Blowing in the wind?

The effect of weather on the intensity and spatial distribution of crime

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Abstract

Objectives: Despite an extensive literature on weather and crime, the magnitude of weather effects on crime and their implications for practical policing remain unclear. Similarly, the effects of weather on the location of crime have barely been explored empirically. We investigated how weather influences the intensity and spatial distribution of crime in Oslo, the capital of Norway.

Methods: Geocoded locations of criminal offences were combined with data on temperature, wind, and rain. We used negative binomial count models to assess the effect of weather on the intensity of crime and generalized additive models (GAMs) to test for spatial variations.

Results: The intensity and spatial distribution of crime were not very sensitive to weather in Oslo. The largest effect was for drug crimes, for which maximum relative to minimum temperature was related to a single incident increase every six days. No effects were found for dislocation in the spatial models.

Conclusions: In Oslo, Norway, weather conditions are of little importance for practical policing. The effects of weather on the intensity of crime are miniscule, and effects on the location of crime even smaller.

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1. Introduction

Criminologists have been interested in weather for decades because if weather affects crime, the specific nature of those effects could be useful for crime prevention and policing. Most notably, studies have focused on temperature, with the underlying assumption being that when people are uncomfortably hot, they are more likely to behave aggressively (Cohn, 1990; Cohn and Rotton, 1997; Ranson, 2014). Thus, while ordinary terms in the language such as “hotheads” can possibly be taken quite literally, these relationships deserve scientific scrutiny.

Despite a large number of studies, there is little consensus about the nature of the relationship between temperature and crime or about the magnitude of such effects. There is some debate about whether the relationship is linear or nonlinear (Rotton and Cohn, 2000), but tentatively we can say that there probably is an effect (Bushman, Wang, and Anderson, 2005). Whether such an effect is large enough to be of interest to police agencies remains unclear.

There are two main theoretical approaches in this area. The first approach focuses on physiological reactions and suggests that high temperatures may cause an increase in aggression, even if such reactions are moderated by social context (Anderson, Anderson, Dorr, DeNeve, and Flanagan, 2000; Card and Dahl, 2011). The key mechanism is hypothesized to be a direct physiological effect. The second approach is based on a routine activity framework (Cohen and Felson, 1979), and it suggests that weather influences where people stay and what they do (Agnew, 2012). Weather may affect the number of people who experience opportunities to commit crimes and the number who will be exposed to such crimes. However, changing weather does not necessarily impact overall crime rates; instead, it may rather lead to crimes being committed at alternative locations (Quick, Law, and Li, 2017).

Although the temperature–aggression hypothesis could potentially explain violent crimes, it is less likely to explain nonviolent crimes, such as theft and drug crimes. Routine activity theory suggests that there is no need to restrict the discussion to heat, as rain and fog,

for example, might affect behavioral patterns (Tompson and Bowers, 2015). Moreover, the effects of changes in behavior might not be restricted to the level of crime; they may also influence its spatial distribution.

In this paper we explore these issues in the context of Oslo, the largest city in Norway, which is situated in a typical North European climate zone. First, we assess the effects of temperature on violent crime. We examine whether previous findings generalize to northern climates, address key arguments in the literature regarding the functional form of the relationship between temperature and violent crime (linear vs. inverted U-shape), and determine whether the effects that have been reported have any practical significance. In addition, we assess whether the findings are similar for violent and nonviolent crimes, and we test the temperature–aggression hypothesis indirectly by assessing whether the relationship is stronger in warmer seasons and at warmer times of day.

We then move into more exploratory analyses. First, we examine whether other components of weather besides temperature are related to crime, including variables such as wind, rain, clouds, etc. Second, in line with the argument of displacement, we explore the possible effects of weather on the *spatial* distribution of crime.

2. Background and expectations

The effect of weather on crime

There is a long research tradition documenting that weather can affect crime, although the nature of the relationship may vary between contexts (Cohn, 1990). Using a 30-year panel of criminal activity in USA, Ranson (2014) found a strong positive effect of increasing temperature on nine major categories of crime. A similar study from Japan revealed that aggressive behavior such as suicides increased as the average temperature increased (Takahashi, 2017). Ceccato (2005) found that homicides increased in Sao Paulo, Brazil, with

higher temperatures, and Goin, Rudolph and Ahern (2017) showed that a Californian drought had criminogenic effects. A recent review in *Science* (Hsiang and Kopp, 2017) echoes this worry with respect to climate, hypothesizing that climate changes may impact a variety of domains, such as agriculture, coastal storms, and crime.

The physiological perspective on these effects, often described as the *heat hypothesis* (Anderson, 2001), suggests that hot temperatures increase aggressive motivation and (under some conditions) aggressive behavior. Early studies in this tradition usually were not able to distinguish between temperature effects and varying activity profiles at different times of the year and thus they were not able to address causality. More recent studies have used more sophisticated designs, such as field studies comparing geographic regions and time periods, and they have come closer to identifying possible causal mechanisms. Kenrick and MacFarland's (1986) classic study in Phoenix, Arizona found that aggressive horn honking increased on hot days, but only for drivers without air conditioning. Subsequent research revealed that hot summers in USA produce more violence than do cooler summers (Anderson et al., 2000). A large number of studies have documented a broad array of heat effects on crime (Ranson, 2014), and it seems unlikely that the two major challenges to the heat hypothesis—changes in routine activities (Keller et al., 2005) and “Southern culture” (Cohn and Rotton, 1997; Rotton and Cohn, 2000)—can account for all these findings. There have also been many increasingly sophisticated laboratory studies modeling how high temperature may impact violence. Recent studies suggest that two elements may be involved: an ambiguous provocation followed by multiple opportunities to retaliate. Under such circumstances, there may be an initial increase in aggressive retaliation followed by a decrease in such actions. This pattern is thought to occur because, after the initial, heat-induced aggressive outburst, social norms lead participants to decide that the initial reaction was enough (Anderson, 2001). Thus, the nature of the heat

hypothesis that has gained support suggests that hot temperatures cause increases in aggression, but that such reactions are usually moderated by context and social norms.

The starting point of the broader routine activity approach is that individuals make decisions based on rational considerations of the costs and benefits of alternative choices (Becker, 1968). From this perspective, weather conditions may affect the likelihood that one can commit a crime and not get caught (Jacob, Lefgren, and Moretti, 2007). This approach also links crime to social interactions in people's daily lives, and weather conditions may affect people's exposure to criminogenic opportunities (Rotton and Cohn, 2003). For example, people may leave their homes to enjoy good weather, increasing the pool of targets for pickpocketing, burglary, and violent crime in public places. It is likely that both offenders and targets spend more time in public places when the weather is good (higher temperatures and less wind and rain). For instance, a study from Brisbane, Australia, shows that weather significantly affects the use of public transportation (Tao, Corcoran, Rowe, and Hickman, 2018), a strong indicator of how people move about in a city. Effects may be larger in the evenings and at night, when most activities are discretionary or recreational (LeBeau, 1994; Thompson and Bowers, 2015). Compared with mandatory activities (such as going to work), discretionary activities are thought to be more readily influenced by the weather. Routine activity theory suggests that crime increases in good weather merely as a side effect of increased activity in public places, by targets and offenders alike. The rational choice approach to crime further suggests that offenders are aware of the increased opportunities afforded by more targets being out when the weather is good and they are more likely to engage in criminal activities on such days. In contrast, bad weather may facilitate criminal acts because potential "capable guardians" stay at home. For instance, Thompson and Bowers (2013) suggest that fog increases crime through reduced visibility and the presence of fewer capable guardians.

The effect of weather on the spatial distribution of crime

The criminology of place has documented that “hot spots” account for a large proportion of crime in cities and that such patterns seem to be relatively stable over time (Weisburd, Groff, and Yang, 2012). There are crime hot spots in “good” neighborhoods, and most streets even in so-called “bad” neighborhoods have little or no crime (Weisburd, 2015: 149). In Hipp’s (2016) theory of spatial crime patterns, he uses the locations of persons, typical spatial movement patterns, and situational characteristics to estimate crime potential. This theory suggests that police work should be geographically focused, and studies of policing effectiveness support such strategies (Weisburd and Eck, 2004).

Theories of social disorganization are also closely associated with this approach, as crime in these theories is typically linked to neighborhoods characterized by low income, many people living on social welfare, ethnic heterogeneity, and residential instability (Braga and Clarke, 2014; Sampson, Morenoff, and Gannon-Rowley, 2002). In addition, neighborhoods with numerous places to buy alcohol have been linked to high rates of crime (Gorman, Speer, Gruenewald, and Labouvie, 2001). Reflecting these findings, a recent study from Malmö, Sweden, found that concentrated social disadvantage, residential instability, and numerous alcohol outlets were predictors of violent crime hot spots (Gerell and Kronkvist, 2017). Open illegal drug scenes are associated with violence and burglary as well as drug crimes (Fast, Shoveller, and Kerr, 2017; Sandberg and Pedersen, 2009).

Research studies on the effect of weather on the spatial distribution of crime share an emphasis on criminogenic *contexts*: crime happens when and where potential offenders and targets meet (Carleton, Hsiang, and Burke, 2016; Kelly and Kelly, 2014). Hence, routine activity theory predicts that a relatively larger share of crime takes place at such places when the weather is good. This pattern would be strengthened if potential offenders were seen as rational actors, taking the effect of weather on victims’ locations into account when considering

where to find potential targets. Taking these lines of research together, we can suggest that the relative attractiveness of locations varies with the weather. A park is an appealing meeting place on a warm summer evening, but less so on a cold and windy winter night. In support of this, Quick et al. (2017) found that, in warm seasons, crime rates are higher in areas dominated by parks, whereas in colder seasons, crime rates are higher in areas with nightlife. Corcoran, Higgs, Rohde and Chhetri (2011) found some evidence that the increase in city fires on warm days is greater in poor neighborhoods.

A very limited number of studies have directly addressed the effect of weather on the spatial distribution of crime. Brunsdon, Corcoran, Higgs, and Ware (2009) studied the effect of weather on the spatial distribution of police-related incidents in an urban UK area. They used a comap approach (Brunsdon, 2001), in which spatial kernel densities of crime are estimated based on four weather characteristics, controlling for time-of-day effects. Temperature and humidity affected the spatial distribution of crime significantly in both summer and winter, whereas there were no effects of rain and wind. Using the Spatial Point Pattern Test (SPPT) (Andresen, 2009), Schutte and Breetzke (2018) found differences in the spatial distribution of violent crime and property crime, but not sexual crime, by temperature and rainfall in Tshwane, South Africa. Due to climatic and other contextual differences, we expect estimates from the UK to be more similar to the results from Norway.

A small number of studies have assessed seasonal differences in the spatial distribution of crime, with effects often attributed to variations in weather. Andresen and Malleon (2013) found seasonal variations in the spatial distribution of crime in Vancouver, BC, Canada. In a study of homicides in St. Paulo, Brazil, Ceccato (2005) found that more homicides occurred with high temperatures, with clusters of homicides spreading to less privileged areas in warmer seasons. In Dallas, Texas, Harries, Stadler, and Zdorkowski (1984) found stronger seasonal variations in crime in neighborhoods with lower socioeconomic status. In contrast, Haberman,

Sorg, and Ratcliffe (2018) found that the effect of criminogenic features, such as the availability of alcohol, did not vary by season. Morken and Linaker (2000) found significant seasonal variation in violence in Norway, and the relationship varied with latitude. Such variations in violence are interpreted in light of the varying length of day captured by season and latitude.

Taken together, these studies suggest that temperature alters the spatial distribution of crime in contexts as different as the UK, South Africa, and Brazil. Seasonal changes in the spatial distribution of crime also tend to be attributed to weather changes, yet the empirical underpinning for this is weak. With only one study conducted in a Western context (Brunsdon et al., 2009), more studies must be conducted before we can speak of a general pattern.

Expectations

Based on the theoretical arguments, we can expect some effects of weather, but the direction of the effects is uncertain, as both heightened and reduced crime rates are possible, and the effects might be best described by an inverted U-curve. There is empirical support for the effect of high temperature on aggression and violent crimes, but there is a lack of evidence for its effect on other types of crime. Some of the variation might be related to very different geographical and climate locations, and although most studies are from warmer climates, the reported effects take place within temperature ranges that are not uncommon also in more northern climates. The effects of other dimensions of weather are uncertain.

In this study we run interactions by time of day and season to test if stronger effects of temperature emerge in the warmer seasons and at warmer times of day, as one would expect from a physiological explanation. Along similar lines, one could expect that the effects of uncomfortable weather (rain, wind) would be stronger in seasons and at times when weather is already uncomfortable (e.g., temperatures are low and wind is strong). We also acknowledge that there may be threshold effects, such that small increments in rain matter little, but very

heavy rainfall negatively affects crime. We test possible threshold effects by allowing free functional form for all of the weather variables.

Displacement effects of weather are a novel topic, and our approach here is more exploratory. We expect to replicate the finding that crime is concentrated in the central parts of Oslo, around drug scenes and places where alcohol is sold. Simply put, displacement effects can take one of two forms. First, *concentration effects* occur when changes in a weather variable cause crime to shift proportionally to areas where crime is already high. Conversely, *diffusion effects* manifest when changes in a weather variable lead to more crime outside of high crime areas. Note that concentration and diffusion effects work independently of the direction of the effect of weather on crime; more rain may simultaneously reduce and concentrate or diffuse crime. However, empirical applications tend to find that increases in the level of crime go together with the diffusion of crime in space (Ceccato, 2005).

Of course, apart from concentration and diffusion effects, weather can also have location- and context-specific effects. Andresen and Malleson (2015) suggest that good weather increases crime in recreational spaces. In the case of Oslo, this would suggest an increase in crime in the Western–Central areas of the city (around parks and drinking spots) when the weather is good.

3. The context of Oslo

With about 600,000 inhabitants, Oslo is a small European capital. Although crime rates are low by international standards, Oslo is by far the most criminogenic area in Norway.⁴ Norway is one of the Nordic welfare states, and despite the overall low social and economic inequality (Barth, Moene, and Willumsen, 2014), there are considerable socioeconomic differences

⁴ Statistics Norway StatBank: Table 08485. Obtained from ssb.no/statbank.

between different parts of Oslo, with higher incomes and more wealth in the western parts of the city (Toft and Ljunggren, 2016).

Despite a restrictive alcohol policy (Rossow and Storvoll, 2014), crime linked to heavy drinking in a typical North European binge-drinking pattern (Pedersen and von Soest, 2013) has been a cause of public concern in Oslo, and has been met with both increased policing efforts and stricter legislation regarding alcohol sales (Rossow and Norstrom, 2012; Skardhamar, Fekjær, and Pedersen, 2016). Alcohol consumption is clearly highest among young people in the wealthiest western part of the city, whereas the risk for alcohol-related problems among alcohol users is greater in the poorer eastern areas (Pedersen, Bakken, and von Soest, 2015). Outside of private homes, it is only legal to consume alcohol at licensed premises. However, recreational drinking in parks and other outdoor meeting spots is generally not targeted by the police unless it appears to be related to other criminogenic behavior or public disorder. Hence, possible criminogenic effects of heavy drinking can be expected both in areas dense with licensed premises in the center of the city and in areas with recreational spaces (although, in the latter spaces, mainly in the warmer seasons). Much crime has also been linked to the two illegal drug distribution scenes in Oslo. Drug dealers in one area near the Central Railway Station specialize in hard drugs such as heroin (Sandberg and Pedersen, 2008), whereas cannabis dealing has been taking place in a larger area along a river in Central East Oslo (Sandberg and Pedersen, 2009).

According to the police, the “functional city center” (marked by full lines on the map of Figure 2a) has the busiest shopping districts and most places to buy alcohol. Open drug scenes are also located in this area, and this is the most criminogenic and most heavily policed part of Oslo. The two “arms” of the functional city center are the western arm, which goes through the busy shopping and nightlife area around Bogstadveien, and the eastern arm, which goes towards the gentrified restaurant and nightlife area of Grünerløkka.

Oslo has a typical Northern European climate. Relative to the overall mean temperature of just below 10 degrees Celsius, summer days and nights are typically warmer, and winter days and nights are much colder (Figure 1). Maximum temperatures are sufficiently low to make physiologically induced aggression effects unlikely (Anderson et al., 2000), supporting the argument that temperature effects (if any) will be mediated by changes in social interactions and/or routine activities.

4. Methods and data

Data

We obtained crime data from police registers (STRASAK), including all crimes reported in the municipality of Oslo from July 2010 through December 2014, inclusive. For each reported incident, we obtained data about its location (aggregated to 250-square-meter grids), time of occurrence, and type, as well as when the report was filed. Our data set was restricted to property, drug, and violent crimes. Crimes geocoded at locations outside of the six most central districts of Oslo were excluded (see Figure 2a and b).⁵ Because we needed to locate events precisely in time and space, we only included crimes for which the time of day was known, allowing up to 4-hour intervals of uncertainty.⁶ Crime counts were aggregated in 6-hour slots separately for each of the three crime types and jointly for all three types.

The Norwegian Meteorological Institute makes data on weather publicly available through an API service.⁷ Starting in July of 2010, data on temperature, wind, and rain were recorded hourly. We aggregated this information into 6-hour slots (00:00–05:59, 06:00–11:59, 12:00–17:59, 18:00–23:59). For each slot, we calculated maximum wind, maximum temperature, and the sum of precipitation (rain/wind). Missing data were rare and ignored in

⁵ Crimes recorded outside Oslo could have geocodes outside the Oslo county, in the fjord (likely misrecordings), or in the “Marka”, or woods surrounding the city.

⁶ The data include a start- and stop-date time stamp for intervals, and if the interval is less than 4 hours it is included in the analysis using the start time.

⁷ <https://data.met.no/index.html>

the calculations.⁸ Figure S.1 (Supplementary Material) shows descriptive statistics for weather separately by season and time of day. To avoid unduly influential observations, rain was capped at the 99th percentile in all models. Descriptive statistics are given for the capped variable.

We constructed two data sets. The first data set summarizes crime counts in 6-hour slots, starting on July 27, 2010 (the first date of complete weather data) and ending on December 31, 2014 (the end point of the crime data), which yielded 6,473 6-hour observation slots from 1,619 unique dates.⁹ The second data set holds spatial data that use time and grid-specific crime counts as the outcome. There were 604 grid cells observed in 6,475 time slots, which yielded 3,910,900 observations (see Figure 2b for the projection of grids on the six most central city districts of Oslo). Both of the data sets were linked to information on weather conditions, specific to the 6-hour slot. As weather is truly exogenous to crime, reverse causality was not a concern, and subsequent predictors merely constituted noise. (Inclusion of lagged temperature predictors did not improve the model (results available upon request).) Descriptive statistics for the crime variables are shown in Figures 1 (count data set, separately by crime type) and 2c (spatial data set, counts collapsed for all three crime types).

Modeling effects of weather on crime counts

We first investigated if weather has any effect on the overall level of crime. To estimate the effects of weather on the intensity of crime, we used negative binomial count models, taking the following basic form:

$$\log(\lambda_t) = \alpha + \gamma W_t$$

⁸ We had missing wind data in one time slot, and that record was deleted from all analyses.

⁹ In addition to the slot with the missing wind data, two slots were excluded from the first data set because they had missing values for the lagged predictors. The first observation in calendar time (00-0059 July 27th 2010) by construction has no preceding observation, and hence missingness on lagged predictors. The one slot with missing wind data led to an additional observation with a missing value for wind lagged.

where λ_t is the number of reported crimes in Oslo on day t , W is a vector of variables measuring weather (wind, rain, temperature), with regression coefficients of interest γ . We estimated this model separately for drug crimes, violence, and property crimes to check if the effects of weather vary by crime type. In the basic model, coefficients should be interpreted as the effect of an incremental change in weather on the incremental change in crime counts.

To the extent that temporal variation in weather is correlated with seasonal/time of day variations in crime, estimates from the basic model will be biased. (Figure S.1 in the Supplementary Material documents the well-known seasonal and time-of-day variations in temperature.) To handle this, we estimated a controlled model, including fixed effects for season, ζ , and time of day, η :

$$\log(\lambda_t) = \alpha + \gamma W_t + \zeta + \eta$$

With these fixed effects included, weather coefficients are interpretable as effects of deviation from the average weather in that season and at that time of day.

The main results from the count models are presented in Table 1 as Average Marginal Effects (AME), interpretable as change on an absolute scale. Standard errors are corrected for autocorrelation and heteroscedasticity (Zeileis, 2006). To test if effects vary with season and time of day, we ran interactions between these variables and the weather characteristics (results available upon request).

Modeling effects of weather on the spatial distribution of crime

We have proposed that weather might not only affect the level of crime but also *where* crime takes place. We tested this by modeling the spatial distribution (as captured by the coordinates) directly, and allowing the spatial surface to vary with weather. We estimated Generalized Additive Models (GAM) by the *bam* command (Wood, 2017). To efficiently fit a complex model to a large data set, the procedure discretizes covariate values. The coordinates are

included as a semiparametric smoothing spline (tensor product smooth) that captures the spatial surface, and other covariates are included as fixed terms. The basic spatial regression model (Model 2a) then becomes

$$\log(\lambda_{it}) = \alpha + s(\text{lat}_{it}, \text{lon}_{it}) + \gamma W_t + \zeta + \eta$$

where λ_{it} is the number of crimes in grid cell i at time t , and s denotes a smoothing surface over the coordinates¹⁰. As above, ζ and η are fixed effects for season and time of day, respectively.

To estimate the effects of weather on the spatial distribution of crime, we grouped the weather variables into factors: a dummy variable taking 1 if there is any precipitation (otherwise 0), and terciles for wind and temperature. (Descriptions of each weather variable by categories of the corresponding factorized variable are shown in Supplementary Material Figure S.4.) For each weather characteristic, we estimated a separate spatial surface based on the value of the grouped variable. The estimations were done separately for rain (Model 2b), temperature (Model 2c), and wind (Model 2d). Letting $W_j F$ be the factorized interaction variable for weather characteristic j , the model then becomes:

$$\log(\lambda_{it}) = \alpha + s((\text{lat}_{it}, \text{lon}_{it}) | W_j F_{it} = w) + \gamma W_t + \zeta + \eta$$

The inclusion of W holds the other weather variables constant, and nets out the effect of the interaction variable on the *level* of crime.

The main results from the spatial models are given in the form of spatial (grid-specific) predictions, and differences between grid-specific predictions (Figure 3). For the basic model (2a), predictions are made at the median of all weather variables, setting the season to summer and the time of day to nighttime (00:00–05:59). For interaction models (2b–d), predictions are made at the conditional median within each level of the factorized interaction variable (e.g., the median temperature in the third temperature tercile). Such conditional spatial predictions are,

¹⁰ Our data use a UTM-32 projection, which is on the scale of meters. Thus, the grid structure implies that we model the data as continuous, measured with an accuracy of 250 meters.

in a broad sense, an application of the comap approach suggested by Brunsdon (2001), though our conditional predictions are obtained from GAMs rather than from kernel density estimations.¹¹

To better illustrate the distribution and magnitude of effects, we also present differences between predictions from Models 2b–2d (also Figure 3). Fixed term estimates, statistical significance, and estimated degrees of freedom for smoothers, and fit statistics for Models 2a–d are shown in Table 2. Fit statistics (adjusted R^2 and deviance explained) comparing each interaction model to the basic model were used to assess the importance of the effects of weather on the spatial distribution of crime. All analyses were done using R (R Core Team, 2018).

5. Results for intensity of crime

Our first research questions concern the effects of weather on the intensity of crime as measured by the number of incidents. We explored the simple association in Model 1a (Table 1), in which the three crime outcomes (frequency of drug, property, and violent crimes) were regressed on the three weather measures (temperature, rain, and wind). We included the measures as linear terms, adding a curvilinear term for temperature to test the hypothesis of a curvilinear relationship between temperature and crime. We present AME, which in Model 1a are to be interpreted as the effect of an incremental change in weather (a one-degree increase in temperature, a one-millimeter increase in rain, or a one-millimeter/second increase in wind) on crime counts on an absolute scale.

We found a significant and positive relationship between temperature and all three crime types. The AME estimates ranged from an average increase in crime counts of 0.09 counts per degree of temperature (for property crime) to 0.03 (for violence). The confidence limits of the

¹¹ Furthermore, Brunsdon (2001) suggests some overlap between categories of the classifying variable (a “moving window” approach), to corroborate test strength and ensure that it is even across categories. The tercile/dummy categories that we used were mutually exclusive. High test strength is ensured by sample size, and the tercile categories were of equal size by construction.

three estimates overlap, indicating that the estimates are not statistically different across types of crime. Hence, the hypothesis of an effect of temperature primarily on violent crime was not supported. The curvilinear terms for temperature were negative and statistically significant, yet small in magnitude. The overall picture from Model 1a is one of a modest impact of weather on crime counts: wind and rain had no significant influence on counts of violence and property crimes, but there was a significant and negative relationship between rain and drug crimes. For each additional millimeter of rain, drug crime counts fell 0.05 per 6-hour slot, on average. An increase from the minimum (0) to the maximum (10) on the rain variable will lead to 0.5 fewer drug crimes on average in Oslo in a 6-hour time slot.

The effects reported in Model 1a may be confounded by season and time of day, as explained in the methods section. We addressed the potential confounding in Model 1a by adding controls for season (dummies) and time of day (dummies for 6-hour-slots) in Model 1b. A comparison of Akaike Information Criterion (AIC) values indicated that all models were improved (lower AIC). The estimates now capture the effect of a deviation in weather from the seasonal and time of day means. For instance, an unusually warm winter night constitutes a positive deviation, even if the night is colder than that of the average yearly 6-hour slot. Some changes in point estimates and significance tests are noteworthy. For property crimes, both the linear and curvilinear terms for temperature were rendered insignificant by the controls, and for violence, the curvilinear term lost significance. Drug crimes were most strongly influenced by deviations from the seasonal and time-of-day climate: the positive influence of temperature and the negative influence of rain remained after controls. Additionally, a negative and statistically significant effect of wind emerged.

To further explore the functional form of the relationship between weather and crime, we allowed a free functional form in Model 1b by grouping each weather variable into decile dummies. For precipitation, the more than 75 percent of observations with zeros (see Figure 1)

were grouped together, so the remaining observations were grouped into the upper deciles (8th, 9th, and 10th). The results are shown as predicted counts (Supplementary Material, Figure S.2), and they revealed a very weak linear relationship between temperature and crime. There was no evidence of nonlinearity beyond the curvilinear shape or of threshold effects. The same was true for wind and rain.

Some noteworthy patterns emerged. First, the expectation of a stronger effect of temperature on violent crime was not supported. Second, there was some evidence that the relationship between temperature and crime (for property crimes) and the curvilinear shape of this relationship (for violent crimes) are artifacts of temporal variations in both temperature and crime in our sample. Finally, drug crimes were by far the crime type that was most strongly influenced by weather in Oslo. On days with relatively better weather (higher temperatures and less rain and wind), drug crime counts in Oslo increased. However, even when relationships were statistically significant, the effects were very modest in magnitude.

Testing for subgroup effects

If the effects of weather change are nonlinear, they could differ between season/time of day because of differences in baseline weather conditions (see Section 2). Figure 1 shows that temperatures are higher in the summer and lower at night, and that winds are stronger in the fall. As outlined in Section 2, any physiological mechanism linking temperature and crime would indicate a stronger impact at higher temperatures.

We tested whether the effects of weather vary with season and time of day by adding interaction terms to Model 1b for all outcomes (results available upon request). In brief, the separate models by season and time of day did not reveal any new, clear patterns of weather effects. Because of the large number of tests, we are cautious about interpreting small and isolated changes. The overall conclusion from the main model, that variation in weather is not

a strong predictor of variation in crime, remains when season and time-of-day variation effects are allowed.

6. Results from the spatial models

Descriptive statistics for the spatial distribution of crime are shown in Figure 2. The six central city districts and the “functional city center” (the areas with shopping districts as well as night life in Oslo, see Section 3) are indicated on the descriptive map by light and dark full lines, respectively. The statistics displayed on the maps are mean yearly crime counts by 250-meter grid. The means support the notion that the area around the central station, a major trade area as well as an open drug scene, is a major “hotspot.” Some areas, concentrated in the southern islands and the northernmost part of the city center, have a yearly mean of zero (and hence no variation in the outcome variable).

The multivariate spatial results are shown in Figure 3, with auxiliary results in Supplementary Material Figure S.4. For the regression analysis, the weather variables were included as linear predictors, as there was little evidence of nonlinearity in Model 1. The results of the basic specification (Model 2a, Panel A) confirmed the impression gleaned from the descriptive plot, with a concentration of crime around the central station, and somewhat elevated crime levels in the “functional city center” and around these areas. Predicted incidents per 6-hour slot peak at 0.5 around the central station, they are somewhat elevated in the rest of the “functional city center” (dark gray lines), and they fall to zero in the western and southern parts of the city.

For the effect of weather on the spatial distribution of crime, we started with rain (Model 2b, Panels B–D). Figure 3 shows the predicted distribution of crime in 6-hour slots with precipitation (“Rain,” Panel C) and in 6-hour slots with no precipitation (“No rain,” Panel D). The two distributions are strikingly similar. The differences between the distributions are small

(“Rain-no rain,” Panel B), with a maximum difference per grid per 6-hour slot of 0.012 incidents for positive effects and 0.004 incidents for negative effects. The largest effect (0.012) is equivalent to an increase of one crime incident per 21 days.¹² Despite the small magnitude of the coefficients, some systematic differences are discernible. Compared with sunny days, rain shifts crime from the outskirts of the “functional city center” and its surroundings towards the most central parts of the city. It is important to note that these estimates are controlled for the effect of rain on the *level* of crime. The fixed term estimates (Table 2) reveal that rain has a small negative effect of on the level of crime. Hence, rainfall has two effects: it lowers crime and it *concentrates* crime to the most central areas of the city. Unsurprisingly, significance tests of the smoothing terms show statistically significant spatial variation in crime, both when there is precipitation and when there is not (Table 2). We see that both in terms of adjusted R² and deviance explained (Table 2), the values for the basic model and the rain-specific surface model are identical to the third decimal. This indicates that allowing the spatial distribution of crime to vary with rain does not improve the predictive power of the model at all.

We divided wind and temperature results into terciles. The tercile-specific plots for wind and temperature are strikingly similar (Figure S.4, Supplementary Material). The differences between the predictions are of main interest. Starting with wind (Figure 3, Panels E and F), we see a similar pattern to that found for rain, with higher relative crime counts in the areas around the central station, and relatively lower crime counts in the outskirts of the functional city center. This is true both when comparing Tercile 3 (most wind) to Tercile 2 (medium wind), and when comparing Tercile 2 to Tercile 1 (least wind). The fixed term estimates shown in Table 2 indicate that wind had a small but statistically significant negative effect on the level of crime. As observed for rain, the results for wind corroborate the overall finding of crime rates being lower in worse weather, and the crime that did occur was shifted to the most central parts of the

¹² Days per event is calculated as 1/daily effect, where daily effect is four times the effect in a 6-hour slot.

city. Also in Table 2, comparing fit statistics for the wind-specific surface model (2d) with the basic model (2a) shows that R^2 increased 0.1 percentage points when wind-specific surfaces are allowed, whereas there was no change in the deviance explained. The magnitude of the effects was very modest. Grid- and slot-specific counts changed with a maximum of 0.04, or one event in 6.25 days. Again, the weather-specific surfaces are of marginal or no importance for prediction.

Turning to the results for temperature, we note that higher terciles now mean more comfortable weather in a Nordic context. Comparison of the first and second terciles (Figure 3, Panel E) reveals that on warmer days, crime was less concentrated in the very center of the city; it spread out more to the full functional city center and its outskirts. This pattern is similar to that observed for wind and rain: with worse weather, crime concentrates, whereas with better weather, crime diffuses. Comparing Temperature Tercile 3 to Temperature Tercile 2, the opposite pattern emerges: positive deviations from very high temperatures spark a peak in crime in the city center and in the northwestern tip of the functional city center, with a corresponding decline in the less central areas. As with the wind findings, the effect sizes for temperature were modest. Adjusted R^2 increases with 0.1 percentage points when surfaces are modeled separately by temperature (Model 2c, Table 2) versus joint modeling (Model 2a, Table 2), while the deviance explained is identical. This indicates that differences in the spatial distribution by temperature are of little practical importance for predicting crime, and differences of this magnitude could also easily be an artifact of chance in our sample.

In summary, the effects of weather on the spatial distribution of crime were very modest in size, and they had no or only a miniscule effect on the predictive power of the spatial model. The overall pattern in our sample indicated that, when the weather was worse (more wind and precipitation, and lower versus medium temperatures), crime was concentrated in the areas where most of the nightlife and commerce takes place. The exception to this pattern was that

when temperatures increased from high to very high (second versus third terciles), crime counts were more spatially concentrated.

7. Discussion

The relationship between weather and crime has intrigued criminologists for decades, but theoretical explanations and the empirical findings have been inconclusive. In this study, we extended previous research in three main ways. First, we tested weather effects in a Northern European climate, contrasting our findings with effects from comparatively warmer climate zones. Second, we examined the magnitude of statistically significant effects to assess whether they have practical importance for policing. Finally, we used spatial models to assess the effects of weather on the dislocation of crime, providing a rare intersection between the criminological literature on weather and research on the spatial distribution of crime.

Although previous studies have tended to find an effect of warm weather, our results suggest this effect is, at best, minimal in our northern climate and culture. The weather affected crime by increasing counts when the weather was better (higher temperatures) and decreasing them when the weather was worse (more rain and wind). Of the three crime types that we assessed, drug crimes were most weather sensitive, whereas property crimes were not influenced by weather. Violent crimes were moved by temperature only, and to a lesser extent than were drug crimes (although the difference was not statistically significant). The size of the significant effects were consistently too small to have any practical implications for policing.

The finding that crime counts were higher in good weather fits with expectations from both routine activity theory (Cohen and Felson, 1979) and the rational choice perspective of crime (Becker, 1968). In better weather, both targets and offenders are more likely to be outside and thus more likely to meet. The notion that worse weather may increase crime by incapacitating capable guardians (Tompson and Bowers, 2013) was not supported by our data.

The effect of heat on drug crimes was less consistent with the physiological explanation, but there might be other reasons for this association, such as drug dealing occurring in more visible places on warm days. Compared with incidents of violent crime and property crime, to a greater extent, drug crime incidents were based on “proactive” (rather than “reactive”) policing (Ashby and Thompson, 2017; Black and Reiss Jr, 1970). In other words, the number of drug crimes was likely the most sensitive type of crime to policing efforts, as such crimes are known to be influenced by contextual factors such as the day of the week and large events (Ashby and Thompson, 2017), and potentially by weather as well. Thus, the effects on drug crime incidents may be evidence of a more active drug scene in good weather or of more intense policing when the weather is good.

Our results yielded little support for the physiological aggression hypothesis. Most importantly, the strongest effect of temperature was not found for (aggression driven) violent crimes but for the more transactional drug crimes. Furthermore, given that the Nordic climate is relatively cool, physiological mechanisms should lead to stronger positive effects in warm seasons and at warm times of day. This expectation is not supported. Finally, the expectation of a curvilinear relationship between temperature and crime was not supported for violence. The only statistically significant curvilinear term, found for drug crimes, was of negligible magnitude.

Some limitations of our study are noteworthy. First, Norway has a generally cool climate, and to the extent that only very high temperatures influence aggression, it may not get warm enough to trigger aggressive behavior. The same holds for displacement weather effects; it may be that effects are stronger in other social structures or different climates. Thus, our findings do not rule out that such an effect might exist in warmer climates. However, previous studies have suggested a gradual effect of temperature (inverted U-shape), so we should expect some signs of higher effects at higher temperatures in a Nordic climate. There is the possibility

of a threshold effect such that the temperature relationship does not apply in cool climates, but this has not been proposed in the literature so far. However, it should be noted that the significant variation in weather found in Oslo's Nordic climate is a strong point when attempting to model weather effects.

Second, there is the possibility of cultural differences in response to weather, particularly with respect to drinking culture and nightlife. If the effect of temperature is influenced by social factors, that would be contrary to the physiological explanation, even if recent contributions in this tradition emphasize the interplay between physiological and contextual factors, such as social norms (Anderson, 2001), as well as degree of strain, social control, and social support (Agnew, 2012). However, cultural explanations have not been suggested in the previous literature, and we see no reason why the Nordic binge-drinking culture would ameliorate a temperature effect. Finally, the multivariate modeling strategy we used may make it more difficult to find local (grid-specific) effects that differ from their geographic surroundings. On the other hand, our model correctly identified known hot spots, easing this concern.

Our study is one of very few to directly model the effect of weather on the spatial distribution of crime. Studies of seasonality in the spatial distribution of crime (Andresen and Malleson, 2013; Ceccato, 2005) typically attribute this (in part) to weather differences. We tested this hypothesis directly, and the use of multivariate GAM models allowed us to net out the confounding effects of season and time of day. In general, characteristics that reduce the level of crime (rain, wind) also concentrate crime spatially, a pattern that is similar to the one Ceccato (2005) found for homicide in Sao Paolo. However, these patterns have very small predictive values. With the magnitude of impact that we found, weather characteristics are unlikely to explain strong seasonal variations in crime in our context. In contrast, in the study that is most comparable to ours in terms of both methodology and context, Brunsdon et al.

(2009) reported a significant dislocation effect of temperature on crime. The absence of temperature effects in Oslo could be attributable to smaller contextual differences, or to the fact that we focused on the practical significance of effects, whereas Brunsdon et al. (2009) emphasized statistical significance.

Although it is reasonable to assume that people adjust their behavior according to weather, these findings suggest that such adjustments have very small effects on crime. Even small effects might be of interest when the purpose is to understand human behavior in response to external stimuli. For operational decisions, such as those made by the police, one should hesitate to rely on the weather forecast.

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Table 1. Results from binomial regression models for three crime outcomes. Average marginal effects with 95 per cent confidence intervals in parenthesis. N = 6,473 for all models. Models 1a include the three weather predictors only, while models 1b additionally includes controls for season and time of day.

	Model 1a					Model 1b		
	AME	C.I.			AME	C.I.		
Y: Drugs								
Temperature	0,03908	(0.02302;	0.05514)	***	0,05015	(0.03159;	0.06871)	***
Temperature sq.	-0,00131	(-0.00214;	-0.00048)	**	-0,00166	(-0.00249;	-0.00083)	***
Rain	-0,05479	(-0.10403;	-0.00555)	*	-0,0477	(-0.09158;	-0.00382)	*
Wind	0,00241	(-0.03625;	0.04107)		-0,06003	(-0.0967;	-0.02336)	**
AIC	30203				28614			
Y: Property								
Temperature	0,09293	(0.02967;	0.15619)	**	0,01735	(-0.04606;	0.08076)	
Temperature sq.	-0,00515	(-0.00815;	-0.00215)	***	0,00004	(-0.00266;	0.00274)	
Rain	-0,1431	(-0.31566;	0.02946)		-0,10203	(-0.24101;	0.03695)	
Wind	0,00891	(-0.1274;	0.14522)		-0,07986	(-0.19299;	0.03327)	
AIC	45740				43119			
Y: Violence								
Temperature	0,02728	(0.01482;	0.03974)	***	0,01552	(0.00226;	0.02878)	*
Temperature sq.	-0,00215	(-0.00276;	-0.00154)	***	-0,00023	(-0.00082;	0.00036)	
Rain	-0,01781	(-0.05693;	0.02131)		-0,00793	(-0.04143;	0.02557)	
Wind	-0,01926	(-0.04927;	0.01075)		0,01982	(-0.00629;	0.04593)	
AIC	23352				22069			

Note: ***p<0.001, **p< 0.01, * p<0.05

Table 2: Results from Generalized Additive Models for crime counts in 250-meter grids and 6-hour slots. N=3,910,900 grid-slots. The outcome is grid-specific crime counts. The basic model includes a spatial surface (as a semiparametric smoothing spline), as well as three weather characteristics, and sets of dummies for time of day and season. In the weather specific models, the spatial surface is additionally allowed to vary with one discretized weather characteristic (rain, temperature or wind). See Figure 4 and A.3 for a visual presentation of results from these models.

	Weather specific surfaces											
	2a) Basic			2b) By rain			2c) By temp.			2d) By wind		
Fixed term estimates	Est	(SE)		Est	(SE)		Est	(SE)		Est	(SE)	
Intercept	-33,722	(0,429)	***	-33,277	(0,533)	***	-33,315	(0,761)	***	-35,285	(0,733)	***
Temperature	0,003	(0,001)	***	0,003	(0,001)	***	0,000	(0,001)		0,003	(0,001)	***
Rain	-0,007	(0,002)	***	-0,008	(0,002)	***	-0,007	(0,002)	***	-0,007	(0,002)	***
Wind	-0,006	(0,002)	***	-0,006	(0,002)	***	-0,006	(0,002)	***	-0,007	(0,003)	*
Time of day (ref=Night 00-05)												
Morning (06-11)	-1,009	(0,010)	***	-1,009	(0,010)	***	-1,011	(0,010)	***	-1,009	(0,010)	***
Day (12-17)	-0,002	(0,008)		-0,002	(0,008)		-0,003	(0,008)		-0,002	(0,008)	
Evening (18-23)	-0,150	(0,008)	***	-0,150	(0,008)	***	-0,152	(0,008)	***	-0,150	(0,008)	***
Season (ref=fall)												
Spring	0,031	(0,008)	***	0,031	(0,008)	***	0,032	(0,008)	***	0,031	(0,008)	***
Summer	-0,094	(0,009)	***	-0,094	(0,009)	***	-0,103	(0,010)	***	-0,094	(0,009)	***
Winter	-0,091	(0,010)	***	-0,092	(0,010)	***	-0,093	(0,010)	***	-0,092	(0,010)	***
Smoothing splines	EDF			EDF			EDF			EDF		
Baseline surface	23,966	***										
Weather specific surfaces												
3rd tercile/rain				23,960	***		23,925	***		23,933	***	
2nd tercile							23,922	***		23,942	***	
1st tercile/no rain				23,924	***		23,927	***		23,934	***	
Model fit												
Adj, R2	0,121			0,121			0,122			0,122		
Dev, expl	0,351			0,351			0,351			0,351		

Note: *** p<0,001, **p<0,01, *p<0,05

Figure 1: Descriptive statistics for the outcome variables of negative binomial regressions: Counts of drug, violence, and property crime incidents. Counts are per 6-hour slot in central Oslo, displayed separately by time of day.

Note: Dotted lines show (unconditional) mean count of plotted variable.

Figure 2: Description of Oslo and its crime patterns. Panel a) shows map of Oslo with city districts. Map: © Google. Dashed (light gray) lines give city district borders, full (dark gray) lines give “functional city center” borders. Panel b) gives distribution of grids by city districts. Panel c) gives yearly mean counts of crime per grid (sum of property, drug, and violence).

Figure 3: Effects of weather on the spatial distribution of crime in Oslo. Results from generalized additive models. Predicted baseline surface for spatial distribution of crime in Oslo (Panel A, Model 2a); spatial surfaces estimated separately by level of precipitation (Panels C and D, Model 2b); and differences between spatial surfaces by level of precipitation (Panel B, Model 2b), temperature in terciles (Panels E and F, Model 2c), and wind in terciles (Panels G and H, Model 2d). For predicted surfaces by temperature tercile (Model 2c) and wind tercile (Model 2d), see Supplementary material, Figure A.3. The model includes fixed terms for season dummies, time of day dummies, and linear terms for temperature, rain, and wind. See Table 2 for fixed term estimates, significance of smoothers, and model fit statistics. See Section 4 for details on predictions and model specification. Red panels indicate differences between predictions, dark gray panel indicates basic (not interacted) model.

Supplementary material

Figure S.1: Descriptive statistics for the weather predictors: temperature, wind, and rain. Measured in 6-hour slots, and displayed separately by time of day and season. Dotted lines give the unconditional mean of the plotted variable.

Figure S.2: Testing for nonlinear effects using sets of dummy variables. Predicted crime counts from negative binomial models taking counts of drug, property and violence as their outcome. Grey bands give 95 per cent confidence intervals for the predicted counts. $N = 6,473$ for all models. All models include fixed effects for season and time of day. Each model includes one weather predictor in dummy specification, and the two other weather predictors in linear specification.

Figure S.3: Effects of weather on the spatial distribution of crime in Oslo. Results from generalized additive models. Predicted surfaces by temperature tercile (Panels A–C, Model 2c) and wind tercile (Panels D–E, Model 2d). The model includes fixed terms for season dummies, time of day dummies, and linear terms for temperature, rain, and wind. See Table 2 for fixed term estimates, significance of smoothers, and model fit statistics, and see Figure 4 for differences between predictions. See Section 4 for details on predictions and model specification.

Figure S.4: Description of weather variables by tercile (temperature and wind) and precipitation dummy. Boxplots. Boxes give interquartile range (Q1-Q3), mid lines give median, whiskers indicate range.