif:A					12.548	18.079
Dif:M:A					−115.071	95.164
D:Dif:M:A					633.784	1597.736

Note.

* = $p<.05$. In the “Centered” model, daily wind speed is centered around the monthly mean. In the Extreme model, daily wind speed is a dichotomous variable that indicates whether the wind speed on that day exceeded 15MPH. The Difference model includes centered daily wind speed and the difference between the current day’s wind speed and the previous day’s wind speed.

Table 6

Estimates for Humidity Models.

	Centered		Extreme Low		Extreme High		Difference	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	3.391*	0.003	3.391*	0.003	3.391*	0.003	3.390*	0.003
Daily (D)	0.000	0.005	0.001	0.008	−0.001	0.002	−0.005	0.006
Monthly (M)	−0.001	0.012	−0.002	0.013	0.013	0.014	−0.007	0.013
Area (A)	−0.038	0.031	−0.046	0.032	−0.036	0.031	−0.040	0.031
D:M	−0.066	0.101	0.017	0.091	−0.054	0.031	−0.054	0.116
D:A	0.017	0.060	0.024	0.038	−0.014	0.031	0.037	0.067
M:A	−0.006	0.102	0.078	0.131	0.010	0.111	−0.001	0.106
D:M:A	0.303	0.808	−0.082	0.387	0.322	0.372	0.535	0.883
Difference (Dif)							0.014*	0.006
D:Dif							0.049	0.037
Dif:M							−0.026	0.122
Dif:A							−0.102	0.083
D:Dif:M							1.214	0.668
D:Dif:A							0.401	0.428
Dif:M:A							−0.285	1.163
D:Dif:M:A							−1.908	6.014

Note.

* = $p<.05$. In the Centered model, daily humidity is centered around the monthly mean. In the Extreme High and Extreme Low models, daily humidity is a dichotomous variable that indicates whether the humidity on that day was above 95% or below 50%. The Difference model includes centered daily humidity and the difference between the current day's humidity and the previous day's humidity.