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Key Points:
- The observed covariability between climate and crime rates was analyzed; regional and monthly averaging is critical for climate signal detection
- Interannual regional violent crime rates are influenced by climate variability; strongest correlations exist with wintertime temperatures
- Findings support Routine Activities Theory as the primary causal mechanism of this relationship linking climate and violent crime

Supporting Information:
- Supporting Information S1

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The Influence of Interannual Climate Variability on Regional Violent Crime Rates in the United States

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Abstract While the impact of climate on regional geopolitical stability and large-scale conflict has garnered increased visibility in recent years, the effects of climate variability on interpersonal violent crime have received only limited scientific attention. Though earlier studies have established a modest correlation between temperature and violent crime, the underlying seasonality in both variables was often not controlled for and spatial heterogeneity of the statistical relationships has largely been overlooked. Here a method of spatial aggregation is applied to the United States, enabling a systematic investigation into the observed relationships between large-scale climate variability and regionally aggregated crime rates. This novel approach allows for differentiation between the effects of two previously proposed mechanisms linking climate and violent crime, the Routine Activities Theory and Temperature-Aggression Hypothesis. Results indicate large and statistically significant positive correlations between the interannual variability of wintertime air temperature and both violent and property crime rates, with negligible correlations emerging from summertime data. Results strongly support the Routine Activities Theory linking climate and violent crime, with climate variability explaining well over a third of the variance of wintertime violent crime in several broad regions of the United States. Finally, results motivate the development of observationally constrained empirical models and their potential application to seasonal and potentially longer-term forecasts.

Plain Language Summary Higher wintertime temperatures lead to higher crime rates across several broad regions of the United States. We combined more than 30 years of climate and crime data from five U.S. regions with similar climate and found a very strong relationship between temperature and both violent and property crime, particularly in the winter. That milder winters–when people are more apt to be out and about compared to harsh winters–see that higher levels of crime provides support to a theory that simply increasing the number of interactions between people is likely the primary driver of this climate-crime connection.

1. Introduction

1.1. Motivation

Research into the influence of climate on violence and conflict is a small but emerging area of study (Adger et al., 2014; Clayton et al., 2017; Oppenheimer et al., 2014). While much of the scientific research to date has been focused on governmental and societal stability in developing nations, such as the likelihood of civil war among African nations (Burke et al., 2009; Hsiang et al., 2011) or the potential impact of anthropogenic climate change on the beginning of the Syrian conflict (Kelley et al., 2015), there has been relatively little examination of the influences of climate on criminal behavior. A wide variety of causes for increasing levels of interpersonal violence in the face of climate change have been identified including, but not limited to, rising competition for scarce resources, mass migration from sea level rise or drought, regional destabilization exacerbated by crop failures and changing frequencies of natural disasters (Adger et al., 2014), or more immediately through personal biological or psychological impacts of weather (Agnew, 2011).

The influence of weather on crime has been speculated upon since Adolph Quetelet examined the relationship in 1842 (Quetelet via Block, 1984). Interest in the topic grew after a report by the U.S. Riot Commission tied a series of 1967 U.S. riots to high temperatures (United States National Advisory Commission on Civil Disorders, 1968). Subsequent studies have examined a broad array of meteorological factors including temperature, sunlight, precipitation, wind, and humidity (Cohn, 1990), though recent research has narrowed the focus to the effects of temperature on crime (Anderson & DeLisi, 2011; Gamble & Hess, 2012; Mares, 2013a; Ranson, 2014).

Understanding the mechanisms and temporal variability of violent crime is also a matter of global public health. In 1996, the World Health Assembly declared violence a leading worldwide public health problem (Krug et al., 2002), as evidenced by interpersonal assault being the primary cause for 3.9% of U.S. 2015 emergency room visits related to injury, poisoning, or adverse effect (see Table 17 in Rui & Kang, 2015). The present study thus aims to address a potentially important pathway between climate variability and public health that has received little attention relative to the severity of its outcomes. The ramifications of a connection between violent crime rates and temperature, particularly in the face of anthropogenic climate change, place this research within the growing field at the intersection of climate change and human health. Following a brief review of the relevant literature and data sets, we conduct an examination of the observed covariability between interannual climate variability and the human response—criminal activity—over recent decades, garnering insight into the likely mechanisms.

1.2. Theoretical Background

Many theories have attempted to explain the apparent relationship between temperature and crime, but most recent studies have converged on two potential causal mechanisms: the Temperature-Aggression Hypothesis and the Routine Activities Theory. Both theories are briefly reviewed here.

The Temperature-Aggression Hypothesis postulates that aggression is increased during periods of extreme heat due to "distortion of the social interaction process in a hostile direction" (Anderson, 2001). Originally proposed as the General Affective Aggression Model (Allen et al., 2018; Anderson et al., 1996) but also known as the heat hypothesis (Anderson, 2001), it is most well known as the Temperature-Aggression Hypothesis and will be referred to as such herein. According to Anderson (2001), the "heat hypothesis states that hot temperatures increase aggressive motivation and (under some conditions) aggressive behavior." Increasing hostile affect during periods of higher heat stress primes aggressive thoughts and attitudes, with a resulting enhancement of individual aggressiveness. Temperature-Aggression has received support from both laboratory studies (Anderson et al., 2000; Baron & Bell, 1976) and real-world examples, like the raised likelihood of baseball pitchers hitting batters during games played on hot days (Krenzer & Splan, 2018; Larrick et al., 2011; Reifman et al., 1991) and increasing levels of frustration-inspired car honking with higher temperatures in Phoenix (Kenrick & MacFarlane, 1986). These examples agree with and complement existing studies on criminal activity (Anderson & DeLisi, 2011; Bruederle et al., 2017).

A second postulated explanation is the Routine Activities Theory (L. E. Cohen & Felson, 1979). Routine Activities acts as a framework for examining the relationship between weather and criminal behavior (Cohn, 1990) by suggesting that crime necessitates the convergence of three elements: a motivated offender, a suitable target, and the absence of a guardian capable of preventing a violation of the law (L. E. Cohen & Felson, 1979). Since Cohen and Felson also describe daily activities as relatively habitual and composed of patterns repeated over time, changes in the environment lead to deviations in the everyday activities of individuals (e.g., rainy weather will keep more individuals inside of their residences) and daily weather conditions can shift the probability of the aforementioned convergence of offender, target, and absence of guardian (Agnew, 2011). During periods of pleasant weather (e.g., warmer weather in the winter and lack of rainfall in the summer), individuals are more likely to be outside of their residences and encountering other individuals, resulting in an increase in both the number of interpersonal interactions and victim availability.

1.3. Previous Studies

A number of studies spanning a range of locations and spatial and temporal scales have independently found relationships between temperature and violent crime. Investigations at the scale of individual cities, such as Dallas, TX (Gamble & Hess, 2012); St. Louis, MO (Mares, 2013a; Mares, 2013b); Philadelphia, PA (Schinasi & Hamra, 2017); and Tangshan, China (Hu et al., 2017), have uniformly demonstrated a positive relationship between temperature and violent crime. Still, other studies have produced similar findings at a broader scale, either by examining a conglomeration of data at the city or county level in the United States (Hipp et al., 2004; Jacob et al., 2007; Ranson, 2014), New Zealand (Horrocks & Menclova, 2011; Williams et al., 2015), or South Africa (Bruederle et al., 2017), or by examining annual, nationally aggregated data for the United States (Anderson et al., 1997; Rotton & Cohn, 2003), Finland (Tiihonen et al., 2017), Malaysia (Habibullah, 2017), England and Wales (Field, 1992), or multiple countries around the globe (Mares & Moffett, 2016). A recent meta-analysis by Hsiang et al. (2013) concurred with these findings; variation in relationship strength between different crime types is a common conclusion (e.g., Rotton & Cohn, 2003), though aggravated and simple assault consistently yield the strongest relationship with temperature.

In addition to strong support for a relationship between temperature and violent crime, a wide variety of studies have uncovered robust positive relationships between temperature and property crime (Cohn & Rotton, 2000; Field, 1992; Hipp et al., 2004; Horrocks & Menclova, 2011; Jacob et al., 2007; Ranson, 2014; Rotton & Cohn, 2003). For example, Cohn and Rotton (2000) examined property crime in Minneapolis, MN, and determined "temperature also emerged as a significant predictor of property offences" and that "Minneapolis police received more reports about [property crimes] during warm than during cool or cold periods." While there remains a slight level of disagreement on the presence of the relationship between temperature and property crime, the preponderance of evidence clearly favors the existence of a positive relationship.

Precipitation has also been explored as an explanatory variable for both violent and property crime, although without a clear consensus emerging to date. Some studies have found evidence of the effects of precipitation on crime (Horrocks & Menclova, 2011; Hsiang et al., 2013; Jacob et al., 2007), but other investigations have unveiled either an inconclusive relationship or a lack of relationship entirely (Field, 1992; Mares, 2013a; Ranson, 2014).

The seasonality of criminal activity is well established (e.g., McDowall et al., 2012), and most recent work investigating the relationship between weather or climate and crime considers seasonality in some regard or another (e.g., Ranson, 2014). For instance, Hu et al. (2017) examined the relationship between a variety of temperature-based indices and various crime types and attributed the resulting high correlations to seasonality. Hipp et al. (2004) detected significant seasonal oscillations for crime rates between 1990 and 1992 and claimed that the broad seasonality across both violent and property crimes lends support to Routine Activities Theory over the Temperature-Aggression Model. Mares (2013a) found strong positive relationships between crime and expected monthly temperatures. This is further confirmed by direct examination of seasonality, such as in recent studies by Carbone-Lopez and Lauritsen (2013) and McDowall and Curtis (2015). Put simply, crime has a strong seasonality that needs to be properly accounted for in any examination of the relationship between weather and crime. In the case of the present study, which focuses on *interannual* variability, all data sets are carefully deseasonalized (see section 2.4) such that the shared annual cycle between temperature and crime in temperate regions does not artificially inflate correlations.

Most of the studies on the effects of temperature on crime have either aggregated data from an entire country (Hipp et al., 2004; Ranson, 2014) or compiled a detailed time series for an individual city (Gamble & Hess, 2012; Mares, 2013a). However, it is important to recognize the spatial heterogeneities that are present within aggregated data. Several studies have uncovered within-city (J. Cohen et al., 2003; Mares, 2013a; Mares, 2013b) or between-city (Linning et al., 2017; de Melo et al., 2017) spatial patterns in the relationship between temperature and crime. On the opposing end of spatial resolution, Mares and Moffett (2016) examined relationships between annual homicide rates and temperature across 57 countries and determined vastly different relationship strengths among countries. As will be apparent in the following sections, carefully addressing spatial heterogeneity, including choosing appropriate spatial scales for a given temporal resolution, proves vital for identifying meaningful signals in phenomena that are inherently noisy at the local level.

2. Data and Methods

2.1. Climate Data

The period over which data are analyzed in this study is particularly well observed in terms of interannual climate variability (e.g., via satellites and in situ observations). In addition, the development of data assimilative products, known as retrospective analyses (or reanalyses), is a major advance in the field of climate science (Trenberth et al., 2008). Reanalyses employ weather forecast models in a retrospective mode while assimilating enormous volumes of observational data to constrain the model solutions and produce the best possible estimate of the time-evolving state of the atmosphere.

Time-varying climate fields were derived from the North American Regional Reanalysis (NARR), a well-established climate reanalysis designed as a "long-term, consistent, high-resolution climate dataset for the North American domain" (Mesinger et al., 2006). NARR is produced and distributed by the National Centers for Environmental Prediction, part of the National Oceanic and Atmospheric Administration. The NARR incorporates a wide array of meteorological observations, including data from geostationary satellites, surface measurements, and radiosondes. The full list of assimilated observations can be found in Tables 1 and 2 of Mesinger et al. (2006).

The full NARR product consists of 311 output variables, mostly available at 29 vertical levels and at 3-hourly, daily, and monthly averaging intervals from 1979 to 2016 (National Centers for Environmental Prediction, 2018). Raw data are provided on a Northern Lambert Conformal Conic grid with corners at 1.00°N, 145.50°W; 0.90°N, 68.32°W; 46.35°N, 2.57°W; and 46.63°N, 148.64°E at an irregular spatial resolution of 32 km (~0.3°). Five monolevel (near surface) monthly mean NARR variables were used in the present study: 2-m air temperature, 2-m dew point temperature, 2-m relative humidity, accumulated total precipitation (monthly mean of daily accumulation), and accumulated snow (monthly mean). To facilitate cross analysis with crime data, the NARR data were linearly interpolated from the native grid described above onto a uniform $0.1° \times 0.1°$ latitude-longitude grid.

2.2. Crime Data

U.S. crime data were obtained from the Uniform Crime Reporting (UCR) Program of the U.S. Federal Bureau of Investigation (FBI). Law enforcement agencies throughout the United States report monthly counts of crime and arrest data to the FBI, where it is collected and published in an annual report, "Crime in the United States" (Maltz & Weiss, 2006). Though UCR reporting began in 1930, the present study utilized data beginning in 1979, coinciding with the start of the high-quality NARR climate data set, and ending in 2016. Reporting gaps occur occasionally and for a variety of reasons, including agency budget problems, personnel changes, or natural disasters (Maltz & Weiss, 2006). The version of the UCR data set used in this study is free and in the public domain.

The UCR data set consists of seven Part I offenses, which are grouped into violent and property crime categories. Violent crime as defined by the FBI for construction of the UCR data set consists of the following: murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault. Property crime includes the following: burglary, larceny, and motor vehicle theft. Data for simple assault and arson are also reported but not included within the UCR-calculated violent or property crime totals due to known systematic issues in reporting. The UCR data are compiled at the agency level and have a monthly temporal resolution, though agencies are not required to submit monthly data and may instead report on a quarterly, semiannual, or annual basis (this is expanded upon in section 2.3). Note that in many cases, an agency is not equivalent to a city. In addition to crime summary statistics, various agency demographic information is also included. Of relevance to the present study are city name, state, primary originating agency identifier (ORI), and population.

The location of each agency was compiled by cross-referencing the city's primary originating agency identifier with information found in the Agency Crosswalk index, a separate appendix published by the FBI, which contains a more complete set of demographic information for each agency (United States Bureau of Justice Statistics, 2015). It should be noted that the location specified within the Crosswalk index is the latitude and longitude of the geographic center of the county they reside in. This necessitated the manual correction of locations where the county spanned a large body of water (e.g., counties bordering the Great Lakes) as the geographic center of the county would be skewed by the surface area occupied by the adjacent body of water. These corrections manually set the latitude and longitude of affected counties to the geographic center of a given county's land area.

For the purposes of investigating the relationship between climate variables and violent crime and the underlying causal mechanisms (i.e., Routine Activities Theory vs. Temperature-Aggression Hypothesis), discussion herein will be focused on aggregated totals of violent crime and property crime, though results for specific crime types can be found in the supporting information. Though the present study does not specifically aim to investigate property crime, analyzing property crime serves as a useful diagnostic tool when exploring explanatory mechanisms, as elaborated upon in section 3.

2.3. Data Processing and Quality Control

Once the UCR data were compiled into 21,670 agency-specific time series, several processing steps were applied with the goal of systematically standardizing the data while retaining the interannual variability of crime rates. Each step is described in detail below.

Removing long-term variability in crime rates (see Figure 1 in Cooper & Smith, 2011), which may be artifacts of changes in agency reporting protocol, broader city, state, or federal policy changes, or underlying socioeconomic trends, allows for a stricter focus on interannual fluctuations that may potentially be influenced by natural climate variability. First, a 4-year running mean was calculated to effectively apply a low-pass filter to each time series. This also represents an *expected* total for a given month in an agency's time series. A 4-year running mean, as opposed to other lengths of time, was selected as the shortest time scale, which appropriately followed the low-frequency variability without being influenced by regular, higher-frequency cycles like seasonality. In addition to providing a baseline from which to calculate monthly anomalies, use of a running mean provides a mechanism to minimize the influence of long-term externalities. These externalities could include rising or falling levels of law enforcement, policy changes, and demographic changes within a given city. While these externalities are vitally important for determining the actual crime rate, they inhibit the ability to identify the interannual signal with which we aim to confront with climate data.

Once the 4-year running mean has been calculated for each agency-level raw crime record, it is used in a quality control process designed to identify bad data owing to anomalies in reporting frequency. As noted in the description of the UCR data set, agencies occasionally report raw crime totals quarterly, biannually, or annually, instead of monthly. Given that later analysis steps require a monthly resolution and that it is impossible to accurately disaggregate these multimonthly summed reports into their actual monthly distributions, these multimonthly reports need to be removed from the time series entirely. To systematically remove these multimonthly totals, a simple two-step test was applied to each time series. A reported monthly total qualified for removal if (1) the previous monthly report was listed as zero or as containing no data, implying that the month in question may be a sum of multiple months and (2) a given month's reported total is greater than both 2 times the 4-year running mean and an empirically derived allowable threshold. This quality control process removed approximately 10% of the initial data set, leaving 90% of the initial data from 1981 to 2014 available for processing (see supporting information Table S1 for percentages by crime type). This same surviving sample totaled about 86% of the total FBI estimates over the same time period (U.S. Department of Justice Federal Bureau of Investigation, 2018; see supporting information Table S1 for percentages by crime type).

After completion of the above quality control process, the low-frequency variability in crime rates was again accounted for by calculating a new 4-year running mean. This reapplication of a low-pass filter accounts for any remaining spurious features in the initial 4-year running mean, which may have been an artifact of poorly reported data. In totality, this process produces two complete sets of agency-level time series, both an actual and expected crime count (supporting information Figure S1, bottom). Ultimately, all analysis of crime herein is based on time series of the ratio of actual to expected crime count for a given agency.

2.4. Region Determination

To isolate the effects of the climate variability signal from those of nonclimate drivers within a given agency's crime rates, a method was employed which aggregated crime totals within each of several regions. Regional boundaries were determined with a data-driven blend of objective and subjective analyses, through the complementary processes of (1) an empirical orthogonal function (EOF) analysis of seasonal temperature patterns over the United States and (2) identifying regions with homogeneous strong relationships between temperature and crime anomalies that were distinguishable from all other regions. Five regions demonstrated sufficient homogeneity, as well as clear distinction from neighboring regions, which are enumerated below and illustrated in Figure 1.

1. Northeast, from 38.0°N to 49.5°N and 88.0°W to 66.5°W
2. Southeast, from 30.0°N to 38.0°N and 92.0°W to 75.0°W
3. South Central, from 24.5°N to 42.0°N and 104.5°W to 92.0°W
4. West, from 30.0°N to 49.5°N and 125.0°W to 104.5°W, and
5. Midwest, from 38.0°N to 49.5°N and 104.5°W to 88.0°W (excluding the portion accounted for within the South Central region)

It should be noted that Florida was not included as a region—or within any region—primarily due to systematic reporting issues, as well as a comparatively small population and low amplitude of seasonal and interannual temperature variability.

To demonstrate the objective approach involved in the process of region determination, Figure 2 depicts the three leading EOFs of January surface air temperature overlaid with the regional boundaries. The main features of these three EOFs aid in forming a justifiable differentiation of the various regions. For instance, the

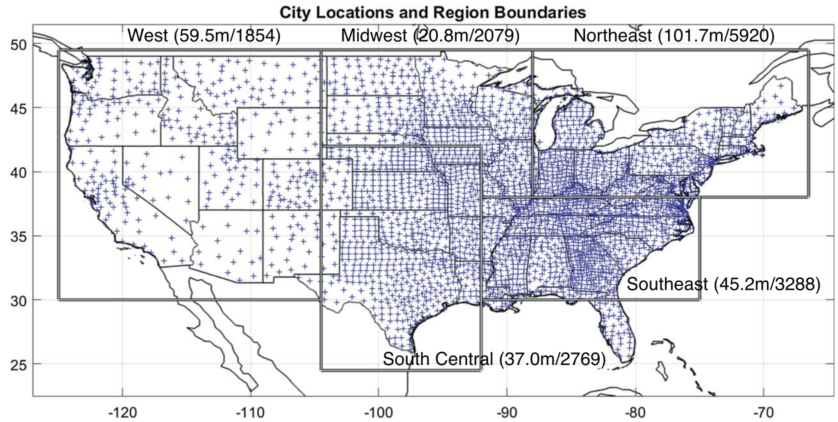

Figure 1. All five regions (outlined) with summary statistics (total population/number of agencies) and all city locations (blue plus signs). Note that city locations are mapped to the geographic center of their county and that each plus sign may represent multiple agencies.

first EOF displays a strong loading maximum centered over the Midwest region. The second EOF has two notable loading maxima, one spanning the entirety of the West region—which also blends into the South Central region, allowing for differentiation between the South Central and Southwest regions—as well as a more localized but prominent feature within the Northeast region. The third EOF reveals an isolated loading maximum within the Southeast region. See supporting information Figure S2 for a summer (July) version of the aforementioned EOF analysis.

Ultimately, the premise of the regional analysis depends on each agency within a region being subject to the same external forcing, which is interannual climate variability according to the time scale we have isolated through the above processing steps. To confirm that this is the case, correlations between the temperature time series for all unique pairs of agencies within each region were calculated (Figure 3). This analysis was performed both before and after removing the mean annual cycle from the temperature time series, confirming that the interannual climate forcing on the human systems as defined by each region are indeed highly consistent. For reference, an hypothetical region encompassing the entire United States shows no homogeneity of interannual climate forcing.

These results reveal two important findings. First, it is critical to account for known seasonality as Figure 3 (left) demonstrates how the correlation for a variable exhibiting an annual cycle (temperature) is artifically high between any pair of agencies. Many things have a seasonal cycle, yet they are not necessarily causally linked. Second, recalculating correlation strength after removing seasonality (Figure 3, right) demonstrates that not only are the regions as defined in this study subject to relatively consistent interannual climate variability, but there is a clear necessity to split the United States into distinct regions rather than construct a single, nationwide analysis.

In fact, the negative peak in the nationwide frequency distribution of city-to-city correlations even detects the well-known fact that the different regions of the United States can vary out of phase (likely the western and eastern United States) given the characteristic spatial scale of climate anomalies. This can be validated on a smaller scale by looking closely at the Northeast, Southeast, and Northeast + Southeast regions in Figure 3 (right). Though the Northeast and Southeast regions both show strong uniformity in temperature with median correlations between agency pairs of 0.87 and 0.90, respectively, combining the two adjacent regions tempers the homogeneity of the climate and reduces the median correlation to 0.77. Further, comparing correlation coefficients of within-region actual/expected crime ratios to between-region correlation coefficients provides an additional demonstration of the necessity of establishing distinct regions (Figure 4).

Finally, in addition to being guided by the temperature variance patterns as discussed above, the uniformity within a region's boundaries (and lack thereof outside a region's boundaries) of the relationship between aggregated crime and the local temperature field was also examined. Figure 5 shows an example using the Northeast, Southeast, South Central, and Midwest regions. There is a strong relationship between violent crime within the region and the temperature at every gridded location within the region. Notably, the

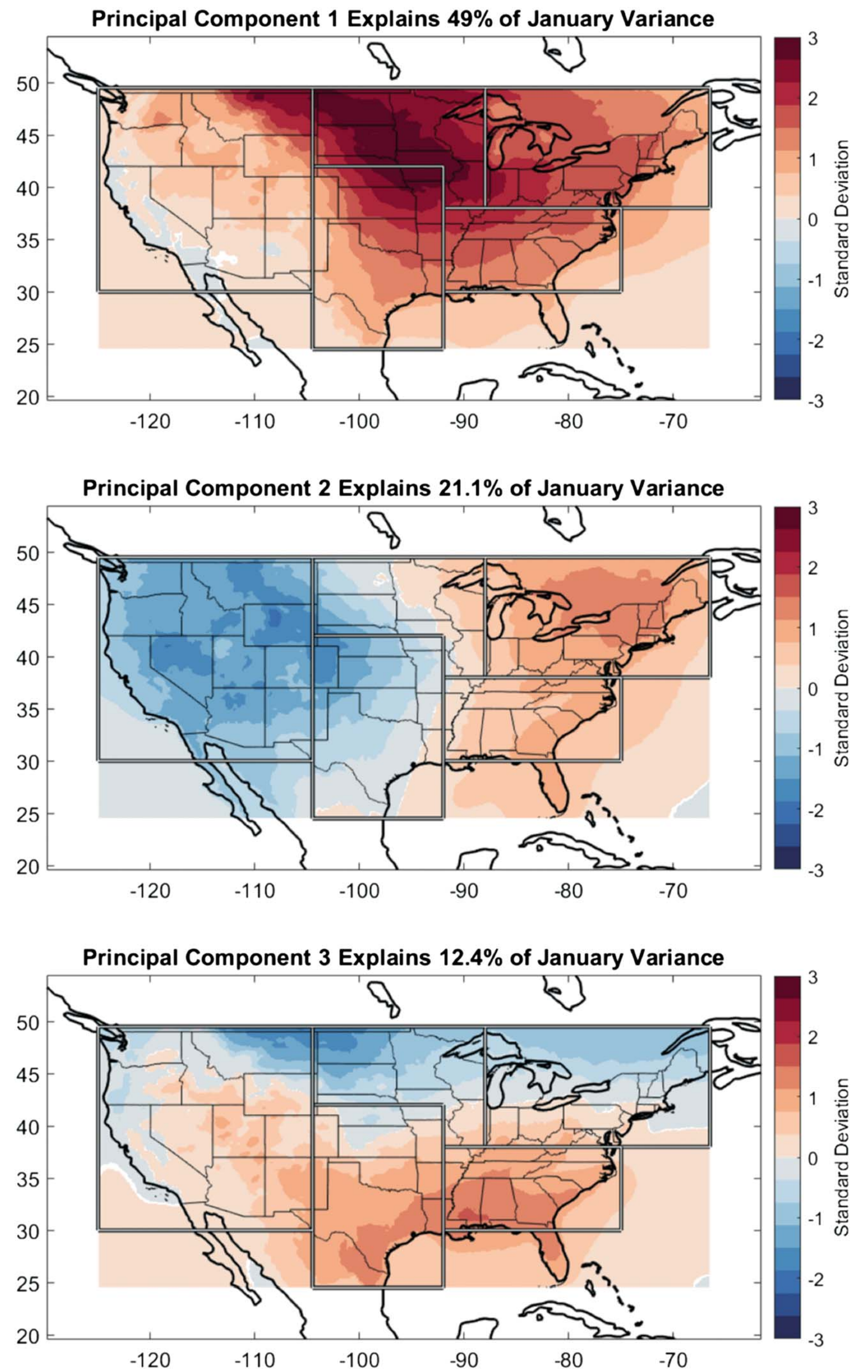

Figure 2. First three principal components of an empirical orthogonal function analysis of January temperature. The variance explained by each principal component in descending order is 49%, 21.1%, and 12.4%, with 83.5% of the total variance explained by these three patterns.

correlation maxima are primarily focused over the specified region. Though the peak strength of this relationship does sometimes spread into surrounding regions, it is important to remember that the region-defining process also considers the climate pattern analysis described earlier. These results are not critically sensitive to the domains of the regions within ±3° latitude or longitude.

As was briefly described above, once regions had been established, the relationship between climate variables and crime were analyzed by calculating the Pearson correlation coefficient between the aggregated ratio of

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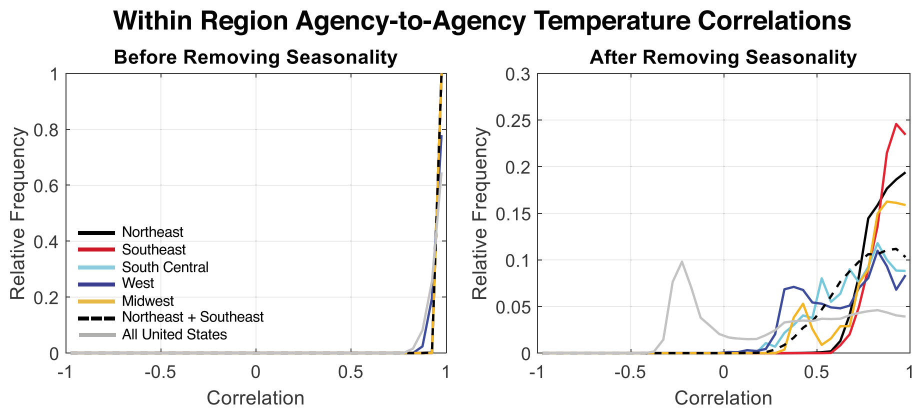

Figure 3. (left) Relative frequency of correlations of temperature for each unique city pair in a region. (right) Same as left but with the annual cycle removed.

actual to expected crime totals and temperature weighted by expected crime for every agency with a population within a given region. Using the ratio of actual to expected crime provides several benefits, including (1) overcoming inconsistent reporting at the agency level, which is particularly important when agencies are aggregated together, (2) pseudostandardizing raw count data to account for higher raw count variation during periods when crime rates are high, and (3) the creation of normal distributions at the region level. Correlation coefficients were calculated for each month individually to effectively remove seasonality.

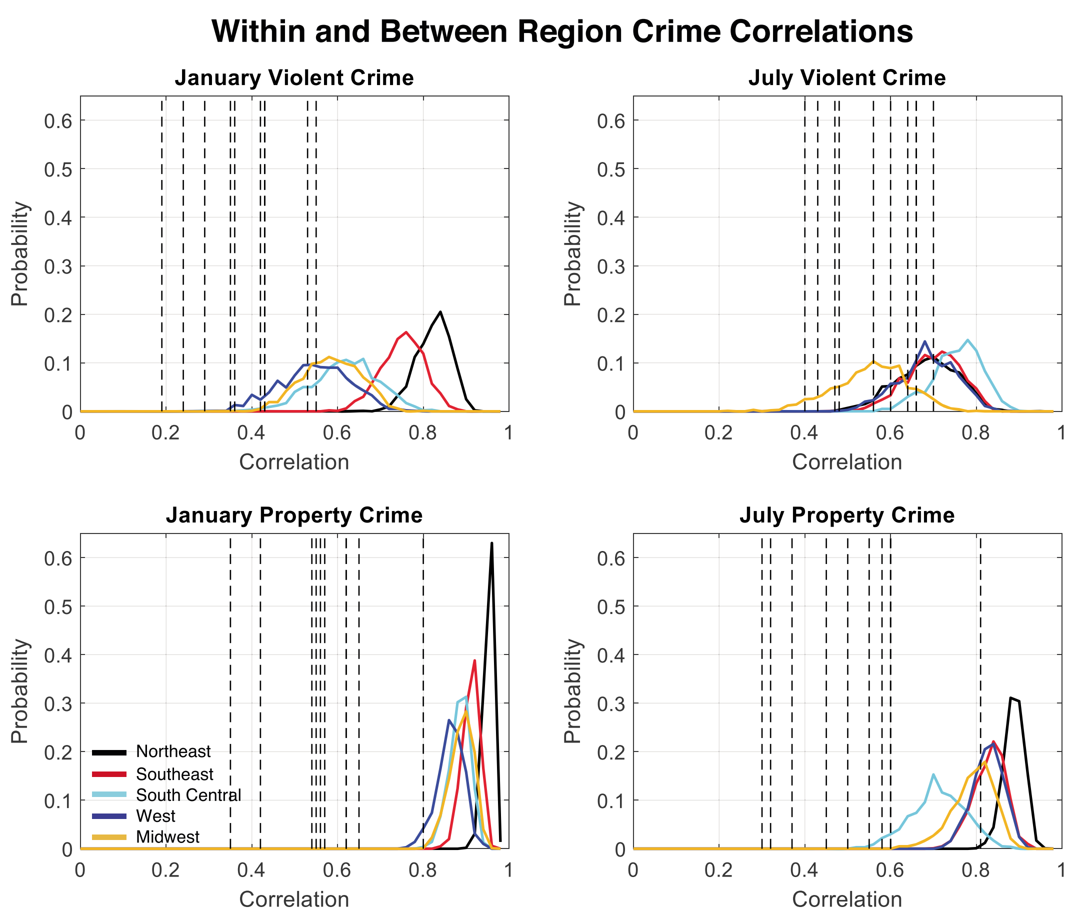

Figure 4. Histogram of bootstrapped correlations for within-region crime correlations (thick colored lines) overlaid with between-region crime correlations (dashed black lines).

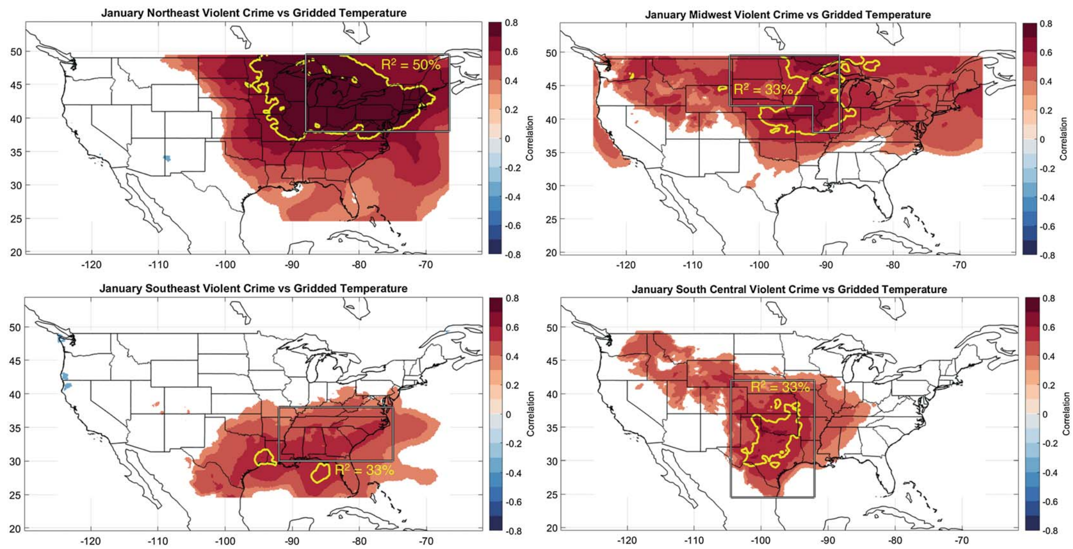

Figure 5. Correlations (shaded) between the ratio of actual to expected violent crime counts in each region (boxed) and temperature at each location throughout the United States for January. Correlation strength is shown if significance confidence is greater than 95%. The yellow line borders the region where temperature at that location explains at least a third of the variance in violent crime for that region.

3. Results

3.1. Violent and Property Crime and Temperature

Across all five of the defined U.S. regions—Northeast, Southeast, South Central, West, and Midwest—violent crime demonstrates a near universally positive relationship with temperature (see Figure 6, left). In addition, there is a distinct seasonality evident to the relationship. The relationship strength peaks with statistically significant relationships in the winter months but is reduced and loses statistical significance during the summer and fall months.

As expected given the spatial heterogeneity of the relationship between temperature and violent crime, regions exhibit varying strengths of the relationship, (Figure 6). Significance thresholds were calculated using the more conservative two-tailed Student's *t* test for all relationships despite a priori evidence in favor of a

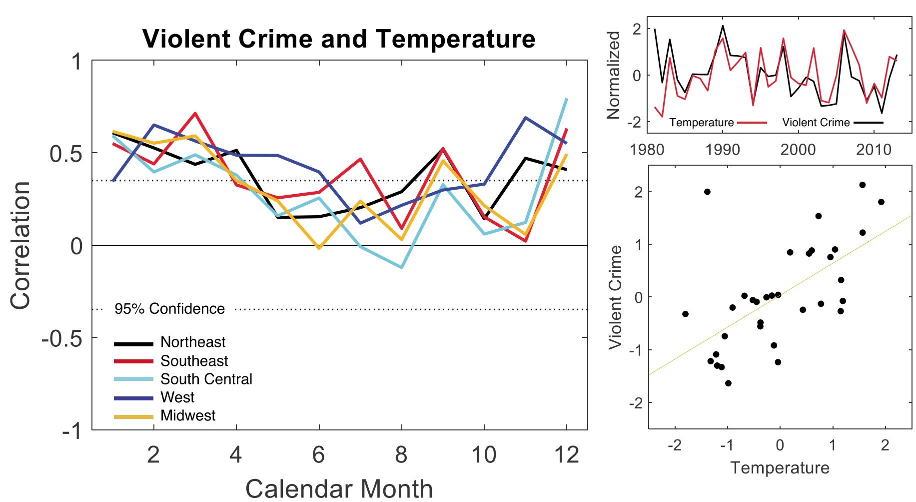

Figure 6. (left) Monthly correlations between violent crime and monthly temperature anomalies within each region. The dotted black line indicates the 95% confidence in significance threshold. (upper right) Time series of normalized January temperature and violent crime for the Northeast region. (lower right) Scatter plot of normalized January temperature and violent crime for the Northeast region.

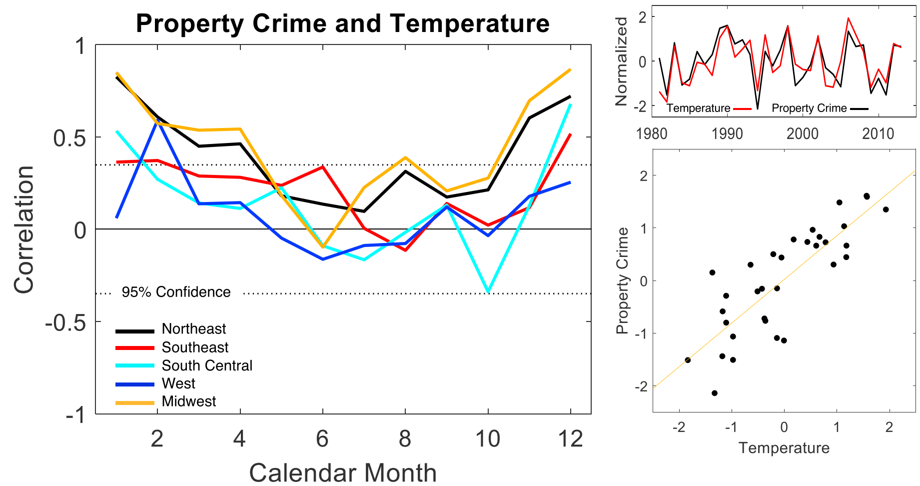

Figure 7. (left) Monthly correlations between property crime and monthly temperature anomalies within each region. The dotted black line indicates the 95% confidence in significance threshold. (upper right) Time series of normalized January temperature and property crime for the Northeast region. (lower right) Scatter plot of normalized January temperature and property crime for the Northeast region.

positive relationship between temperature and violent crime. This choice of statistical methodology does not result in meaningful changes in results or their interpretation.

That the relationship between temperature and violent crime is mainly a wintertime phenomenon lends support to the Routine Activities Theory as the primary causal mechanism. If the Temperature-Aggression Hypothesis is the primary driver, we would expect to see higher correlations in the summer months across all regions since physiological heat stress would not be a factor in the winter due to low temperatures. To further test this hypothesis, the same analysis was performed on property crime. If Routine Activities is indeed a causal mechanism, a relationship between temperature and property crime should exist as well. This would not be the case for Temperature-Aggression as Temperature-Aggression only impacts social interactions (i.e., applies to violent crimes but not property crimes) and would not, to our knowledge or according to published literature, physiologically drive one to commit property crime.

Upon performing identical analysis between temperature and property crime as was employed for violent crime, similar trends in relationship strength are seen (see Figure 7, left). Once again, most regions show a statistically significant relationship during the cold weather months, with the exception of the West region, which demonstrated consistently lower correlations than the rest of the regions across nearly all calendar months. The majority of calendar month correlations were again positive.

To summarize, results indicate large and statistically significant positive correlations between the interannual variability of wintertime air temperature and both violent and property crime rates with negligible correlations emerging from summertime data. The Routine Activities Theory is supported as the primary causal mechanism.

3.2. Other Crime Types and Climate Variables

Similar calculations and relationship tests were completed for all specific crime types given in the UCR data set. This included homicide, forcible rape, robbery, aggravated assault, simple assault, burglary, larceny, and motor vehicle theft, in addition to the aggregated violent and property crime totals discussed above. Though several of these crime types, particularly aggravated assault, simple assault, and larceny, do demonstrate strong positive relationships, their relationships will not be broken down here, for brevity. The relationships between temperature and the remaining crime types can be seen in the supporting information (Figures S3–S6 and Tables S4–S11).

In addition to temperature, the relationships between crime and dew point, relative humidity, accumulated precipitation, and accumulated snowfall were also examined. Though some of these climate variables independently displayed significant relationships with various crime types, this was likely driven by the physical interdependencies between temperature and those other climate variables. When temperature is controlled for, no other climate variables display a significant predictive relationship with crime. Finally, a sensitivity analysis of the temperature and crime relationship on population revealed no systematic difference; results were similar when cities with either large (greater than 250,000) or small populations (less than 50,000) were included in the regional totals (not shown).

4. Summary and Discussion

4.1. Evidence for Routine Activities Theory

A comprehensive analysis of the observed covariability between climate and violent crime in the United States was presented. The novel methodology employed within the present research has allowed for several findings. By aggregating data across regions that were found to be relatively homogeneous, the present study was able to overcome the consistent noise prevalent in each individual agency's crime data. By doing so, this is the first study to examine the effects of synoptic-scale (~1,000-km length) spatial heterogeneity within the relationship between climate and crime. By noting strong wintertime relationships between temperature and both violent and property crime, the present findings provide strong support for the Routine Activities Theory as a causal mechanism for the relationship between temperature and criminal activity. This conclusion follows for two logical reasons. First, by finding statistically significant relationships primarily in the winter and limited, at best, relationships in the summer, it is demonstrated that Routine Activities Theory is a stronger explanatory mechanism than the Temperature-Aggression Hypothesis, which requires the body to experience heat stress that can only occur at high summertime temperatures. Outside of extreme heat waves in the southern United States, it is unlikely that conditions leading to heat stress would arise in the winter in any climate regime. Second, it is important to note that strong relationships are unveiled in both violent and property crime. Though Routine Activities can explain this finding, an increase in property crime is unable to be explained by Temperature-Aggression, which postulates that hostile affect is a driver of the action, making it unlikely to contribute to property crime. It is perhaps unsurprising that the Northeast and Midwest regions produce the strongest relationships between temperature and crime due to the relative extremes of their respective climates. This example clearly demonstrates the importance of considering spatial heterogeneities during an analysis of climate and crime.

Conversely, it should be noted that while we have uncovered evidence supporting Routine Activities, the present study is unable to make any strong claims regarding Temperature-Aggression, outside of its low impacts relative to Routine Activities. While stronger relationships would be expected in the summer if Temperature-Aggression is a driving mechanism, it should be noted that the effects of Temperature-Aggression may be dampened by Routine Activities during periods of extreme heat. Though extreme heat would lead to maximum heat stress, it would also diminish the number of interactions between potential aggressors and victims as individuals are more likely to stay indoors or otherwise take actions to avoid the heat. This opposing relationship depresses the effects of Temperature-Aggression and precludes any determination of its effects. It is possible that future work could provide stronger evidence for or against Temperature-Aggression by utilizing data sets with finer temporal resolution.

4.2. Seasonality of the Temperature and Crime Relationship

In addition to the primary findings regarding analysis of climate variability and crime at the synoptic scale, the seasonality of the relationship between temperature and both violent and property crime should also be emphasized. Though seasonality has often been discussed as a factor when examining the relationship between temperature variability and crime, it has not been directly implicated in the discussion of the relationships between crime and climate (i.e., wintertime has consistently stronger relationships than summer). Though earlier work (Ranson, 2014) saw a decrease in the efficacy of temperature as a driver of crime as temperatures increased, no notice was made of the seasonal context. This is an important result on its own, as it has helped to provide evidence to differentiate between the Routine Activities Theory and Temperature-Aggression Hypothesis. It is also notable and worth reiterating that the high correlations shown here are *after* removing seasonality—only deseasonalized time series (34-year time series of January averages and so on) were analyzed during the present study. Lastly, it should be noted that the present study avoided splitting consecutive wintertime months during analysis (i.e., December 1997 and January 1998 included in different annual averages), which we believe may be a common pitfall in studies utilizing annual data and attempting to confront them with climate variability, and one which would have tempered, if not masked completely, the strength of the wintertime relationships noted above.

4.3. Limitations

As discussed earlier, there is a component of spatial heterogeneity to the relationships described between criminal activity and climate. This spatial heterogeneity can occur at a variety of scales—from neighborhood to country level, as noted in prior literature, but the present study only focuses on spatial heterogeneity at a synoptic scale. Though pockets of smaller-scale variation certainly exist with the specified regions, the present study did not address this for two reasons. First, the temporal scale of our data sets—monthly resolution in both the UCR and NARR data sets—are best suited to uncover broader-scale relationships, given that the weather patterns that would substantially influence crime rates on the time scale of a month are likely to be larger in scale (i.e., synoptic phenomena such as blocking high pressure systems). Thus, the temporal scale of our data sets inherently limits the ability to investigate smaller-scale features, a weakness of the present study. Utilizing a data set with finer temporal resolution, such as the FBI's National Incident-Based Reporting System which provides date and timestamp for individual crimes, may present possibilities in this regard. Second, looking at the relationship at a larger scale better enables the isolation of the climate signal from the background noise of individual locations (as noted in section 2). Though the small-scale differences may exist, isolating the nature of finer-scale relationships would require data with daily or hourly temporal resolution.

Another potential limitation is a lack of directly accounting for various socioeconomic variables, such as income inequality or age demographics of an agency's covered population. While inclusion of these factors has the potential to increase the overall accuracy of an analysis or potential future predictions, we believe this has been accounted for by use of the 4-year running mean. Using this as a baseline allows for longer-term fluctuations in socioeconomic variables and other influences to be accounted for while retaining the interannual variations upon which the analysis of the present study is built. Additionally, as noted in Dell et al. (2014), including exogenous variables that may also be affected by climate can result in an overcontrolling problem.

4.4. Recommendations for Future Work

Having established strong and robust statistical relationships between wintertime climate and crime rates, future work should aim to exploit these relationships through the development of multiple regression models, which could potentially be applied to seasonal forecasting of violent crime rates and long-term projections associated with anthropogenic climate change. Such applications of this work would serve to widen the aperture of the research looking at relationships between climate and human health.

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Erratum

In the originally published version of this article, the following line was missing from the acknowledgment section: "Publication of this article was funded by the University of Colorado Boulder Libraries Open Access Fund." This error has since been corrected, and this version may be considered the authoritative version of record.