Local consequences of climate change: State park visitations on the North Shore of Minnesota

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Introduction

Ongoing climate change is one of the major environmental challenges of our time, and economists have been actively engaged in trying to project its economic impacts. Economists are in broad consensus that these impacts are potentially quite large, but also that they are likely to vary significantly over different sectors of the economy. Agriculture, for example, is one sector that is likely to be disproportionately affected because of the likely impact of changing climate on the length of growing seasons, precipitation patterns, and so forth [Cline(1992); Mendelsohn, Nordhaus and Shaw(1994); Mendelsohn and Nordhaus(1999); Deschenes and Greenstone(2006); Schlenker and Roberts(2009); Tol(2009); Murray and Ebi(2012)].

The tourism industry is another sector likely to be heavily affected, especially those forms of tourism that are based on outdoor amenities likely to be impacted by climate change. A large recent scholarly literature examines likely impacts of climate change on outdoor recreational activities.[1] The economic impact could be quite large: outdoor recreation currently accounts for nearly $650 billion in consumer spending in the United States alone, according to the main industry trade association.[2] Nevertheless, the scholarly study of climate change impacts on tourism remains underdeveloped compared to the study of impacts on other sectors [Wall(1998); Lise and Tol(2001); Hamilton and Tol(2006); Shaw and Loomis(2008)].

Researchers have taken a variety of empirical approaches to determining the likely impact of climate change on recreational tourism. Most of these studies use a revealed-preference approach, based on some actual measure of tourism activity, such as destination choice, fishing activity, visits to national parks, or even rounds of golf.[3] Such studies model their chosen measure of tourism activity as determined by a set of variables, including some variables that measure climate change. In economic terms, the typical assumption, implicit or otherwise, is that climate change has the potential to shift the demand for the recreational activity by altering the quality of the recreational experience [Elsasser and Burki(2002); Richardson and Loomis (2004); Maddison(2015)]. Recent studies have commonly found climate variables to have a systematic effect on tourism activity, while the magnitude and direction of the effect differs with regard to various factors, including the type of activity, time of year, and geographic location.[4]

An interpretive concern with many previous findings in the recreational tourism literature is that they fail to control for, nor to provide insight into, the impact of extreme climate events on tourism activity. As students of climate change know, a clear finding of the scientific literature is that ongoing climate change is likely to lead to increased incidence of extreme events, such as drought, floods, fires or heat wave[see, for example, McKibben and Wilcoxen(2002), Weitzman (2007), Murray and Ebi(2012); IPCC (2013), NOAA(2016)]. In terms of affecting recreational tourism, the increased incidence of extreme events may well swamp the impact of marginal changes in the levels of climate variables such as temperatures.

It is not surprising that existing studies are unable to convincingly investigate the impact of extreme climate events, because the data used have typically been aggregated at the monthly, quarterly, or even annual level.[5] Data aggregated at these levels are unable to capture many extreme events such as fires, floods, and short-term heat waves, which either last a few days or may extend across calendar periods. In these cases, the data fail to capture the actual climate phenomena that may have significant effects on tourism behavior.

In this paper, we exploit a new data set consisting of daily observations on visitations to state parks in northern Minnesota over a period of thirteen years, along with daily observations on various climate variables. These data are used to derive estimates of impacts on tourism activities of increased incidence of extreme climate events likely to occur under ongoing climate change. Using daily visitation activity permits estimation of visitation responses to extreme events – such as short term heat waves – that are typically masked in existing studies that rely on data that are aggregated over longer periods of time.[6] We then use projections of climate models to assess the magnitude of the impacts of extreme climate events on local tourism.

Existing studies have found that climate change impacts are likely to vary dramatically across different times of the year, with the biggest difference being between winter activities (such as alpine and Nordic skiing, snowmobiling and ice fishing) and summer activities (such as hiking, canoeing, swimming, and boating). The impact of climate change will differ significantly across these two tourist seasons, because of the different nature of the activities. In this study, we focus on tourism activities during the warmer months of the year from late spring into early autumn, which is the peak season for tourists in the study area [Davidson-Peterson (2006b), p. 12]. This seasonal emphasis strategy is consistent with a number of other studies that have examined climate change impacts on outdoor tourism activities.[7]

Water-based recreation on the North Shore

For a number of years, the north shore of Lake Superior in northern Minnesota has been an important destination for recreational tourism in the upper Midwest. The area supports a variety of recreational activities year-round. Summer activities, which are the focus of this study, include hiking, hunting, fishing, sightseeing, swimming, boating, canoeing, biking, and golfing [Davidson-Peterson Associates(2006a)]. These activities are affected in various ways by extreme events associated with climate change, such as heat waves, increased fire incidence, changing patterns of precipitation, and increased flooding [USGCRP(2016)].

Intense heat waves, where temperatures rise to uncomfortable levels, may discourage certain activities such as hiking, hunting, fishing, biking, and sightseeing, while possibly encouraging other activities such as swimming and boating. Fires resulting from extremely dry conditions may destroy structures, property, and habitat, and may pose threats to public health and safety [Walsh and Sawyer (2015); USGCRP (2016)]. Floods may also destroy structures and property, as well as pose public safety risks. For example, massive flooding hit the southern North Shore area in June of 2012, damaging roads and inundating residential houses, leading to the evacuation of 250 local residents and over $100 million in damages [Samenow(2012); Huttner(2013)].

Study Area

The eight state parks that are the subject of this study are located at various points on the North Shore (see Figure 1) and receive between 1.6 and 1.9 million visitors per year. Figure 2 graphs annual visitation data for each of these parks from 1996 through 2013. These data reveal an overall steady, perhaps slightly upward trend of visitors over time, which is subject to short-term fluctuations. They also reveal a hierarchy of visitation traffic among the parks, with Gooseberry Falls State Park, the southernmost and therefore most easily accessible to visitors from the south, receiving by far the most visitors.[8]

Data and Econometric Model

The analysis is based upon daily visitation data during the late-spring to summer months for all eight state parks on the North Shore, from May 2002 through September 2014.[9] This comprises 15,914 total observations, though some observations were discarded because of brief periods of time when various parks were closed for renovation or other reasons, and during early July of 2011, when a government shutdown temporarily closed all of the parks. Omitting these observations leaves us with 15,669 usable observations. Table 1 reports park-level summary statistics for this visitation variable and reveals major differences in visitation levels across the parks. Gooseberry Falls is by far the most-visited park, whereas the smallest parks – Crosby-Manitou and Grand Portage – receive a fraction of the visitors that Gooseberry does. This park-level variation in visitation numbers will pose statistical issues that will need to be accounted for in the econometric analysis.

It will be recognized that ours is a panel data set: a pooled time-series cross-section sample of eight parks over thirteen years of daily data, which permits us to exploit both cross-sectional and temporal variation. The model thus uses a standard panel data framework, as presented in equation (1):

$$Y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it} \tag{1}$$

Here, Y_{it} is a vector of observations on daily visitations, where i indexes the parks and t indexes daily observations over thirteen years. X_{it} is a matrix of observations on a set of non-stochastic regressors, β is a vector of coefficients, α_i is a vector of unobserved time-invariant individual effects, and ε_{it} is a vector of idiosyncratic error terms. We will subsequently be estimating this as a fixed effects model, where $E(\varepsilon_{it} / \alpha_i, X_{it}) = 0$. In the standard fixed effects model, the error terms ε_{it} are assumed to be independent and identically distributed (i.i.d.) [Greene(1997), p. 616].

In performing the regressions, the dependent variable Y_{it} is denoted $\textit{Visitations}_{it}$, the number of daily visitors at each park. Conceptually, $\textit{Visitations}_{it}$ measures the demand for park visits. Assuming utility-maximizing consumers, the X_{it} matrix contains regressors that reflect various determinants of Marshallian demand, including the quality of the commodity [see

Richardson and Loomis(2004)]. These regressors will include economic variables, such as income, unemployment, recession conditions, and the price of gasoline.[10]

The key regressors in our analysis are the climate variables, which measure the quality of the park visit experience. This especially includes the variables related to extreme events. The way that extreme events are experienced by park visitors is measured in different ways, depending upon the type of climate variable. An extreme heat event is defined as occurring when the level of ambient heat exceeds some uncomfortably high level. This can be measured with either air temperature or the so-called *heat index*, which combines air temperature and relative humidity and is thus a measure of apparent, or perceived, temperature. For example, an air temperature of 100° Fahrenheit with zero relative humidity is considered to be the same perceived temperature as an air temperature of 80° with one hundred percent relative humidity (See Figure 2). We capture extreme heat events with dichotomous variables that are a function of whether one of these heat measures exceeds a given threshold level. $ExtremeHeat^X$ takes on a value of one if the maximum level of the heat variable on a given day exceeds X.[11]

Increased incidence of flooding is captured in two ways. The first, $Flooding^1$, is based upon the major flooding event that occurred along the southern North Shore in late June of 2012. This event was a 1000-year flood that inflicted major damages to property and infrastructure, and it was the only flood of major consequence along the North Shore during the period under study. This variable is a dichotomous variable that takes on a value of one during the three days of the flood, June 19-21.[12] The second, $Flooding^2$, is a variable that captures many smaller flood events that occurred within any of the three counties of the study area: St. Louis, Lake, and Cook. This variable is defined as actual property damages from actual flooding that occurred anywhere within the three counties on a given day, weighted by the inverse of the distance from the reported event to each park.

Our measure of increased fire incidence is based upon the National Fire Danger Rating System (NFDRS), under which the risk of wildfire dangers is rated on a five point scale from "Low" to "Extreme". This scale corresponds to a variable known as the *energy release component*(ERC), which measures the energy content (in BTU's per square foot) in local combustible biomass in a given area. Our fire variable is a dichotomous variable that indicates whether the risk of wildfires exceeds a given threshold level on this scale. Specifically, $Firerisk^X$ takes on a value of one when the ERC value exceeds X. As with heat events, we perform sensitivity analysis to determine the appropriate threshold level X to use, in terms of influencing visitation behavior.

One issue we investigate is whether recreationists systematically respond to official signals of extreme conditions in the form of heat advisories or unusual conditions of fire risk. Regarding extreme heat events, for example, the National Weather Service issues health advisories when the heat index begins to exceed certain levels. For heat index values between 80 and 90, the public is warned to exercise *caution*, and for values between 91 and 103, the public is warned to exercise *extreme caution*. Similarly, for ERC values between 30 and 35, the risk of fire is considered *high*; for ERC values between 35 and 42, the risk of fire is considered *very high*; and for ERC values greater than 42, the risk of fire is considered *extreme*.

In principle, park visitors may be expected to respond most strongly to official warnings because of their salience as a signal of extreme conditions. However, their responses are likely to be tempered by a number of informational and psychological factors. For example, some people may be unaware of the symptoms of heat stroke, or they may have little experience with extreme heat events [Robertson(2017)]. Furthermore, some evidence suggests that people may become inured to warnings about risk factors that are less salient, obvious, or dramatic [NOAA (2014); Mitchell(2017)]. They may thus respond less strongly to official warnings or advisories about high temperatures and fire risk than to weather events such as tornadoes, flooding, or actual fires. This may be especially the case in Minnesota, a northern state where perceptions of the dangers of heat risk are lower than the nation-wide average.[13] Our econometric analysis will attempt to provide insight into this issue.

Regression results

Here, we report the results of a series of estimations of a regression model with cross-sectional park-level fixed effects.[14] The dependent variable in these estimations is park visitations per capita, which is calculated using state population levels. In addition to the extreme climate variables described earlier, this model includes various control variables, including the average daily heat measure, the daily ERC level, and daily precipitation.[15] This model also controls for: (1)observations that occur on weekends, and (2)the price of gasoline and state per capita income, both adjusted for inflation.[16] Finally, the model controls for possible reduced visitation activity both prior to Memorial Day and after Labor Day. Table 2 lists variable definitions and key summary statistics for all variables.

Table 2 indicates that the visitation data are distributed away from zero, suggesting that normality of the error terms may obtain in a linear model. This is confirmed by park-level histograms. Using a test suggested by Jeffrey Wooldridge, we find significant autocorrelation in the data.[17] We therefore estimate a series of Prais-Winsten regressions assuming a panel-specific first order autoregressive process, as the estimated coefficients of autocorrelation differ significantly across the panels. A likelihood ratio test reveals heteroscedasticity, which is not surprising given that the visitations numbers differ dramatically across the different parks. Therefore, we also estimate panel-corrected robust standard errors.[18]

Table 3 reports the results of a series of estimations of the model, using four different measures of extreme climate event variables ExtremeHeat^{X} and FireRisk^{X}, where the heat variable is the heat index and the fire variable is ERC.[19] Two of these measures – ExtremeHeat^{95} and FireRisk^{35} – exhibited the highest levels of statistical significance in a sensitivity analysis that explored various threshold levels for heat and fire risk, while providing the most conservative basis for our subsequent projections of future extreme climate impacts.[20] The other two measures – ExtremeHeat^{91} and FireRisk^{42} – correspond to levels at which official risk warnings are issued for people to exercise extreme caution. The results of these alternative models are reported in order to shed light on whether official warnings have significant impacts on visitation activity.

Before interpreting these findings, it should be noted that these models have been subjected to various specification checks involving variable definitions, omitted variables, functional specification, and the assumed lag structure of climate impacts. The regression results are robust to various definitions of included variables, including visitation activity, flooding events, heat measures, and peak- vs. off-peak summer seasons.[21] The results are also robust to the exclusion of various economic variables, including unemployment, state income, state population, and a dummy variable capturing the recession years 2008-09. A quadratic specification provides an alternative way of modeling the relationship between park visitations and climate variables such as heat index and ERC. However, a series of estimations of quadratic specifications in both variables consistently yield statistically insignificant coefficients on the quadratic terms. Finally, since the models in Table 3 assume a same-day effect of extreme weather events on visitation activity, we explored alternative lag structures of from one to three days for both ExtremeHeat^{X} and FireRisk^{X}. The results indicated that the same-day conditions exerted the strongest and most consistent impact.[22]

Overall, the results in Table 3 indicate that extreme heat events and heightened fire risk have significant negative impacts on park visitations. Interpreting column (2), the coefficient on ExtremeHeat^{95}, which is significant at a 0.01 significance level, indicates that when the heat index exceeds ninety-five, there are predicted to be roughly 0.022 fewer daily visitors per park per capita. At the sample mean of population during this time period, this translates into roughly 113 fewer visitors per park per day. It should be emphasized that this finding controls for average heat index levels, which are extremely significant in influencing visitations, according to the coefficient on *Heat Index* in Table 5.

Similarly, the coefficient on FireRisk^{35}, which is significant at a 0.05 percent level, indicates that on days when the ERC exceeds thirty-five, there are predicted to be roughly 0.008 fewer park visitors per capita, which translates into roughly 42 visitors per park per day. Note that this finding controls for average ERC levels, which are also extremely significant in influencing visitations.

Important to notice here is that there is somewhat mixed evidence that private behavior is influenced by official warnings of extreme or risky conditions. The negative impact of extreme heat conditions occurs at levels well in excess of the level (Heat index = 91) at which the authorities warn the public to exercise extreme caution. Regarding fire risk, however, the evidence suggests that a negative impact occurs at levels corresponding roughly to a “very high” fire risk warning (ERC = 35) based on the NFDRS system. These findings suggest that people respond more closely to official fire risk warnings than to heat warnings, which is consistent with some of the findings of the psychological literature. High temperatures are less salient than fires, which might make the public less responsive to official warnings [NOAA (2014); Mitchell (2017)]. And the fact that Minnesotans have historically had less experience with intense heat waves might make them less likely to respond to official warnings regarding extreme heat [Robertson (2017)].

Considering the remaining variables, the results reveal a number of other factors that appear to have systematic impacts on state park visitations. The positive and highly significant coefficient on Heat Index suggests that absent extreme heat conditions, warmer temperatures translate into more park visitors. This result controls for visitation differences between the summer months (June through August) and non-summer months. Similarly, additional dryness has a significantly positive impact, while precipitation has a significantly negative impact, on visitations. As expected, park visitations are significantly higher on weekends and at higher per capita income levels, and they are significantly lower when the real price of gasoline is higher.[23]

It should be noted that the coefficients for the variable representing flooding – Flooding^1 – are of the expected sign, but are not significant at standard levels. The results for Flooding^2 are not reported, as they were consistently of extremely low significance. These results suggest that flooding may well matter, but that our flooding variables may be too crude to reveal significant impacts. In our subsequent calculations to quantify the impacts of climate change on park visitation activity, therefore, we will employ the conservative assumption of zero projected flooding impacts. From this perspective, our estimated overall impacts of projected climate change on park visitations should be considered to be lower bounds on our “best guess” projected impacts.

Overall, these results strongly suggest that controlling for other factors, summer tourism activity is affected by changes in extreme conditions. Since the extreme conditions investigated here may well be associated with ongoing climate change, we can conclude that climate variability may well have significant impacts on tourism activity. Quantifying the projected magnitude of these impacts will be the subject of the next section.

Projections of extreme climate change events on tourism activity

In this model, the coefficients on the various measures of extreme heat, fire risk, and flood risk are interpreted as the impact of the various kinds of extreme climate events on daily tourism levels. For example, the coefficient on ExtremeHeat^{95} is interpreted as the impact of the occurrence of an extreme heat event, defined as a day when the maximum heat index exceeds ninety-five, on per capita park visitations. For example, consider model (2) in Table 3. The coefficient of -0.022 on ExtremeHeat^{95} indicates that in the historical data, every additional day when the heat index exceeds ninety-five translates into 0.022 fewer visitors for each park, per capita. Similarly for ExtremeHeat^{91}, and for FireRisk^{35} and FireRisk^{42}. Multiplying a coefficient estimate by the current probability of the occurrence of such an extreme event yields the current expected impact of an extreme heat event on tourism activity, holding other factors constant. Using climate models, we will calculate changes in the occurrence of extreme heat events and increased fire risk under various climate change scenarios. The difference in the expected impacts on tourism activity yields the predicted impact of climate change.

To illustrate our method, Table 6 reports historical data for the five climate variables that were present and significant in our final model during the thirty year period 1980 to 2009, for all of the months of our sample. For comparison purposes, also reported are projections of these variables into the future generated by two climate change scenarios known as Representative Concentration Pathways (RCP)[Smith et al.(2016)]. These scenarios were developed by the Intergovernmental Panel on Climate Change and reflect different assumptions regarding the rate of increase over time and ultimate level of greenhouse gas emissions (IPCC, 2013). The two scenarios are called RCP 4.5 and RCP 8.5, with RCP 8.5 being the more aggressive scenario, assuming larger levels of both. We will call RCP 4.5 the *low-range* scenario and RCP 8.5 the *high-range* scenario.[24] The projections reported here are projected averages for these variables over the thirty-year period 2035 to 2064.[25]

Results from five (daily weather variables) to ten (monthly weather variables) different climate models were used to investigate climate projections for 2035-2064.   The predicted values for each of the models and an ensemble model were compared to the historical record. The historical record for most of the climate variables was for observed data collected for the period 1975-1999. The climate projections are based upon the Beijing Climate Center Climate System Model (bcc-csm1-1). The response from this model was generally in good agreement with the ensemble statistics. In order to capture nonlinear relationships among some of the climate variables, a Markov chain model was developed and used to compute the frequency of different threshold heat indices. This model is described by Wilson et al. (2017).

The future projections are adjusted to control for discrepancies between the current observed values and the current predicted values. To illustrate the adjustment procedure, equation (2) shows the adjustment formula.

$$E_f(T) = E_c(T)\,[E_m^{2050}(T)/E_m^{hist}(T)] \qquad (2)$$

$E_m^{2050}(T)$ is the composite prediction of the models for a climate variable in the year 2050, and $E_m^{hist}(T)$ is the prediction of the models corresponding to the historical record. Multiplying the ratio of the two by the current observed value of the variable $E_c(T)$ yields an adjusted projection for the variable in the future $E_f(T)$.[26]

Table 6 reveals some important differences between current conditions and projected future conditions for a number of our climate variables. The climate models indicate that for the North Shore, precipitation amounts are projected to change relatively little into the mid-term future. However, the same is not true of heat, dryness and fire risk. The average daily heat index is projected to increase by roughly 3-4 degrees Fahrenheit under the low-range scenario and by 5-6 degrees under the high-range scenario, with little variation across the months.[27] The extreme heat variable, however, exhibits a different pattern across the months, increasing significantly only during July and August. Temperatures are indeed projected to increase into the mid-range future, but increases in the incidence of extreme heat are likely to be concentrated in the peak summer months.

The variables measuring dryness and fire risk exhibit a somewhat different, more complex pattern. Projected increases in average ERC is largely confined to the later summer months. However, the fire risk variable is projected to increase in the late spring and early-summer months as well. This is probably at least in part due to the fact that average ERC's are higher in the early summer, so that it would take less climate change to push these ERC's above thirty-five.

Let us consider the implied impact on park visitations of climate change, as projected to the period 2035 to 2064 under our low-range scenario (RCP 4.5). This analysis will account for all five factors that our regression results suggest significantly affect park visitations: two extreme event variables – extreme heat and fire risk – and three other climate variables – heat index, ERC, and average precipitation. Whereas our results suggest that extreme event factors will discourage visitations, other climate factors will have mixed influences on the projected impact of climate change. On the one hand, the estimated positive coefficients on *heat index* and *ERC* imply that higher projected heat indices and ERC in the future should temper the negative impact of extreme events. On the other hand, the estimated negative coefficient on *precipitation* implies that higher projected precipitation levels would exacerbate the negative impact of extreme events. However, since projected changes in precipitation levels under climate models are mixed, it is not clear what the net impact of precipitation will be.

A point projection for the impact on visitations is calculated as follows:

$$\Delta \text{ Per capita visitations} = \beta^{HR}(\text{Days}^{HR}_{Proj} - \text{Days}^{HR}_{Hist}) + \beta^{FR}(\text{Days}^{FR}_{Proj} - \text{Days}^{FR}_{Hist}) + \beta^{HI}(\text{Degrees}^{HI}_{Proj} - \text{Degrees}^{HI}_{Hist}) + \beta^{ERC}(\text{ERC}_{Proj} - \text{ERC}_{Hist}) + \beta^{Prcp}(\text{Inches}^{Prcp}_{Proj} - \text{Inches}^{Prcp}_{Hist}) \quad (3)$$

Let us use our results to illustrate our calculations of climate change impacts for one of the summer months: July. Under the low-range scenario, the projection is that for July, the average daily heat index will increase by 4.16 degrees and that there will be 1.23 more days where the heat index will exceed 95. This model also projects that for July, there will be an average decrease in ERC of 1.0 and 0.4 fewer days where the ERC will exceed 34. Finally, the model projects that average precipitation in July will remain the same. Multiplying these implied impacts by the estimated coefficients on HR^{95}, FR^{34}, heat index, ERC and precipitation and summing yields the point estimate that there will be a decline of about 0.022 visitors per capita per day in July at each of the parks in the future period. At current rates of population growth, the population of Minnesota is projected to equal roughly 6.34 million in the year 2035.[28] This figure thus translates into a per-park reduction of roughly 140 visitors per day. This represents a significant reduction, recalling that over our entire sample, park visitations averaged roughly 1125 visitors per day per park.[29]

Applying equation (3), Table 7 reports the projected impact on visitations for each month under both the low-range and high-range climate scenarios, both in number of visitations and as a percentage of the historical average of visitations during each month. For example, the parks each project to experience a reduction of about 140 July visitors (or 5.5% of the average of historical July visitations) under the low-range scenario. Under the high-range scenario, this number increases to about 244 (about 16.7%).

Table 7 reveals some notable differences across the summer months. In absolute terms, the largest projected negative impact on visitations occurs in July under the high-range scenario and in August under the low-range scenario. The negative impact in July is almost entirely the result of dramatically increased incidence of extreme heat events, especially under the high-range scenario. The negative impact in August is a more even combination of increased incidence of extreme heat events and increased fire risk, with the increased risk of fire actually being greater under the low-range scenario.

During the off-peak summer months, visitations are projected to decrease as well, but here the reductions are due primarily to increased fire risk. During the early summer months, the increased risk of fire is especially pronounced under the high-range scenario, which accounts for the vast majority of the reductions in visitations. By contrast, in September the increased risk of fire is greatest under the low-range scenario, which accounts for virtually all of the reductions in visitations.

Discussion

One of the key likely consequences of ongoing climate change is the increasing incidence of extreme climate events, to which certain sectors of the economy such as recreational tourism are particularly vulnerable. Understanding the behavioral response to extreme climate events should be of keen interest to both policymakers and businesses operating in those vulnerable sectors. A growing set of scholarly studies have attempted to quantify the impact of ongoing climate change on recreational tourism, but in using data aggregated over periods of time as long as a month and in some cases, quarterly or even annual data, they have been unable to provide convincing evidence of the impact of extreme events. Such data do not permit observation of the recreational response to intense, shorter-term events.

In this study, we have exploited a new data set consisting of daily observations on summer visitation activity at state parks in northern Minnesota over a period of thirteen years, and the results are clear. Controlling for a number of other factors, heat waves and greater fire risk have historically had significantly negative impacts on the propensity for tourists to visit these state parks during the summer. The fact that climate models project increases in both types of extreme events into the foreseeable future suggests that there may be associated observable impacts on tourism on Minnesota's North Shore.

The results also strongly suggest that the impacts on summer tourism on the North Shore will vary within the summer months because of the complex nature of climate change on the projected incidence of these different events. Climate models project that average heat indices will increase relatively uniformly across the summer months: roughly 3-4 degrees Fahrenheit under the medium-range scenario and 5-6 degrees under the high-range scenario. This will, however, generate a pattern of uneven occurrence of extreme heat events, which will be concentrated in the peak summer months, especially July and August. This means that the greatest impact of such events will be concentrated most heavily in these months.

The likely effect of climate change on fire risk exhibits a more complex seasonal pattern. Historically, fire risk has been highest in the late-spring and early-summer, steadily decreasing through the rest of the summer into early fall. This basic pattern persists under projected climate change. However, climate models project somewhat elevated projected fire risk toward the end of the summer, probably due to increasing temperatures. This may well discourage some visitation behavior later in the summer. Given the combination of these changes in extreme heat events and fire risk occurring simultaneously, our results suggest a general redistribution of tourist activity within the summer months: most heavily away from the peak summer months. The impacts of ongoing climate change will be mostly to discourage nature-based tourism on the North Shore, but it may also influence the timing of when that tourism occurs.

There are several implications of this analysis for policies regarding projected ongoing climate change. On the broadest level, communities dependent upon summer tourism would be advised to be aware of the likely increased incidence of extreme climate events in the future and the potential impact on their economies. This might turn out to be especially true for tourism-based communities in states that are warmer and drier than Minnesota, where extreme climate events like fires and heat waves may be even more common and pronounced in the future. However, there may well be offsetting factors for alternative types of tourism opportunities like swimming, casinos, and beachfront resorts that will not be similarly affected by climate change.

More research is probably warranted to determine whether these findings can be extrapolated to other tourism settings.

In responding and adapting to ongoing climate change, tourism communities should be aware of possible intra-season effects like those documented here. Communities that rely more heavily on July and August tourism may be particularly hard-hit if the kinds of changes in climate conditions projected to occur in Minnesota are replicated in their localities. Again, the nature and magnitude of the peak-summer impacts may be contingent on the types of tourism opportunities provided. But to the extent feasible, communities may want to consider taking steps to support tourism activities during non-peak summer months. These steps could include the timing of special events and the offering of other tourism-related opportunities.

Finally, our findings suggest that official warnings of extreme heat conditions such as general heat advisories may not be particularly effective in discouraging risky outdoor activities. This fact should be of serious concern, as extreme heat is the leading weather-related cause of deaths in the United States [Robertson (2017)]. It may be warranted to expend more resources on information campaigns targeted at groups that are particularly vulnerable to heat-related stress, such as the elderly and people with circulatory or respiratory conditions. This may be especially true in regions like Minnesota where people may have less experience with extreme heat events and thus, are less likely to recognize the physical symptoms of heat distress, or to know what to do if they experience them. But all communities may well benefit from better information about heat stress, particularly with extreme events associated with climate change likely to occur more frequently into the foreseeable future.

Figure 1: Study Area

Figure 2: Annual Visitors, North Shore state parks, 1996-2013

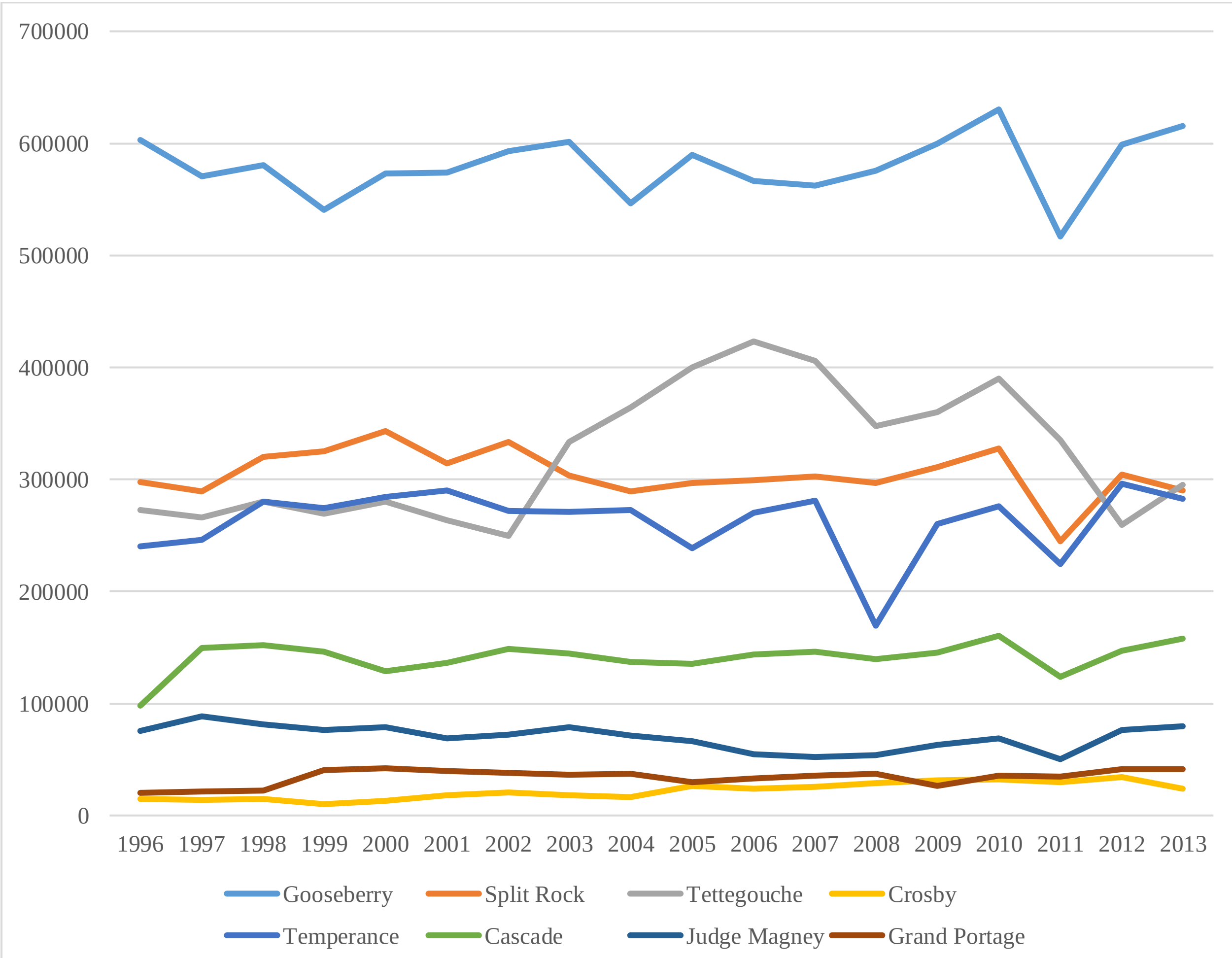

Figure 3: Heat index and air temperature

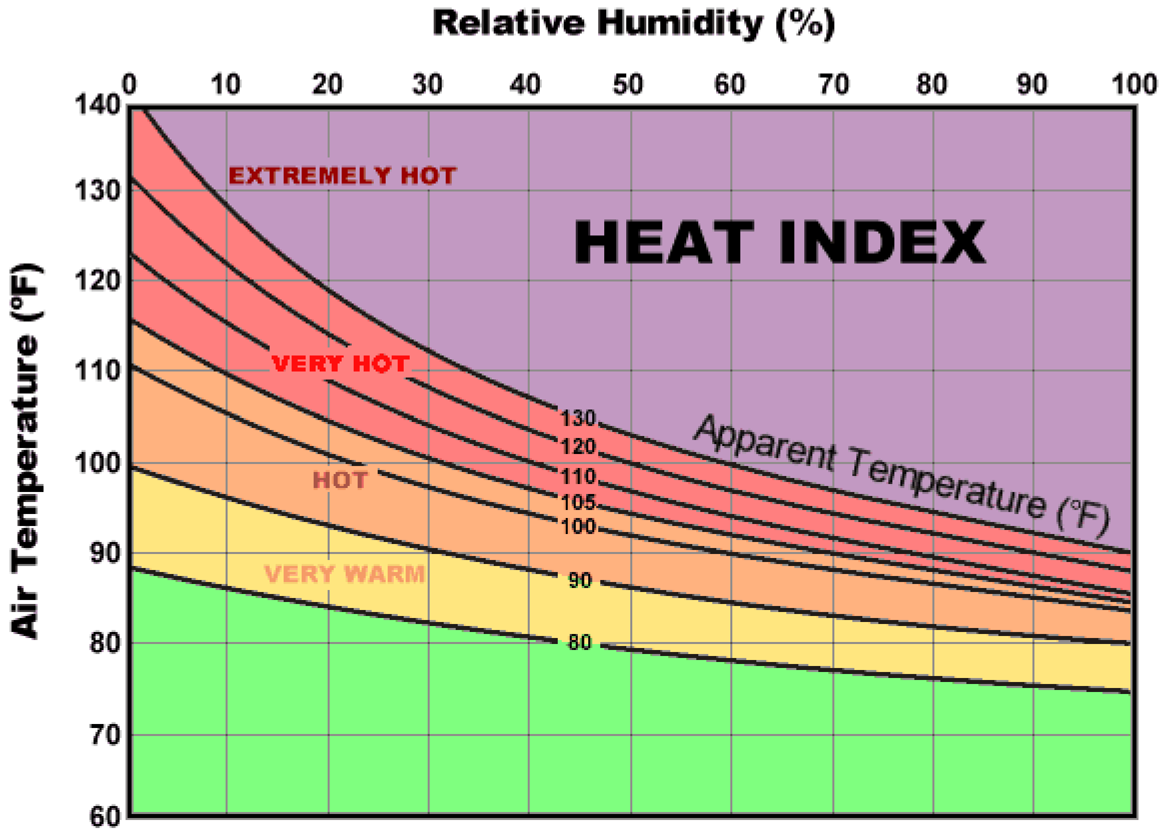

Table 1: Summary statistics on daily visitations, 2002-2014

	Mean	Std. Dev.	Minimum	Maximum
Cascade	767.16	376.39	63.00	2,051
Crosby-Manitou	111.08	88.83	3.00	665
Gooseberry Falls	2,895.36	1,471.37	189.00	9,640
Grand Portage	196.39	122.05	9.00	1,665
Judge Magney	377.72	213.37	6.00	1,320
Split Rock	1,516.83	778.22	122.00	5,624
Temperance	1,447.62	658.68	2.00	5,852
Tettegouche	1,676.90	1,022.68	183.00	10,853

Table 2: Definitions and summary statistics

A. Definitions

Visitations:	Number of visitors at a given state park, per day.
Visits per capita:	Visitations / population; population in thousands.
ExtremeHeat^X:	= 1 if heat index ≥ X, = 0 if not.
FireRisk^X:	= 1 if ERC ≥ X, = 0 if not.
Flooding^1:	= 1 on June 19-21, 2012, = 0 if not.
Flooding^2:	Property damages from a flood event (in any of Cook, Lake, or St. Louis counties) times 1/DIST, where DIST is distance from the flood event to the park.
Precipitation:	Number of inches of precipitation, per day.
Heat index:	Maximum daily heat index.
D^{Weekend}:	= 1 if Saturday or Sunday, = 0 if not.
Gasoline price:	Price of gasoline in dollars, adjusted for inflation.
Per capita income:	State income per capita in dollars, adjusted for inflation.

B. Summary statistics

	Mean	Std. Dev.	Minimum	Maximum
Visitations	1125.30	1159.32	2	10853
Visits per capita	0.211	0.221	0	2.092
ExtremeHeat^{91}	0.016	0.13	0	1
ExtremeHeat^{95}	0.007	0.08	0	1
FireRisk^{35}	0.084	0.28	0	1
FireRisk^{41}	0.028	0.16	0	1
FireRisk^{42}	0.024	0.15	0	1
Flooding^1	0.0010	0.0317	0	1
Flooding^2	0.0003	0.0159	0	1
Precipitation	0.10	0.26	0	4.8
Heat index	69.04	11.94	28.35	101.45
ERC	21.94	9.98	0	52
D^{Weekend}	0.29	0.45	0	1
Gasoline price	3.12	0.73	1.76	4.44
Per capita income	46790.67	1307.65	44480	49047

N for Visitations = 15669; N for Flooding^2 = 15884; N for all other variables = 15912.

Table 3: Determinants of daily visitors, All eight north shore state parks, 2002-2014

	Dependent Variable: Per Capita Visits		
	(1)	(2)	(3)
ExtremeHeat[91](Ext Caution)	-0.010	--	--
	(0.006)	--	--
ExtremeHeat[95]	--	-0.022***	-0.022***
	--	(0.007)	(0.008)
FireRisk[35](Very high)	-0.008*	-0.008**	--
	(0.004)	(0.004)	--
FireRisk[42](Extreme)	--	--	-0.007
	--	--	(0.006)
Flooding[1]	-0.037	-0.037	-0.037
	(0.026)	(0.026)	(0.026)
Heat Index	0.00065***	0.00066***	0.00066***
	(0.00011)	(0.00011)	(0.59)
ERC(dryness)	0.0010***	0.0010***	0.0010***
	(0.00013)	(0.00013)	(0.00013)
Precipitation	-0.015***	-0.015***	-0.015***
	(0.002)	(0.002)	(0.002)
Per capita income	0.00001**	0.00001**	0.00001**
	(0.000005)	(0.00000)	(0.000005)
Real gas price	-0.032***	-0.032***	-0.032***
	(0.0079)	(0.0079)	(0.0079)
Weekend	0.0603***	0.0603***	0.0602***
	(0.0016)	(0.0016)	(0.0016)
R^2	0.198	0.196	0.198

Estimation procedure(STATA): xtpcse[Panel-specific AR(1), panel-level heteroscedasticity].

Panel-corrected standard errors in parentheses. Results on constant term; park, month fixed effects omitted. N = 15,669. *** Significant at .01; ** Significant at .05; * Significant at .10.

Table 4: Sensitivity tests for heat risk variable

	Coeff(z-score)	# Events
EH_{90}	-0.013(-2.49)**	320
	Extreme Heat: Extreme caution	
EH_{91}	-0.010(-1.75)	256
EH_{92}	-0.016(-2.47)**	200
EH_{93}	-0.017(-2.53)**	168
EH_{94}	-0.019(-2.61)***	152
EH_{95}	-0.022(-2.93)***	112
EH_{96}	-0.025(-2.98)***	88
EH_{97}	-0.028(-2.96)***	64
EH_{98}	-0.018(-1.32)	32
EH_{99}	0.005 (0.25)	16

Estimation procedure(STATA): xtpcse[Panel-specific AR(1), panel-level heteroscedasticity].

Other regressors: $FireRisk^{35}$, $FloodRisk^{1}$, Heat Index, ERC, Precipitation, Per capita income, real gas price, WEEKEND, Non-summer dummies.

*** Significant at .01; ** Significant at .05.

Table 5: Sensitivity tests for fire risk variable

	Coeff(z-score)	# Events
	Fire Risk High	
FR_{30}	-0.001(-0.43)	3360
FR_{31}	-0.002(-0.56)	2728
FR_{32}	0.002 (0.61)	2272
FR_{33}	-0.004(-1.09)	1904
FR_{34}	-0.008(-2.15)**	1600
	Fire Risk: Very High	
FR_{35}	-0.008(-2.01)**	1344
FR_{36}	-0.005(-1.08)	1112
FR_{37}	-0.005(-1.15)	960
FR_{38}	-0.005(-0.92)	856
FR_{39}	-0.008(-1.51)	672
FR_{40}	-0.005(-1.00)	536
FR_{41}	-0.008(-1.41)	440
	Fire Risk: Extreme	
FR_{42}	-0.007(-1.01)	384
FR_{43}	-0.001(-0.12)	328
FR_{44}	-0.001(-0.14)	272

Estimation procedure(STATA): xtpcse[Panel-specific AR(1), panel-level heteroscedasticity].

Other regressors: $ExtremeHeat^{95}$, $FloodRisk^{1}$, Heat Index, ERC, Precipitation, Per capita income, real gas price, WEEKEND, Non-summer dummies.

*** Significant at .01; ** Significant at .05

Table 6: Historical and projected incidence of extreme heat and fire risk

	Historical	Projected	
	(1980 – 2009)	Low-range	High-range
	A. Extreme Heat (Number of days HI > 95)		
May	0.00	0.03	0.00
June	0.14	0.40	0.40
July	0.50	1.73	2.50
August	0.18	0.93	0.97
September	0.00	0.07	0.17
	B. Fire Risk (Number of days ERC > 35)		
May	9.80	10.30	11.70
June	3.70	3.80	5.50
July	1.40	1.00	1.00
August	0.10	2.10	1.60
September	0.10	2.20	1.30
	C. Average Heat (Daily heat index, in degrees Fahrenheit)		
May	58.12	61.84	63.67
June	69.72	72.71	75.42
July	76.41	80.57	81.86
August	74.34	78.90	79.60
September	64.05	67.96	68.56
	D. ERC (Average daily ERC)		
May	29.50	29.50	30.50
June	24.20	22.60	24.10
July	20.10	19.10	18.90
August	18.50	21.90	20.10
September	16.40	19.70	19.80
	E. Precipitation (Inches, Duluth)		
May	0.10	0.10	0.11
June	0.14	0.14	0.15
July	0.13	0.13	0.14
August	0.12	0.09	0.09
September	0.14	0.15	0.14

Table 7: Projected impact of climate change on daily park visitations by summer month, low-range and high-range scenarios

	Low-range	High-range
	(a)Number of visitations	
May	-14.0	-67.7
June	-39.0	-105.3
July	-140.2	-244.4
August	-162.5	-136.0
September	-79.9	-44.1
	(b)Percentage of historical visitations	
May	-2.6%	-13.0%
June	-5.0%	-11.2%
July	-5.5%	-16.7%
August	-10.4%	-8.7%
September	-7.2%	-4.0%

Assumption: Projected 2035 Minnesota state population of 6.34 million.

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[1] The recent literature is voluminous. For a few representative studies, see Lise and Tol(2001): Elsasser and Burki(2002); Richardson and Loomis(2004); Jones and Scott(2006); Scott, Dawson and Jones(2008); Shaw and Loomis(2008); Nyaupane and Chhetri(2009); Albano et al(2013); Maddison(2015); Fisichelli et al.(2015)]

[2] Outdoor Industry Association, https://outdoorindustry.org/research-tools/outdoor-recreation-economy/; accessed 2/29/2016. See also Shaw and Loomis(2008), p. 259.

[3] Destination choice: Lise and Tol(2011), Maddison(2015); Fishing activity: Pendleton and Mendelsohn(1998); Visits to national parks: Scott et al.(2007), Albano et al.(2013), Fisichelli et al.(2015); Rounds of golf: Jones and Scott(2006). The other main alternative is the stated-preference approach, based on survey data. See Loomis and Richardson (2006).

[4] Scott, Jones, and Konopek(2007); Shaw and Loomis(2008).

[5] For example, see Jones and Scott(2006); Scott, Jones, and Konopek(2007); Albano et al.(2013); Fisichelli et al.(2015).

[6] See, for example, Jones and Scott(2006); Albano et al. (2013); Scott, Dawson and Jones(2015); Maddison(2015); Fisichelli et al(2015). Loomis and Richardson(2006) is one of the few studies that have focused on extreme events by modeling variability, but they use aggregated monthly visitation data.

[7] See, for example, Pendleton and Mendelsohn(1998); Loomis and Richardson(2006).

[8] Most visitors to the North Shore are from Minnesota, and they tend to be relatively young, white, and have above-average income [Davidson-Peterson Associates(2006a), p. 7].

[9] The year 2002 is the earliest year for which daily records are available from the Parks and Trails Division of the Minnesota Department of Natural Resources.

[10] The own-price of a visit is crudely proxied for by the price of gasoline. There is no entrance fee for visits to the parks, and data on which to base a reasonably precise measure of travel costs are not available. For an application of the travel cost methodology within the context of climate change impacts on tourism, see Pendleton and Mendelsohn(1998).

[11] All heat variables are based upon data measured at a measuring station in Duluth, which varies over time but not across the parks. These variables are highly correlated(> .90) with data from other measuring stations on the North Shore. Fire risk variable is based upon data recorded at Saginaw station in St. Louis County, near Duluth.

[12] The main flooding event occurred on June 19 and 20, and the main highway (Highway 61) from Duluth to the North Shore area was closed through June 21 (MN DNR website).

[13] Based on the result of a survey conducted in 2015 by researchers at Yale University and Utah State, who hypothesized that this was because southerners may have more personal experience with extreme heat events [Robertson(2017)].

[14] A Hausman test permitted us to reject random effects in favor of a fixed effects model specification.

[15] Daily precipitation readings were available from two measuring stations, in Duluth and Grand Marais. These two series were only weakly correlated ($\rho = 0.22$). Therefore, our precipitation variable was an inverse-distance weighted average of the two precipitation readings specific to each park.

[16] See Loomis and Keske(2012), Poudyal et al.(2013) for studies of economic impacts on nature-based recreation.

[17] Wooldridge(2002), pp. 274-75.

[18] The STATA command *xtpcse* is appropriate to use when the number of time periods is large compared to the number of panels [Beck and Katz(1995); Cameron and Trivedi(2010)].

[19] This table reports the results of models that use the daily maximum heat index value rather than air temperature, since heat index was consistently more significant than temperature in a series of regressions.

[20] This sensitivity analysis involved doing a series of Prais-Winsten regressions of the model, using various measures of ExtremeHeat^{X}, and FireRisk^{X}. Heat index and ERC values outside of the reported ranges were consistently insignificant at low levels of significance. The results of these auxiliary regressions are reported in Tables 4 and 5. Table 4 reports the estimated coefficients, associated z-scores, and number of observations of the ExtremeHeat^{X} variable for the various threshold values X = 90 to 99. For example, there are 320 daily observations when the heat index exceeds ninety. Table 5 reports similar results on the fire risk variable for threshold values X = 30 to 44.

[21] An alternative specification employs number of visitations, as opposed to visitations per capita. The patterns of coefficient sign and significance are virtually unchanged.

[22] The Minnesota Department of Natural Resources issues daily wildfire alerts, which specify wildfire preparedness levels for both the state and nation. These alerts specify both the times of day and the area of the state to which the alert applies. See, for example, http://www.dnr.state.mn.us/forestry/fire/wildfire_update.html. Similar information is also carried on broadcast television networks and on-line sources such as weather.com. This rapid turnover of time-and space-specific information is consistent with our finding that contemporaneous correlation is most significant.

[23] All of the results are robust to various specification tests, including interactions between climate events and weekend visitations, controlling for extreme precipitation events, and the omission of the largest park – Gooseberry Falls – from the sample.

[24] The low-range scenario assumes greenhouse gas emissions stabilize by mid-century and then fall thereafter. The high-range scenario assumes continued increases in greenhouse gas emissions through the remainder of the twentieth century.

[25] The projections are from the Coupled Model Intercomparison Project phase 5 (CMIP5) multi-model ensemble dataset of the World Climate Research Programme.

[26] The ensemble projections perform better than the individual models, both in terms of minimizing projected bias and maximizing goodness-of-fit. More details available on request from the lead author.

[27] These figures represent the daily high heat indices, averaged over the month.

[28] This figure assumes a growth rate of 0.7% per year, the estimated annual rate of population growth over the time period of this study.

[29] This estimated impact is relatively insensitive to different assumptions about population growth. Assuming a growth rate of 0.5%, the projected impact is a reduction of 134 daily visitors per park. Assuming a growth rate of zero, the projected reduction becomes 120 daily visitors per park.