U.S. grassland recreation under climate change: Evidence from big visitation data and weather

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Abstract

Grasslands offer a variety of ecosystem services including recreational opportunities. Unlike forests and coastal beaches, grasslands do not offer natural opportunities for recreators to adapt to extremely warm temperatures, potentially making grassland recreation sensitive to climate change. I use mobility data to estimate a causal model of the relationship between short-run weather shocks and demand for recreation at 16 nationally notable grasslands between January 2019 and April 2022. I use a repeated discrete choice random utility maximization model and specify visit utility as a function of a set of average temperature, precipitation, average wind speed, and snowfall bins. I identify the causal relationship using grassland, month-of-year, and hunting season fixed effects. Willingness to pay (WTP) per household for a grassland day visit is about $53.60 on average - nearly twice the WTP for a coastal fishing trip in the Eastern U.S. I find that grassland recreators are averse to visiting during months with more extreme average temperature days, but having more days with average temperatures slightly above extreme cold has no effect on demand. Snowfall is also a significant demand determiner. Responses to temperature and snowfall are heterogeneous across historical climate regions. Projections for 2081 - 2100 suggest grassland recreators are likely to experience average annual welfare gains from climate change of up to $1.3 million from increased visit quality rather than quantity.

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"The question is always asked by the curious travelers who have crossed the Plains at Interstate speeds, 'How can you live here without the mountains, the ocean, the woods?' But what they are really speaking to is their desire to 'get it' right away. The sublime of this place that we call the prairie is one of patience and looking... If one is to understand the beauty of this place, the old answers just won't do."

Keith Jacobshagen (1995)

1 Introduction

Grasslands, or prairies, once covered large swaths of what is now the Midwestern and Western United States. Conversion of native grassland for agriculture and development has occurred since the first European settlers came to the region continuing to this day, but what remains of the prairie is a primary outdoor recreation option for people living in this vast region. When driving to the mountains, ocean, or woods for a day's recreation is not an option, they walk, bike, view wildlife, and hunt on nearby grasslands. What threat does climate change pose to grassland recreation? This paper uses mobility data in a structural econometric model to estimate how changing weather patterns will affect the well-being of people who engage in grassland recreation and change the flows of tourists - which have important value to local economies - to grassland sites.

The recreational value literature thus far has treated grassland recreation and its value as a passenger on a plane does a "flyover state" - at most a footnote to a journey to a seemingly more interesting and desirable destination. Yet, grassland recreation has value. In the only study to estimate the value of U.S. grasslands as distinct recreational sites, Wells (2023) finds that residents of three Midwestern states are willing to pay about $10 per-visit, which translates to a value of $52.2 million over 16 months.

This research estimates the value of grassland recreation in the U.S. at a broad geographic scale tying grassland recreation to weather as a first step toward identifying and valuing potential impacts from climate change. The dearth of research on grassland recreation in general may be due in part to limited data availability. Even for publicly accessible grasslands managed by large federal agencies, visitation data at the monthly or annual level is unavailable with few exceptions. Likewise, climate change is expected to impact outdoor recreation (Hicke et al., 2022) but measures of its impacts for many recreation types and settings are non-existent because of intensive data requirements (Chan and Wichman, 2022). Grassland recreation may be particularly sensitive to climate change as grasslands naturally offer few of the on-site adaptation opportunities available in other settings like forests (e.g., shade trees) and beaches (e.g., bodies of water) to mitigate increasing temperatures.

This research has implications for policy-making and natural capital accounting. The question of whether climate change will produce net benefits or costs to outdoor recreators is far from settled and may be highly specific to the setting and activity (Chan and Wichman, 2022). If the welfare damages (or gains) to outdoor recreators can be incorporated into the calculation of the social cost of carbon, it will be necessary to understand the relationship between climate and weather for a variety of settings and activities. This research is also relevant to tracking the impacts of climate change on the economy. In January 2023, the White House released its plan to develop a set of natural capital accounts for the country to track how the flow of goods and services within the economy impact our stock of natural capital (Office of Science and Technology Policy et al., 2023). In doing so, it recognized that natural capital is an integral part of a healthy, functioning economy requiring us to develop a better understanding of the relationship between its status and our decisions especially in the face of anthropogenic events like climate change. Most relevant for this research, it also shows that grasslands would be one of the last environmental sectors for which a pilot natural capital account is developed because of the time it will take to conduct the necessary research.

Some research has identified causal relationships between weather and outdoor recreation, finding that extreme heat reduces visits but that responses to extreme heat vary across historically colder and warmer climates. The same research generally also finds climate change is likely to provide a net benefit to outdoor recreators. However, the related literature is small and reduced form methods are prevalent, which limits our understanding of how weather changes impact welfare. Reduced form methods dominate this small literature primarily because they require less information on individual decision-makers and decisions (Chan and Wichman, 2022). Structural methods like travel cost models require knowledge of the cost of traveling to a recreation site, which includes time spent traveling, the value of the individual's time, and the cost of operating a vehicle; the most readily available datasets rarely contain this information. Although the data is more readily available, Chan and Wichman (2022) show that using reduced form methods can lead to underestimates of the welfare impacts of climate change on outdoor recreation. There is also suggestive evidence that whether a study finds a net benefit or net loss from climate change can depend on the methodological approach (Dundas and von Haefen, 2020, 2021; Chan and Wichman, 2022).

This research is one of only four extant structural analyses on outdoor recreation, weather, and climate change and only the second to conduct this type of analysis using big data. The big data I use comes from StreetLight Data[1] and is a panel of visit estimates from local U.S. Census Block Groups (CBGs) to 16 nationally notable grasslands (see Figure 1) over 40 months. StreetLight aggregates data from mobile devices and other sources and uses a ground-truthed machine learning method to estimate vehicle traffic on roads and at user-designated areas. Because this data goes beyond a simple count of the number of devices visiting a site and produces estimates of actual visitation, it is possible to construct the more holistic picture of recreation needed to estimate a structural model. Likewise visit estimates for these sites are linked to CBGs allowing the researcher to create a representative travel cost value for each CBG based on CBG-specific demographic and travel time and distance estimates.

One advantage of performing a structural analysis is the ability to estimate welfare mea-

[1]streetlightdata.com

sures and demand impacts simultaneously; I estimate a repeated discrete choice travel cost model (Morey et al., 1993) to value grassland recreation among households living within a day's drive of the 16 nationally notable grasslands. I find that household willingness to pay (WTP) for access to any of the 16 nationally notable grasslands is on average about $53.60 per visit - over 5 times as much as the estimate from Wells (2023) and almost double the value of a coastal fishing visit (Dundas and von Haefen, 2020). At approximately 385,000 visits annually, the annual average recreational value is $20.6 million.

To identify the relationship between grassland recreation demand and contemporaneous weather, I use a binning approach for four weather variables (average temperature, rainfall, average wind speed, and snowfall) and fixed effects for each grassland, the months of the year, and hunting seasons. I find that grassland recreation demand generally responds to temperature as in previous outdoor recreation and weather studies. That is, demand decreases in response to increasing numbers of extremely cold (< 20 °F) or hot days (≥ 80 °F) in a month. Each additional day of extremely cold or hot average temperatures in a month relative to additional days in the 60 - 65 °F range decreases WTP for grassland visits by about $1 and $0.60, respectively. The result for snowfall is also intuitive as demand decreases with an increasing number of days with extreme amounts of snowfall (≥ 0.25 inches). Rainfall and wind speed have no significant impact on grassland recreation demand. Grassland recreators tend to also be indifferent between recreating in months with an increasing number of days with slightly less extremely cold average temperatures (20 - 30 °F) and months with more days in the more pleasant 60 - 65 °F range.

I explore heterogeneous responses to average temperature and snowfall across climates using interactions between the average temperature and snowfall bins and indicators for grasslands in warmer or colder climates. There are two climate categories. I identify a grassland as being in a warmer climate if its 30-year cooling degree day (CDD) normals are above the 50th percentile among the 16 nationally notable grasslands in the sample and identify a grassland as being in a colder climate similarly. Grassland recreators with access to grasslands in warmer climates tend to be more responsive to temperature than recreators in colder climates. Grassland recreators in colder climates also appear to drive the unintuituve overall result related to indifference between increasing days of slightly less extremely cold average temperatures and increasing days in the more pleasant reference range. Grassland recreators in colder climates have a significant preference for grassland recreation in months with fewer days of extreme snowfall. On average, WTP for a grassland visit goes down by $1.15 for each additional day of extreme snowfall relative to days of no snowfall among recreators in colder climates. There is no significant change in WTP for additional days of either light (0.01 - 0.25 inches) or extreme snowfall among recreators in warmer climates.

The ultimate goal of this research is to understand how climate change could impact grassland recreation in the U.S. Assuming uniform increases in average temperature across grasslands by the end of the century the net impact of climate change on grassland recreation in terms of welfare is expected to be small but positive with more ambiguous impacts on visit demand. Under the most extreme warming scenario, average annual net gains from climate change would be about $52,000 with a 95% confidence interval of -$300,000 to $1.3 million. As in previous studies on outdoor recreation, weather, and climate change, welfare gains from climate change are likely derive from reducing the number of extremely cold days, which is especially true here are grassland recreators show a preference for slightly less extremely cold temperatures. Given its ambiguous impact on visit demand, welfare gains from climate change are also likely to come from quality enhancements rather than quantity increases.

2 Literature Review

Reduced form modeling in the context of outdoor recreation, weather, and climate change involves the researcher estimating a causal model of the relationship between weather and outdoor recreation without simultaneously estimating welfare parameters. Researchers calculate welfare measures in these studies using a "back of the envelope" benefit transfer process (Chan and Wichman, 2022). Reduced form studies are more prevalent in the literature because they allow researchers to take advantage of large administrative datasets (e.g., Loomis and Crespi, 1999; Mendelsohn and Markowski, 1999; Whitehead and Willard, 2017) and innovative big datasets (e.g., Chan and Wichman, 2020; Wilkins et al., 2021; Parthum and Christensen, 2022).

These datasets often do not include the information researchers need to estimate structural recreation models. For example, Wilkins et al. (2021) construct a dataset of visits to public lands in the U.S. (including national grasslands) from geotagged photos posted on Flickr to estimate the relationship between climatological mean maximum temperature at a site and recreation demand. Although the goal of the research was not welfare estimation, the researchers would have been limited in their ability to produce welfare estimates because very little is known about the Flickr user beyond where and when the photo was taken. Also notably, the authors do not report national grassland-specific estimates but do project increases in outdoor recreation demand in winter and reductions in summer under climate change. The result in Wilkins et al. (2021) is generally consistent with reduced form studies estimating welfare effects including Whitehead and Willard (2017) and Mendelsohn and Markowski (1999). For saltwater recreational fishing in the U.S., Whitehead and Willard (2017) estimate annual welfare gains of about \$2.5 billion from a uniform 4.5 °F temperature increase and 7% increase in precipitation across the country. Under an identical climate change scenario, Mendelsohn and Markowski (1999) predict net gains of about \$2.8 billion annually across seven activities (including skiing).

Despite their relative ease of application, Chan and Wichman (2022) show that welfare estimates from reduced form analyses can underestimate the predicted gains or losses relative to structural analyses. The potential for disparities in welfare estimates between reduced form and structural analyses is evidenced in a comparison between Whitehead and Willard (2017) and Dundas and von Haefen (2020). Dundas and von Haefen (2020) in one of the few other extant structural studies on the relationship between weather, outdoor recreation, and climate change[2] estimate the causal relationship between weather and shoreline recreational fishing in the Eastern U.S. using a large administrative dataset. The dataset differs from Whitehead and Willard (2017), but the setting is similar enough that it is reasonable to expect similar estimates for the welfare impacts of climate change. However, Dundas and von Haefen (2020) find that under the most optimistic climate change scenario, between 2050 and 2079 people participating in shoreline fishing would lose on average, $49 million in welfare annually. The 95% confidence interval around the estimate includes a maximum annual welfare gain of only $13.8 million, well below the $2.5 billion gain Whitehead and Willard (2017) estimate. In another study, Dundas and von Haefen (2021) show that even within the structural modeling framework, the choice to model recreation demand as a linear function of temperature could produce similar disparities in welfare estimates. Welfare estimates from reduced form analyses most often predict gains from climate change to outdoor recreators, but this result is not robust to changes in methodology. This research contributes to the literature an additional structural model of weather and outdoor recreation using an innovative big dataset. It provides further insight into potential impacts from climate in its setting (i.e., grassland recreation) and whether predicting gains from climate change persists across methodologies.

This research also contributes to an emerging area of interest within the outdoor recreation and climate change literature concerning response heterogeneity among people adapted to different climates. In a reduced form analysis of global outdoor recreation response to temperature based on mobility data, Linsenmeier (2024) shows that assuming uniformity in the response of outdoor recreation demand to temperature across climates approximates the climate-specific response well at moderate temperatures but deviates more significantly at the extremes. The author suggests adaptation as a likely mechanism for the deviation

[2]The others are Earle (2023), which focuses on recreation at U.S. national parks and uses data from the National Park Service, and Gellman et al. (2024), which examines camping decisions at federally managed public lands in the U.S. with a big dataset on reservations from recreation.gov.

and that the uniformity assumption is likely to lead to underestimation of benefits to outdoor recreators from climate change. I use variations from normal weather across a range of climates to identify universal weather response functions for grassland recreation but also apply a technique common to the health economics literature (see Heutel et al., 2021) to identify heterogeneity in responses to temperature and snowfall across two climate regions.

3 Repeated Discrete Choice Model

In the repeated discrete choice model of grassland recreation demand, I specify the utility a representative household in census block group (CBG) i derives from visiting a grassland j on choice occasion t as:

$$U_{ijt} = \delta_j + \beta tc_{ij} + \boldsymbol{\gamma}\mathbf{Temp_{jt}} + \boldsymbol{\xi}\mathbf{Rain_{jt}} + \boldsymbol{\omega}\mathbf{Wind_{jt}} + \boldsymbol{\kappa}\mathbf{Snow_{jt}} + \boldsymbol{\tau} + \varepsilon_{ijt} \tag{1}$$

where tc_{ij} is the cost of round-visit travel from CBG i to grassland j, δ_j is a grassland fixed effect, $\mathbf{Temp_{jt}}$, $\mathbf{Rain_{jt}}$, $\mathbf{Wind_{jt}}$, and $\mathbf{Snow_{jt}}$ are vectors of grassland-month specific temperature, rain, wind speed, and snowfall bins, and $\boldsymbol{\tau}$ is a set of fixed effects for month-of-year, big game hunting seasons, and waterfowl hunting seasons. This approach to identifying the causal relationship between weather and grassland recreation draws on Dundas and von Haefen (2020). As in this earlier work, I use fixed effects to control for climate (δ_j) and average weather patterns at the time the visits occurred to identify the impact of abnormal weather on outdoor recreation. I also include fixed effects for big game and fowl hunting seasons[3] to control for increased recreational demand that is likely to be correlated with

[3] Among the 16 nationally notable grasslands I study here, all but the Tallgrass Prairie National Preserve allow hunting. The remaining 15 grasslands allow hunting according to state regulations. For the big game hunting fixed effect, I focus on deer (white-tailed and mule) and elk hunting seasons. Other popular big game species I considered were black bears and pronghorns. Deer and elk harvesting rates are much higher in the relevant regions than black bear hunting (Flather et al., 2013), which may suggest lower supply or tighter regulations on harvest. It also suggests that black bear hunting is less likely to drive demand for grassland recreation. Flather et al. (2013) note that private land holds most of the pronghorn habitat, which also eliminates hunting for the species at the 15 relevant grasslands. I do not consider elk hunting for Texas and Oklahoma as elk are not commonly found in those states. For the fowl hunting fixed effect, I focus on

colder temperatures and snowfall. These fixed effects are essentially state by month-of-year fixed effects only applying to months in which that state allows hunting for at least one of the target big game or fowl species.

To understand heterogeneous responses to weather across different climate regions, I also specify visit utility as:

$$U_{ijt} = \delta_j + \beta tc_{ij} + \boldsymbol{\gamma_1}\mathbf{Temp_{jt}} \times \mathbb{1}(CDDUpper_j) + \boldsymbol{\gamma_2}\mathbf{Temp_{jt}} \times \mathbb{1}(CDDLower_j) + \boldsymbol{\xi}\mathbf{Rain_{jt}} + \boldsymbol{\omega}\mathbf{Wind_{jt}} + \boldsymbol{\kappa_1}\mathbf{Snow_{jt}} \times \mathbb{1}(CDDUpper_j) + \boldsymbol{\kappa_2}\mathbf{Snow_{jt}} \times \mathbb{1}(CDDLower_j) + \boldsymbol{\tau} + \varepsilon_{ijt} \quad (2)$$

where $\mathbb{1}(CDDUpper_j)$ indicates that grassland j is in the upper 50th percentile of sites in terms of 30-year CDD normals and $\mathbb{1}(CDDLower_j)$ indicates that grassland j is in the lower 50th percentile. 30-year CDD normals are the average number of annual CDDs between 1992 and 2021. A CDD represents a one-degree positive difference between the average daily temperature and 65 °F. The number of CDDs per day increases linearly as average daily temperature increases and is zero for average daily temperatures below 65 °F. This approach to understanding heterogeneity in responses to weather follows Heutel et al. (2021) who examine how the number of deaths in response to different temperatures varies across climates within the U.S. I only interact the temperature and snowfall bins with the climate indicators because they are most related to climate as described by CDD normals and the most likely sources for heterogeneous responses across climates.

As a random utility maximization (RUM) model, utility in Equations (1) and (2) can be decomposed as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \quad (3)$$

where V_{ijt} is observable and ε_{ijt} is not. The repeated discrete choice model includes an

wild turkeys and ducks. Ducks are hunted in all states containing a relevant grassland except Wyoming. Wild turkeys are especially popular for hunting in the Southern region that includes Texas and Oklahoma (Flather et al., 2013), which offsets any potential imbalance created by including the elk harvest.

opt-out alternative, $j = 0$, which accounts for all other activities a household could engage in beside visiting one of the grasslands in their choice set. A household's choice set includes any of the 16 nationally notable grasslands that they could visit on a day visit. Utility for the opt-out alternative is as in Equations (1) and (2), however, all parameter values are normalized to zero for identification. Assuming the error terms are distributed Generalized Extreme Value produces the nested logit specification (McFadden 1978) with the probability of a representative household from CBG i visiting a grassland in a month being:

$$P_{ijt} = \left(\frac{e^{\frac{V_{ijt}}{\theta}}}{\sum_{k=1}^{K} e^{\frac{V_{ikt}}{\theta}}} \right) \left(\frac{\left[\sum_{k=1}^{K} e^{\frac{V_{ikt}}{\theta}}\right]^{\theta}}{e^{V_{i0t}} + \left[\sum_{k=1}^{K} e^{\frac{V_{ikt}}{\theta}}\right]^{\theta}} \right) \tag{4}$$

where θ is the dissimilarity parameter. The first term in parentheses is the conditional probability of a household visiting grassland j given that they chose to visit. The second is the probability of a household choosing to visit any grassland. All alternatives for grassland recreation (i.e., $\forall j \neq 0$) are grouped into the visit nest with the opt-out alternative occupying its own nest. The dissimilarity parameter indicates how substitutable the alternatives within the visit nest are relative to the opt-out alternative. For consistency with RUM theory, the dissimilarity parameter should be between 0 and 1. A dissimilarity parameter equal to 1 implies that the nested logit is equivalent to the conditional logit. I estimate the model parameters using a maximum likelihood routine in the `apollo` package in R (Hess and Palma, 2019). WTP for a grassland visit is $-1/\beta$ (Dundas and von Haefen, 2020). I calculate the per-visit welfare impacts implied by weather changes as

$$\Delta WTP = -\frac{\eta}{\beta} \tag{5}$$

where η represents a causal parameter from Equations (1) and (2) (i.e., γ, γ_1, γ_2, ξ, ω, κ, κ_1, or κ_2) (Haab and McConnell, 2002).

4 Data

4.1 Defining the Grassland Choice Set

Accurately defining the choice set visitors consider when deciding where to recreate is essential to producing reliable welfare estimates from any RUM model of recreation. Current best practice for defining a choice set suggests including as many substitutes as possible (Lupi et al., 2020). Parsons et al. (2000) explore the effect of narrowing the choice set definition on welfare estimates in the context of lake site closures. They find that the effect depends on both substitutability and market size. Higher levels of substitutability between included and excluded sites leads to overestimation of welfare impacts. Market size reductions resulting from site exclusion leads to underestimation of welfare impacts. Although Parsons et al. (2000) do not explore the effect of choice set definition on welfare estimates for changes in site quality (e.g., changes in weather) it is likely that narrowing the choice set would produce less overestimation bias because recreators can still visit the site at reduced (or improved) quality.

Defining a choice set for grassland recreation is difficult because many recreational activities conducted on grasslands (e.g., walking, biking, snowshoeing) are highly substitutable to non-grasslands. There are also numerous grassland sites between which recreators could substitute. The most comprehensive list of recreational grassland sites in the U.S. includes thousands of sites across 36 states (Adelman and Schwartz, 2013). Many of these grasslands are small ($<$ 1,000 acres) and more comparable to community parks than the 16 nationally notable grasslands at the center of this research. For reference, the smallest of these grasslands, McClellan Creek National Grassland in Texas, is just over 1,000 acres and larger than about 70% of grasslands open to the public in the three major grassland regions in which the sites are located (Martinez et al., 2024; Adelman and Schwartz, 2013). I focus on this subset of grasslands to isolate the effect of weather on grassland recreation and limit substitutability between grasslands and non-grasslands. The choice set for households in each

CBG includes any of these 16 grasslands within a day's drive. Visiting a nationally notable grassland is a different experience from visiting a smaller grassland because of their size and the activities available to recreators (e.g., hunting), so excluding these smaller grasslands from the choice set should have little effect on resulting welfare estimates. The remaining potential substitutes include large grasslands and non-grasslands.

I am aware of three large grasslands near the target 16 that are potential substitutes but excluded from the choice set: Cedar River National Grassland, Grand River National Grassland, and Konza Prairie. I collect data on Cedar River and Grand River national grasslands but exclude them from the final sample because there are months for which the estimated number of recreational visits were zero. These sites are also located along the North Dakota-South Dakota border making them potential substitutes for some of the more popular grasslands in the potential choice set: Little Missouri National Grassland and Buffalo Gap National Grassland. Because of their limited visitation and substitutability to other sites in the choice set, I expect the exclusion of Cedar River and Grand River national grassland to have little impact on the welfare estimates from this analysis. Likewise, Konza Prairie is likely to only be a substitute for the Tallgrass Prairie National Preserve based on its location in Manhattan, KS. The effect of excluding Konza Prairie from the choice set is more ambiguous than the effect of excluding Cedar River and Grand River national grasslands because including Konza Prairie would likely increase the size of the market for grassland recreation.

The final group of substitute sites whose exclusion from the choice set may affect the resulting estimates is non-grasslands. As I noted, grassland recreation is generally substitutable to non-grassland sites. Substitution to non-grassland sites may also become more preferred as temperatures increase and recreators look for ways to mitigate the heat. There are many non-grassland sites near the 16 target grasslands, and I expect their exclusion will have an impact on the results of this analysis though the magnitude and sign of that impact is ambiguous. I am exploring this issue in an extension to this research, which I discuss more in the conclusion (Section 6).

4.2 StreetLight Data: Description and Comparison to NPS Data

Unlike the settings for most other structural studies on the relationship between weather and outdoor recreation, there are not large administrative datasets for grassland recreation. Instead, I use mobility data from StreetLight Data. StreetLight is a data provider using a variety of mobility data sources (including mobile devices and connected vehicles) and machine learning models to produce estimates of vehicle, bicycle, and pedestrian traffic. StreetLight acquires its mobility data as well as ground-truth traffic counter data from other companies. It then uses an Extreme Gradient Boosting machine learning algorithm to predict the number of actual vehicle counts on a road or in a specific area (StreetLight Data, 2022a,b). Predictors for actual vehicle counts include the mobility data, demographics of the relevant population, and weather. To obtain the desired estimates, StreetLight subscribers define sites and select the type of estimates to produce in their InSight data portal.

StreetLight uses common model fit statistics and a 10-fold cross-validation procedure to evaluate the prediction accuracy of their models. For 2019-2021, their models explained 98% of the variation in observed traffic counts. All but three of the grassland sites in this analysis have predicted annual average daily traffic values between 0 and 499. For roads or areas at this traffic level, StreetLight's models have a mean absolute percentage error (MAPE) of 20.6 with bias estimates that suggest the model is likely to overestimate the vehicle counts at this traffic level. The three remaining grassland sites have estimated annual average daily traffic values between 500 and 1,999 and between 2,000 and 4,999. The MAPEs for these traffic levels are 14.9 and 12, respectively, with accompanying bias estimates suggesting overestimation is more likely to occur than underestimation.

StreetLight presents data on the representativeness of its sample in terms of the sample penetration rate: the percent of people living in a census tract with mobile devices appearing in the sample (StreetLight Data, 2020). Based on data from 2019, the national sample penetration rate was about 10% of the U.S. population. The sample penetration rate was slightly higher in rural census tracts at 12.2% compared to 10.2% for urban tracts. In terms of race and income, at worst, census tracts with higher proportions of non-white residents have 3% lower sample penetration rates than the national average and people living in census tracts where average household income is \$20,000-\$35,000 are sampled at a slightly lower rate than the national average (8%). Furthermore, StreetLight found no correlation between the percent of people over 70 in a census tract and the sample penetration rate suggesting that elderly people are just as likely to be sampled as others.

Even though a large administrative dataset does not exist for grassland recreation in general, there is administrative data available on visits to the Tallgrass Prairie National Preserve. The National Park Service (NPS) manages the Tallgrass Prairie National Preserve. NPS publishes monthly visit estimates for the sites it manages. Conversely, the Forest Service, which manages national grasslands, collects visitation data every five years and mostly at the national forest level making it impossible to distinguish national grassland recreation from recreation at other sites within the forest (English et al., 2020). A comparison between two visit estimates from NPS and the StreetLight Data estimates is presented in Figure 2. The dashed line represents the NPS estimates for the number of individual visitors to the grassland in a month. The dashed and dotted line represents the NPS estimates for the number of vehicles visiting the grassland in a month. The solid line represents the StreetLight estimates for each month. The StreetLight estimates more closely align with the NPS vehicle count and StreetLight estimates mostly exceed the NPS vehicle counts. NPS only conducted vehicle counts at one site within the preserve and it is possible that the difference between NPS and StreetLight estimates occurs because not all vehicles visiting the Tallgrass Prairie National Preserve stopped there during their visits (U.S. National Park Service, 2022). Although double counting could be inflating the NPS individual visit counts, it seems that StreetLight estimates more closely align with the vehicle counts. This informs my decision to frame the StreetLight estimates as household-level decisions rather than individual-level decisions, which I discuss in more detail in the subsections to follow.

4.3 Grassland Visitation Data

To collect visit count estimates for the 16 grasslands in this analysis for each month between January 2019 and April 2022, I create a shapefile using the Protected Areas Database of the United States (U.S. Geological Survey, 2021) for entry in StreetLight's data portal. I perform an Origin-Destination analysis in the data portal using the grassland sites as destinations and the set of 2020 CBGs as origins. Origin-Destination analyses produce estimates for the number of visits starting in the origin and ending in the destination during a specified period. From this analysis, I recover average daily visit estimates for each grassland-CBG-month combination with at least one estimated visit per day. To calculate an estimate for the number of visits in a month, I multiply the average daily visits by the number of days in each month. To limit the sample to recreational visits, I then multiply the monthly visit estimate by the proportion of visits from each CBG to the grassland that were from an individual's home to a non-work location. In determining an individual's home location, StreetLight Data (n.d.) relies on the location of the device overnight during the relevant month and assigns a home location probability to the 5 most likely home CBGs for each device. Summary statistics are presented in Table 1 and the distribution of visit counts per month for each grassland is shown in Figure 3. Both show a wide range of visitation intensity levels across sites. The most intensively visited site is Little Missouri National Grassland followed by a group of 4 sites with average monthly visits between 3,000 and 4,000 (Buffalo Gap National Grassland, Lyndon B. Johnson National Grassland, Pawnee National Grassland, and Thunder Basin National Grassland). The remaining grasslands range from about 200 to just over 1,000 monthly visits.

4.4 Supplementing StreetLight Data

Because the visit estimates from StreetLight are estimates of the population values and not merely counts from a subsample of the population, I consider them representative of the market for visits to each of these grasslands. I assume that each estimated visit in the data corresponds to a visit a household made from their home CBG to the grassland. A full picture of the market would include non-visitors. The StreetLight data is only concerned with visitors. To construct a full picture of the market, I collect data on households living in the set of CBGs from the U.S. Census Bureau (2020, 2021) American Community Survey (ACS) 5-year estimates using the `censusapi` package in R (Recht, 2024). This data includes the number of adults (18 and over), number of households, and annual household income. I identify visiting CBGs based on the StreetLight data. I calculate the one-way travel time and distance for each CBG to potential substitutes within the choice set using the `osrmtime` package in Stata if the CBG-grassland pair does not appear in the StreetLight data (Huber and Rust, 2016)[4]. CBG-grassland pairs with one-way travel times exceeding the longest one-way travel time (5 hours) in the StreetLight data are removed.

4.5 Calculating Travel Cost

I calculate travel cost for each CBG-grassland pair as

$$tc_{ijt} = \frac{1}{3}\left(\frac{hhinc_{it}}{2080}\right) travtime_{ijt} + opercost_t \times travdist_{ijt} \tag{6}$$

where $hhinc_{it}$ is average household income in the CBG at the time of the visit, $opercost_t$ is the per-mile vehicle operation cost, and $travtime_{ijt}$ and $travdist_{ijt}$ are round-visit travel time and distance in hours and miles. Average household income varies semi-annually for each CBG because I use household income from the 2020 U.S. Census Bureau American Community Survey (ACS) to describe household income in 2019 and 2020 and household

[4]The `osrmtime` package uses the Open Source Routing Machine to calculate travel time and distance.

income from the 2021 ACS to describe household income in 2021 and 2022.[5] Travel time and distance may vary monthly for visiting CBGs because StreetLight produces estimates for each month. If I compute the travel time and distance manually, it is constant across months. Vehicle operating cost includes the per-mile fuel, maintenance, and depreciation cost (American Automobile Association, 2019, 2020, 2021, 2022) as is best practice (Lupi et al., 2020).

4.6 Weather Data

I construct fourteen 5 °F daily average temperature bins and three 0.25-inch daily rainfall bins for each site in each month using data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group (2023). I use the National Weather Service's (2024b) National Gridded Snowfall Analysis dataset to construct three 0.25-inch daily snowfall bins as well. Both average temperature and rainfall are calculated as daily averages across the 2.5-mile×2.5-mile PRISM grid cells within the boundary of each grassland. Snowfall is calculated as a daily average across the 2.5-mile×2.5-mile National Gridded Snowfall Analysis grid cells within each grassland's boundary.

In addition to the bins for average daily temperature, rainfall, and snowfall, I construct bins for average wind speed. Wind speed is an important control in identifying the relationship between grassland recreation and weather in the context of climate change. Because grasslands tend to be treeless, grassland recreators may be particularly exposed to wind. Pleasant breezes may also mitigate the effect of hotter temperatures on grassland recreators. Zeng et al. (2019) show that average annual surface wind speeds slowed between 1978 and 2010 but began an upward trend in 2010 that persisted through the end of their dataset in 2017. Although Zeng et al. (2019) are agnostic about the relationship between climate change and wind speed trends, it is possible that the effect of changes in wind speed could

[5]If average household income is unavailable for a CBG in either 2020 or 2021, I replace the missing value with the value for the non-missing year. If average household income is unavailable for both years, I replace the missing values with per-capita income.

be confounded with climate change impacts because wind speed trends persist over multiple decades just as changes in climate are observed over similar time spans. I collect daily average wind speed data for each grassland during the study period from gridMET (Abatzoglou, 2013). I construct three average wind speed bins. The first bin counts the number of days in a month where average wind speed is strictly below 8 MPH, the second counts days where average wind speed is between 8 and 13 MPH, and the final bin counts days where average wind speed is at or above 13 MPH. Meteorologists and weather observers use the Beaufort Scale to describe wind speeds (U.S. National Weather Service, 2024a). Wind speeds below 8 MPH correspond to calm to light breeze conditions. Wind speeds between 8 and 13 MPH correspond to a gentle breeze. Wind speeds at or above 13 MPH correspond to moderate breeze to strong breeze conditions.

Figure 4 shows the distribution of each weather variable across the 16 nationally notable grasslands during the study period. Average daily temperature (Figure 4a) has a bi-modal distribution with frequency peaks in the 40-45 ˚F and 70-75 ˚F bins. Figure 5 shows the temperature distribution for each grassland by climate. I define climates based on 30-year CDD normals. These values range from 420 for Little Missouri National Grassland to 2253 for Lyndon B. Johnson National Grassland. I calculate 30-year CDD normals based on PRISM Climate Group (2023) data. Figures 6 and 7 show monthly average daily temperature and total visits for Little Missouri and Lyndon B. Johnson national grasslands. In both cases, visits peaks do not occur in peak average temperature months and tend to coincide with hunting seasons. Figures 4b and 4c show that the grasslands I focus on received little rainfall or snowfall during the study period. Figure 4d shows that on most days during the study period average wind speed was in the calm to light breeze category. Average daily wind speed does not exceed 31 MPH at any of the grasslands during the study period.

5 Results & Discussion

5.1 Demand for Grassland Visits, Value, and Weather

Parameter estimates for the model without climate interactions (Equation 1) are presented in Table 2. Across all three specifications, the travel cost parameter is negative, and the dissimilarity parameter is between zero and one, as theory predicts. Estimates for both parameters are also statistically different from zero. The average temperature bin estimates generally follow the inverted-U shape common to temperature response functions in the literature (see Figure 8). The further the average temperature is from the base temperature bin (60 - 65°F), the less households prefer to visit a grassland, except for average temperatures in the 20 - 25°F and 25 - 30°F bins. The estimates suggest that households are indifferent between (or prefer) visiting a grassland in months when there are additional days in this slightly less extremely cold average temperature range and visiting when there are additional days in the reference bin. This result is robust to the inclusion of the big game and fowl hunting season fixed effects, which suggests that correlation between colder temperatures and strictly defined hunting seasons is not causing the unintuitive result.

Rainfall is not a significant predictor of demand for grassland recreation in either specification with month fixed effects nor is wind speed. An additional day with small amounts of snowfall (0.01 - 0.25 inches) relative to no snowfall has a positive and significant effect on monthly demand. An additional day of snowfall at or above 0.25 inches of snowfall has a negative and significant impact on monthly demand. Despite opportunities to participate in snow-related activities at grasslands, it may be that these grasslands are sufficiently rural to make traveling for recreation more difficult in snowy conditions deterring potential visitors. It could also be that participating in certain snow-related activities (e.g., cross-country skiing) is more enjoyable when there is snow on the ground, but not when it is snowing heavily. The results from the specifications including month-of-year fixed effects (Columns 2 and 3) are roughly equivalent, but I focus my discussion of welfare impacts on the specification including hunting season fixed effects.

WTP impacts from weather changes based on the specification in Column 3 are presented in Figure 8 and Table 3. The WTP estimates for the weather parameters represent the per-visit welfare loss (or gain) for a household if there was an additional day in a month in the relevant average temperature range rather than the reference range. For example, if there was an additional day in a month where the average temperature was at or above 80°F, households would lose about \$0.60 per visit relative to an additional day in the 60 - 65 ° range. Given per visit WTP for grassland visits is \$53.60, this would amount to an approximately 1% decrease in the use value of a grassland visit per additional day at or above 80°F. For reference, the results in Dundas and von Haefen (2020) suggest that an additional day in the extreme temperature range in 2004 would decrease WTP for coastal fishing in the Southeastern U.S. by about \$0.25. In an average month, there are 32,043 visits to the 16 nationally notable grasslands. The total use value of those visits is nearly \$1.72 million. With an additional day of extreme temperatures in an average month, visiting households would lose over \$19,000 in welfare from the change in quality of the grassland experience assuming they still decide to visit. The expected net gain or loss from climate change will depend on changes in the entire distribution of temperature, which I explore in the next subsection. Table 3 shows that the only other significant impact on welfare from weather is from additional days of snow at or above 0.25 inches. This is another source of potential gains to grassland recreators from climate change as snowfall would likely decrease with increasing temperatures.

I use interactions between the temperature and snowfall bins and indicators for whether a grassland was above or below the 50th percentile in 30-year CDD normals to examine heterogeneous responses to weather across climates. Grasslands above the 50th percentile have relatively warmer climates than grasslands below the 50th percentile. This model does not include the hunting season fixed effects for identification purposes but retains the site and month-of-year fixed effects. The travel cost and dissimilarity parameter estimates are essentially identical to the estimates from the other specifications. Per visit WTP and marginal WTP impacts from non-temperature weather variables are reported in Table 4. The WTP impacts from rain and wind are similar to those from the model without climate interactions. The first evidence of heterogeneity in responses to weather is in the difference between WTP for visits under increasing amounts of snowfall. For grasslands in colder climates, households are willing to pay significantly less for a grassland visit for each additional day with snowfall greater than or equal to 0.25 inches. The estimated loss of \$1.15 per additional day of high snowfall is also significantly less than the estimated gain of \$0.99 households in warmer climates would see from an extra day of similar snowfall levels.

Preferences for grassland visits under moderate temperatures tend to align across the two climate regions (Figure 9). Significant divergence in WTP occurs at more extreme temperatures. This result is consistent with Linsenmeier (2024) except that households with access to grasslands in colder climates appear to value grassland recreation more in some higher temperature ranges than households in warmer climates. Access to non-weather dependent substitutes may drive this result. The most visited grassland among those in colder climates is Little Missouri National Grassland in Western North Dakota. The most visited grassland among those in warmer climates is Lyndon B. Johnson National Grassland just outside of the sprawling Dallas-Fort Worth metropolitan area in Texas. Households who can visit LBJ National Grassland probably have more non-weather dependent recreational substitutes to grassland recreation than households who can visit Little Missouri National Grassland making LBJ visitors more responsive to warmer temperatures.

5.2 Climate Change Impacts on Visits and Welfare

I project annual climate change impacts on grassland visits and related welfare using three warming scenarios for 2081 - 2100 from the Intergovernmental Panel on Climate Change (IPCC, 2023). The three warming scenarios predict increases of 2.52 °F, 4.86 °F, and 7.92 °F over 1850-1900 global surface temperature levels and correspond to very low, intermediate, and very high greenhouse gas emissions scenarios. Using the difference between the predictions for 2081 - 2100 and the global warming that has already occurred (1.96 °F), I increase the average daily temperature at each grassland for each day in the study period and recount the temperature bins to get the predicted temperature distribution. I invoke the ceteris paribus assumption for all other variables in the model and also assume that the population of grassland recreators does not change between the study period (January 2019 - April 2022) and 2081 - 2100.

To predict visits under each scenario, I calculate

$$Visits_{it} = \left(\frac{\left[\sum_{k=1}^{K} e^{\frac{\hat{V}_{ikt}}{\hat{\theta}}}\right]^{\hat{\theta}}}{e^{\hat{V}_{i0t}} + \left[\sum_{k=1}^{K} e^{\frac{\hat{V}_{ikt}}{\hat{\theta}}}\right]^{\hat{\theta}}} \right) \times C_{it} \tag{7}$$

where C_{it} is the total visits households in CBG i made to any grassland in month t. Month t is one of the 40 months in the original study period (January 2019 - April 2022). The term in brackets is the probability that a household visits any grassland evaluated at the parameter estimates and relevant weather distribution. This procedure calculates the number of visitors in the original study period who would still visit if the temperature distribution during a given month changed according to each warming scenario. Following Dundas and von Haefen (2020), I calculate the average number of visits for each month of the year from 2019 - 2022 and sum the values to get average annual visits under each warming scenario. I then take the difference between the predicted average annual visits under the warming scenarios and the predicted number of visits under the observed conditions during the study period. The change in average annual visits and 95% confidence intervals for the mean estimates are shown in Table 5. I calculated the confidence intervals using the Krinsky and Robb (1986) method with 1,000 draws. Average annual visits increase under all three warming scenarios, but those increases are expected to be small ($\leq$ 66 visits for under the very high emissions scenario). The 95% confidence intervals bound the predicted average annual gains (losses) in visits between -4,480 and 5,537, which is about a 1% change in either direction given observed average annual visits of 385,000. For reference, Dundas and von Haefen (2020) predict visit losses between 5.5% and 22.7% for coastal fishing over the same time period and similar warming scenarios.

To predict welfare changes under each scenario, I follow Haab and McConnell (2002) and Dundas and von Haefen (2020) and calculate compensating variation as

$$CV_{it} = \left[\ln \left(e^{\hat{V}^*_{i0t}} + \left[\sum_{k=1}^{K} e^{\frac{\hat{V}^*_{ikt}}{\hat{\theta}}} \right]^{\hat{\theta}} \right) - \ln \left(e^{\hat{V}_{i0t}} + \left[\sum_{k=1}^{K} e^{\frac{\hat{V}_{ikt}}{\hat{\theta}}} \right]^{\hat{\theta}} \right) \right] \times C_{it} \tag{8}$$

where $\hat{V}^*_{ikt}$ is the observable portion of utility in Equation 1 evaluated at the estimated parameter values and warming scenario temperature levels and $\hat{V}_{ikt}$ is the observable portion of utility evaluated at the estimated parameter values and conditions observed within the study period. I calculate this value for each month, take the average by month and CBG, and sum the values to obtain an estimate for the average annual compensating variation under each warming scenario. These estimates are shown in Table 6 along with 95% confidence intervals calculated by the Krinsky and Robb (1986) method with 1,000 draws. As in the predicted visitation response, the point estimates for average annual compensating variation are relatively small compared to studies on other activities, but the confidence intervals provide more information on the range of outcomes we might expect under each scenario. Although only two of three point estimates are positive, all of the confidence intervals skew toward positive net benefits from climate change to grassland recreators. Under the very high emissions warming scenario, grassland recreators could see as much as $1.3 million in welfare gains annually.

6 Conclusion

This research estimates the value of a visit to any of 16 nationally notable grasslands in the U.S., the relationship between visit demand and weather, how that relationship varies across climates, and how increasing temperatures from climate change could affect visit demand and welfare among grassland recreators. I find that the value of a grassland visit is $53.60 per household. This is the second estimate of grassland recreational value in the U.S. after Wells (2023) and could inform the government's development of a pilot natural capital account for grasslands.

In terms of the relationship between weather and grassland recreation, I find average temperature and total snowfall to be significant determiners of grassland visit demand. Grassland recreators prefer to visit a grassland when there are fewer days of either extremely cold or hot temperatures, which is consistent with other studies on outdoor recreation and weather. Interestingly, there is a slight preference for more days of slightly less extremely cold average temperatures suggesting a possible avenue for gains from climate change. There is a small positive effect of additional days of light snowfall (0.01 - 0.25 inches) on demand relative to days of no snowfall, but snowfall above 0.25 inches significantly decreases demand.

Responses to temperature and snowfall across climates differ the most at or close to the extremes, which is consistent with previous work (Linsenmeier, 2024). Grassland recreation in colder climates drives the demand for grassland recreation at slightly less than extremely cold average temperatures as well as the preference for grassland recreation in month with fewer days of extreme snowfall. People living in warmer climates appear to be more responsive to changes in temperature, which I attribute to increased substitution opportunities to non-outdoor recreation because more of the grasslands in warmer climates are closer to populated areas.

Climate change is expected to have little effect on grassland recreation demand and related welfare on average. Under the most extreme warming scenario, point estimates for net changes in average annual grassland recreation demand and compensating variation are increases of 66 visits and about $52,000, respectively. The confidence intervals around these estimates suggest uncertainty that could see gains of up to 5,537 trips and about $1.3 million in welfare or losses up to 4,480 trips or about $300,000 in welfare under climate change. The expected gains and losses from climate change for other outdoor recreation activities and settings generally dwarf these estimates, but quantifying these impacts for grassland recreation ensures that it can be counted if recreation values start to factor into social cost of carbon calculations.

As I mentioned in Section 4.1, future work should explore how choice set definition affects these results. I am working on an extension to this research that examines weather responses at three of the nationally notable grasslands and set of grassland and non-grassland substitutes like national forests and state parks. There are over 300 substitutes in the choice set. This allows me to explore how substitution opportunities affect the results presented here but also how substitution away from grassland recreation in response to warmer temperatures may be a mechanism for adaptation to climate change.

Future work should also test whether my results are robust to my assumptions about the spatial and temporal distribution of temperature increases, how other weather variables change as climate changes, and the population in affected areas. Temperature is unlikely to change uniformly across space and time. When and where temperature changes occur will likely affect these results especially given the heterogeneity in responses to temperature across climates. Just as temperature is unlikely to change uniformly it is also unlikely to change in a vacuum. Rainfall and snowfall will likely change with temperature and similarly affect these results. Population changes could also affect demand for visits whether population is expected to increase or decrease could meaningfully impact the magnitude of the expected gains or losses from climate change to grassland recreation.

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Tables

Table 1. Summary statistics for grassland visitation data

	Monthly Visits					Travel Time (hrs)		Travel Distance (mi.)		Travel Cost ($)	
	Mean	sd	Min	Max	CBG Count	Mean	sd	Mean	sd	Mean	sd
Black Kettle NG	1,039	511	126	2,363	161	1.3	0.8	50.2	44.5	176.97	68.15
Buffalo Gap NG	2,875	1,158	1,243	5,610	205	1.4	0.7	53.5	38.5	173.21	98.75
Caddo NG	1,115	594	253	3,091	324	1.2	0.7	41.9	31.4	162.47	58.98
Cimarron NG	1,168	431	564	2,476	75	1.2	0.7	42.9	34.1	186.9	69.2
Commanche NG	1,022	435	463	2,240	174	1.4	0.9	56.8	54.3	228.07	91.31
Fort Pierre NG	467	246	85	1,167	47	1.0	0.6	32.0	36.8	195.62	87.55
Kiowa NG	349	164	98	704	68	1.3	1.0	49.3	55.0	207.86	63.34
Little Missouri NG	10,613	4,164	4,258	22,425	222	1.5	0.7	60.3	37.8	162.03	81.56
Lyndon B Johnson NG	3,997	1,310	2,035	7,424	953	1.2	0.6	41.6	23.2	132.80	61.03
McClellan Creek NG	380	329	56	1,468	116	1.1	0.5	41.8	21.2	157.76	72.98
Oglala NG	333	297	26	1,225	57	1.4	0.7	48.2	30.3	187.57	64.38
Pawnee NG	3,093	1,420	1,086	5,872	894	1.5	0.6	53.7	26.7	143.19	70.45
Rita Blanca NG	209	132	34	800	45	1.1	0.8	39.4	41.6	174.75	59.61
Sheyenne NG	706	524	20	2,457	167	1.1	0.6	37.0	25.6	144.38	94.73
Tallgrass Prairie Nat Pres	598	423	70	2,005	363	1.5	0.8	61.4	44.0	143.60	66.07
Thunder Basin NG	3,348	993	1,399	5,946	108	1.5	0.6	58.0	31.2	172.21	71.71

Note. Summary statistics describe monthly visit data from StreetLight data for each site between January 2019 and April 2022. Visits are trips from households living in a CBG to a grassland. CBG count is the number of CBGs with households making a positive number of trips to a grassland in the study period. Travel time and distance are one-way measures for visitors only. Travel cost is round-trip and includes visitors and non-visitors. NG = National Grassland. CBG = U.S. Census block group.

Source. Author calculations (StreetLight Data, U.S. National Census Bureau, and Open Source Routing Machine)

Table 2. Repeated discrete choice model results without climate interactions

	(1)		(2)		(3)	
	Est.	S.E.	Est.	S.E.	Est.	S.E.
Travel Cost	−0.019***	0.001	−0.019***	0.001	−0.019***	0.001
θ	0.505***	0.019	0.504***	0.019	0.505***	0.019
Temperature (Ref: 60-65 °F)						
< 20	−0.038***	0.004	−0.021***	0.005	−0.020***	0.005
20-25	0.003	0.006	0.009	0.007	0.008	0.007
25-30	−0.007	0.005	−0.002	0.006	−0.001	0.006
30-35	−0.029***	0.005	−0.025***	0.006	−0.025***	0.006
35-40	−0.019***	0.004	−0.018***	0.005	−0.017***	0.005
40-45	−0.006	0.004	−0.002	0.004	−0.002	0.005
45-50	−0.003	0.004	−0.004	0.005	−0.003	0.005
50-55	−0.011**	0.005	−0.019***	0.005	−0.016***	0.005
55-60	0.001	0.005	−0.006	0.006	−0.004	0.006
65-70	−0.005	0.004	−0.010**	0.005	−0.008*	0.005
70-75	−0.003	0.003	−0.006	0.004	−0.005	0.004
75-80	−0.007**	0.003	−0.011***	0.004	−0.009**	0.004
≥ 80	−0.010***	0.003	−0.015***	0.004	−0.011***	0.004
Rainfall (Ref: < 0.01 in.)						
0.01-0.25	−0.008***	0.002	0.001	0.002	0.001	0.003
≥ 0.25	−0.008**	0.004	−0.001	0.004	0.000	0.004
Wind Speed (Ref: Calm)						
Gentle Breeze	0.001	0.002	−0.001	0.002	−0.002	0.002
Moderate-Strong Breeze	−0.004*	0.003	−0.003	0.003	−0.003	0.003
Snowfall (Ref: < 0.01 in)						
0.01-0.25	0.010**	0.005	0.010**	0.005	0.009*	0.005
≥ 0.25	−0.005	0.005	−0.020***	0.005	−0.020***	0.005
N	268,117		268,117		268,117	
LL	−178,778		−178,706		−178,697	
AIC	357,630		357,511		357,496	
BIC	358,018		358,025		358,031	
Site FEs	×		×		×	
Month FEs			×		×	
Hunt FEs					×	

Note. Standard errors are clustered at the census block group level. Parameters were estimated using a maximum likelihood routine and two-level nested logit model in the `apollo` package in R (Hess and Palma, 2019).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Per visit willingness to pay (WTP) and marginal impacts from non-temperature weather variables (no climate interactions model)

	WTP	95% CI	
Per Visit	\$53.60	\$50.67	\$56.53
Rainfall (in.)			
0.01-0.25	\$0.08	-\$0.19	\$0.35
$\geq$ \$ 0.25	-\$0.03	-\$0.47	\$0.41
Wind			
Gentle Breeze	-\$0.08	-\$0.30	\$0.14
Moderate - Strong Breeze	-\$0.16	-\$0.47	\$0.15
Snowfall (in.)			
0.01-0.25	\$0.48	-\$0.02	\$0.98
$\geq$ \$ 0.25	-\$1.05	-\$1.63	-\$0.47

Note. WTP estimates based on the model with site, month-of-year, and hunting season fixed effects and no interactions between weather variables and climate indicators. Weather WTP values should be interpreted as the loss (gain) in use value if the weather distribution changed such that a day in the reference bin was replaced by a day in one of the other bins. I calculated the 95% confidence intervals using the delta method.

Table 4. Per visit willingness to pay (WTP) and marginal impacts from non-temperature weather variables (climate interactions model)

	WTP	95% CI	
Per Visit	\$53.53	\$50.61	\$56.45
Rainfall (in.)			
0.01-0.25	\$0.07	-\$0.20	\$0.34
$\geq$ 0.25	-\$0.20	-\$0.65	\$0.25
Wind			
Gentle Breeze	\$0.07	-\$0.16	\$0.29
Moderate - Strong Breeze	-\$0.05	-\$0.37	\$0.27
Snowfall (in.)			
Below 50th Percentile (CDDs)			
0.01-0.25	\$0.04	-\$0.50	\$0.58
$\geq$ 0.25	-\$1.15	-\$1.78	-\$0.53
Above 50th Percentile (CDDs)			
0.01-0.25	\$0.36	-\$1.07	\$1.79
$\geq$ 0.25	\$0.99	-\$0.37	\$2.36

Note. WTP estimates based on the model with site and month-of-year fixed effects with interactions between temperature and snowfall variables and climate indicators. Weather WTP values should be interpreted as the loss (gain) in use value if the weather distribution changed such that a day in the reference bin was replaced by a day in one of the other bins. I calculated the 95% confidence intervals using the delta method.

Table 5. Average change in annual visits under three warming scenarios (2081 - 2100)

Climate Change Scenario	Δ Visits	95% CI	
Very Low Emissions (SSP1-1.9)	5	-4,480	5,537
Intermediate Emissions (SSP2-4.5)	24	-4,480	5,537
Very High Emissions (SSP5-8.5)	66	-4,480	5,537

Note. I assume uniform increases in average temperature across all 16 nationally notable grasslands using the Intergovernmental Panel on Climate Change's (2023) projections for the SSP1-1.9, SSP2-4.5, and SSP5-8.5 greenhouse gas emissions scenarios between 2020 and 2081-2100. I calculated the 95% confidence intervals using the Krinsky and Robb (1986) method with 1,000 draws.

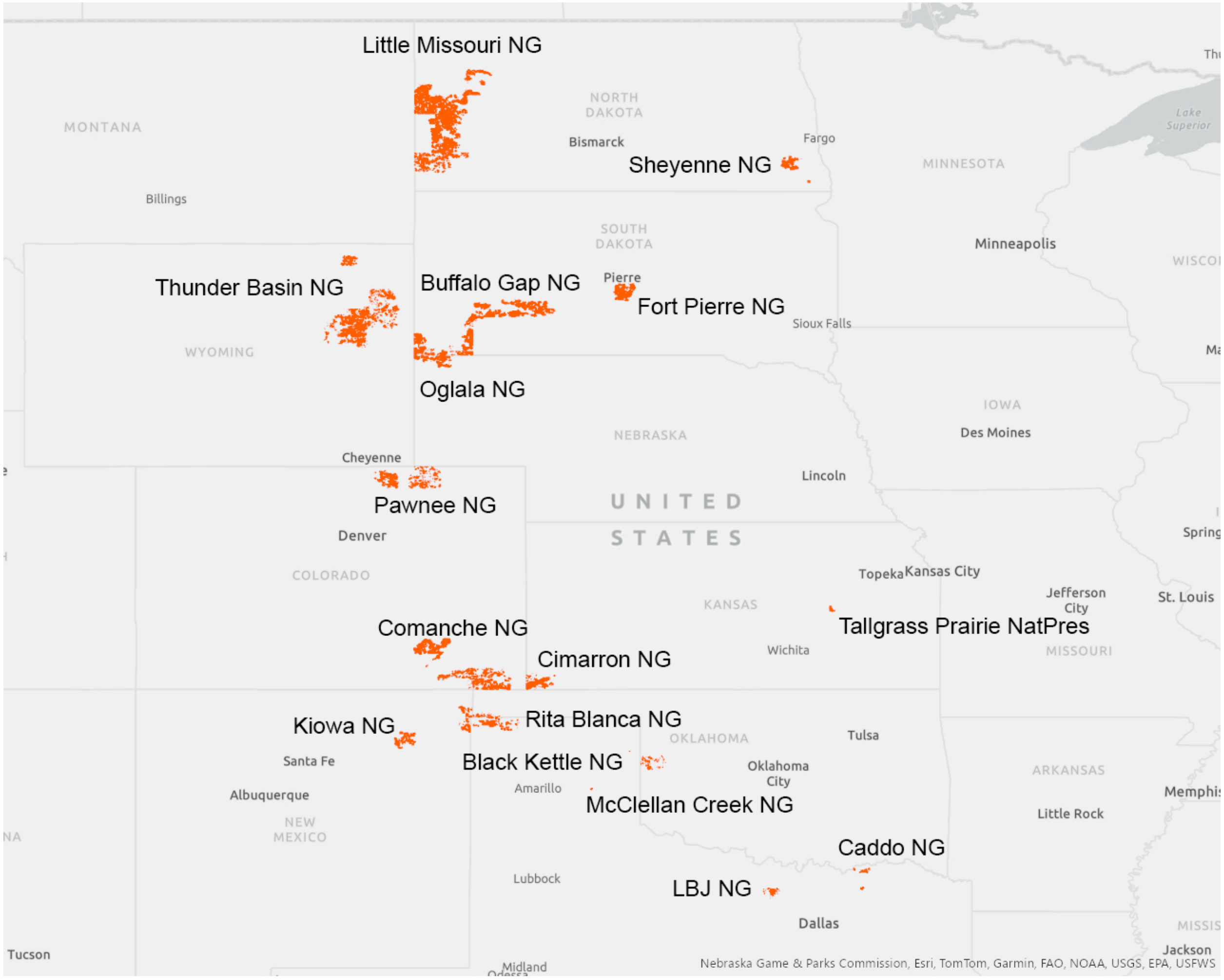
Table 6. Average annual compensating variation under three warming scenarios (2081 - 2100)

Climate Change Scenario	CV	95% CI	
Very Low Emissions (SSP1-1.9)	-$1,513	-$36,061	121,042
Intermediate Emissions (SSP2-4.5)	$23,725	-$152,071	$666,800
Very High Emissions (SSP5-8.5)	$51,963	-$298,431	$1,319,412

Note. I assume uniform increases in average temperature across all 16 nationally notable grasslands using the Intergovernmental Panel on Climate Change's (IPCC, 2023) projections for the SSP1-1.9, SSP2-4.5, and SSP5-8.5 greenhouse gas emissions scenarios between 2020 and 2081-2100. I calculated the 95% confidence intervals using the Krinsky and Robb (1986) method with 1,000 draws.

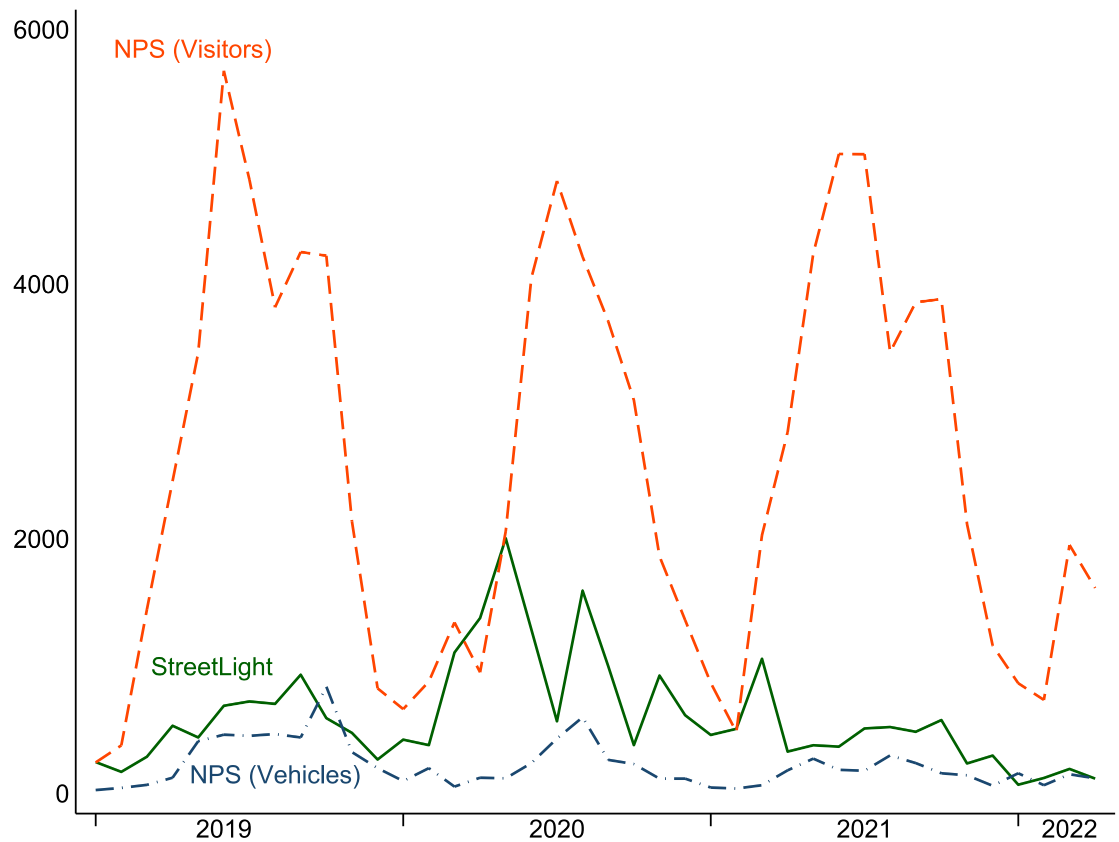
Figures

Figure 1. Nationally notable grasslands in the choice set



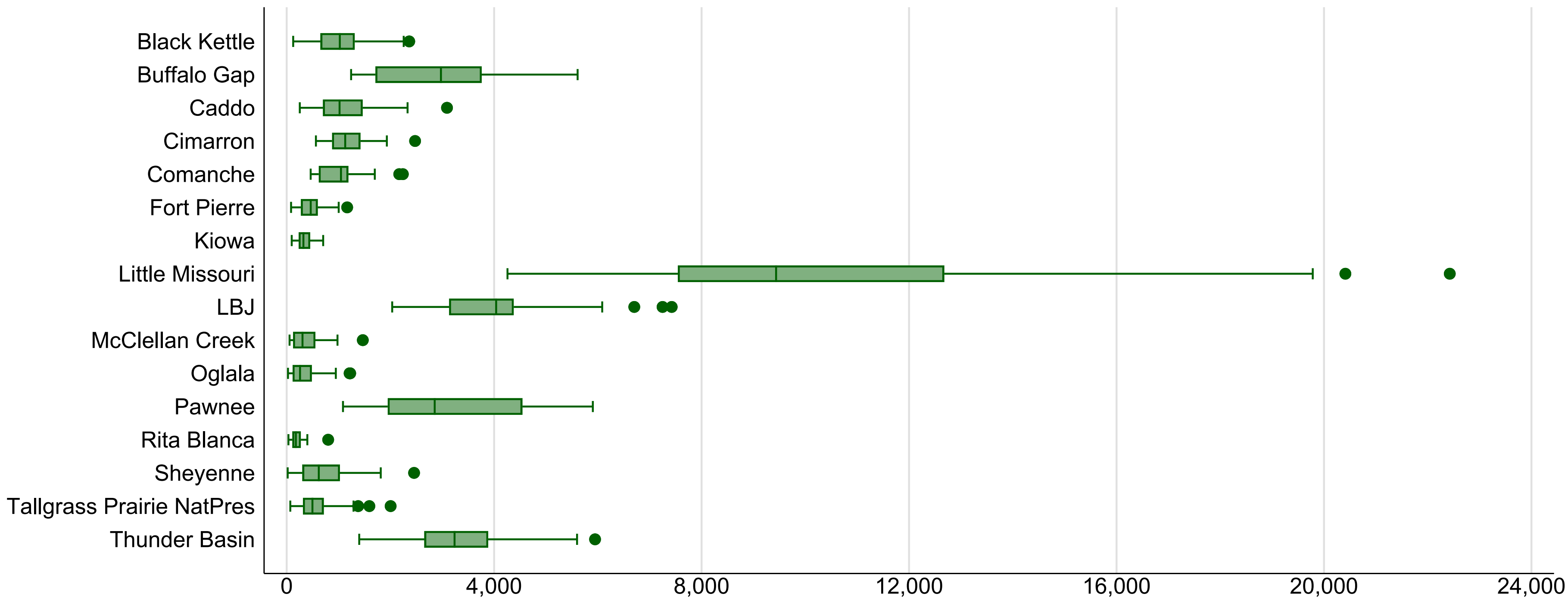
Note. NG = National Grassland
Source. U.S. Geological Survey

Figure 2. Comparison between monthly visit estimates from StreetLight Data and the U.S. National Park Service for the Tallgrass Prairie National Preserve (January 2019 - April 2022)



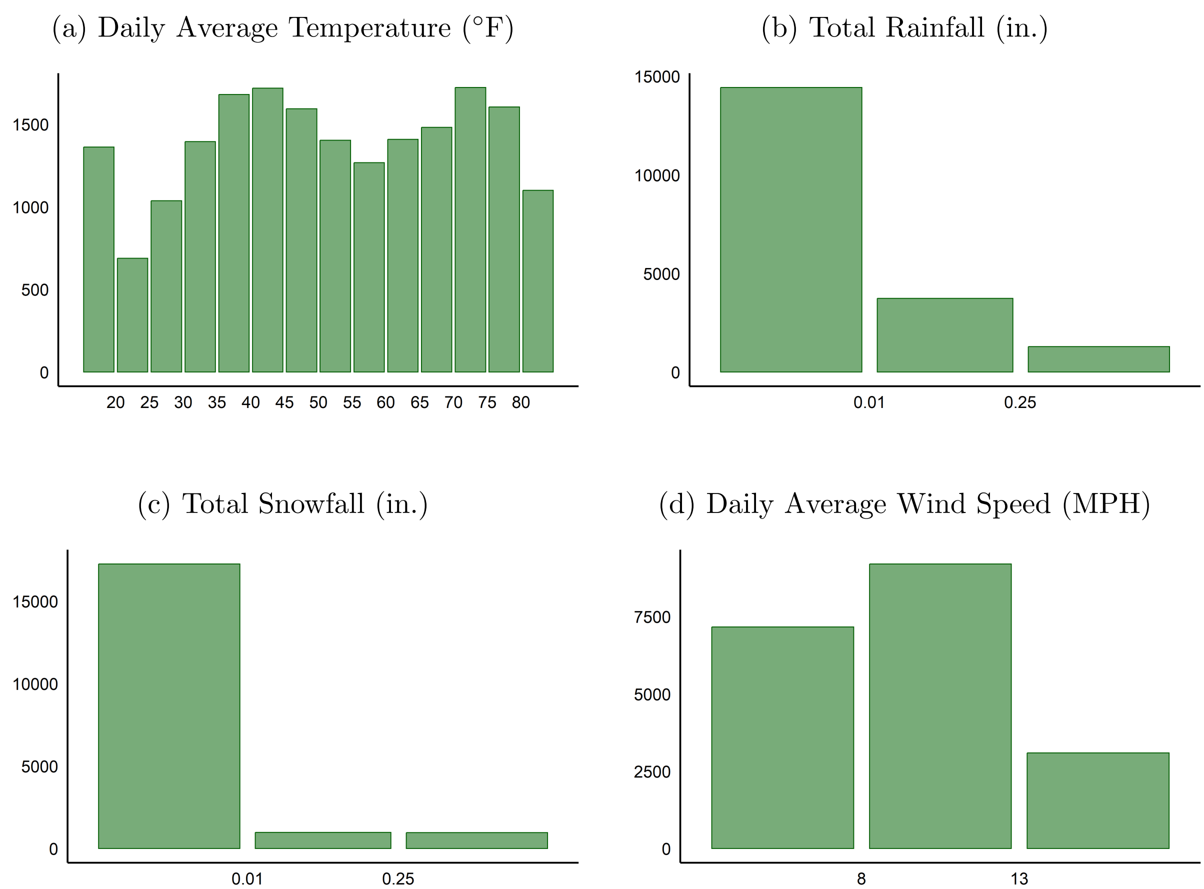
Note. The dashed line represents the number of individuals counted at three locations within the grassland or attending a special event at the grassland (U.S. National Park Service, 2022, 2024a). The dashed and dotted line represents the number of vehicles counted at a single location within the grassland (U.S. National Park Service, 2024b). The solid line is the StreetLight estimate for the number of visits to the grassland in a month.
Source. U.S. National Park Service and author calculations (StreetLight Data)

Figure 3. Distribution of monthly StreetLight Data visit estimates by grassland



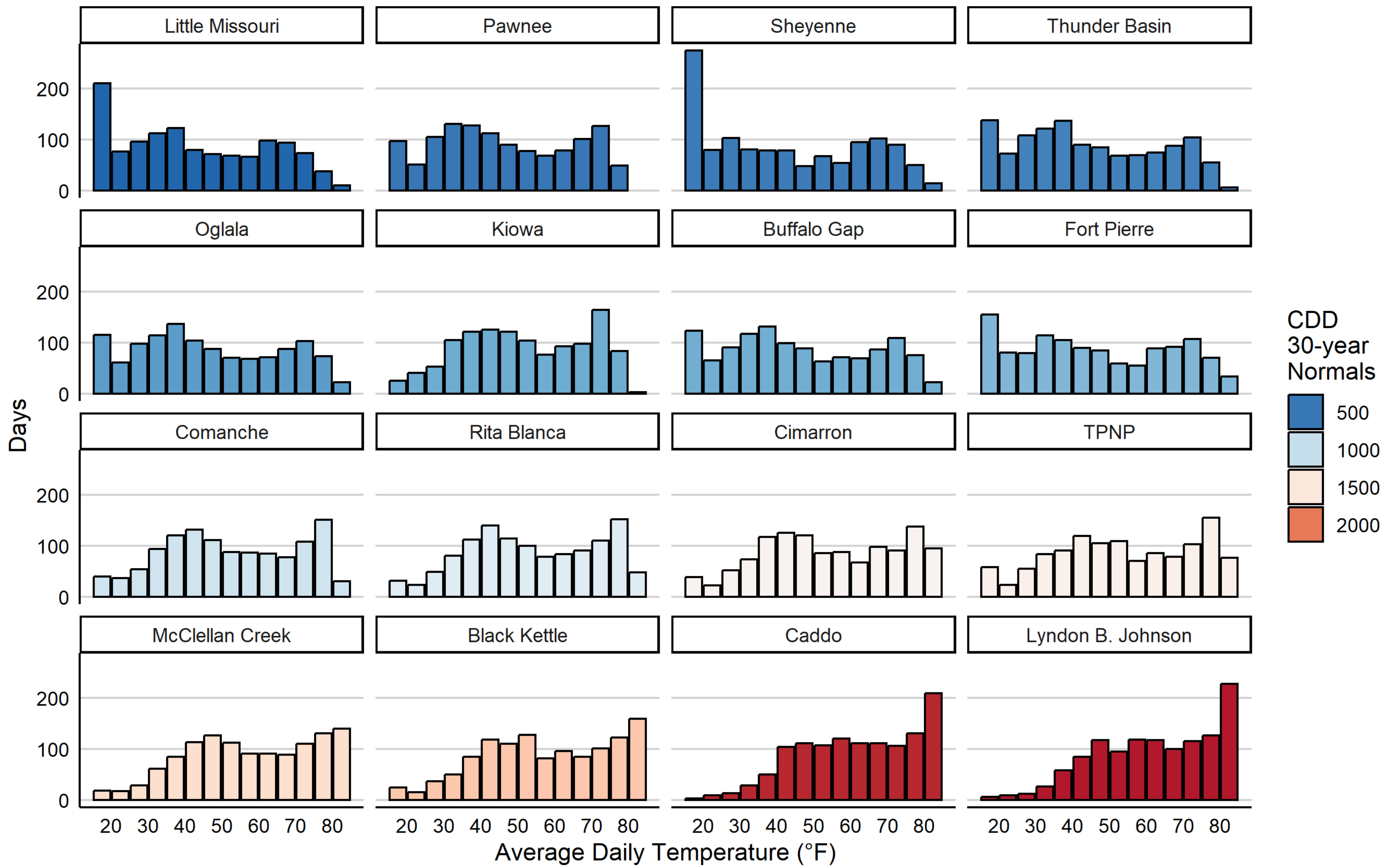
Note. All sites are national grasslands unless otherwise noted.
Source. Author calculations (StreetLight Data)

Figure 4. Number of days observed in each weather bin across all grasslands (January 2019 - April 2022)



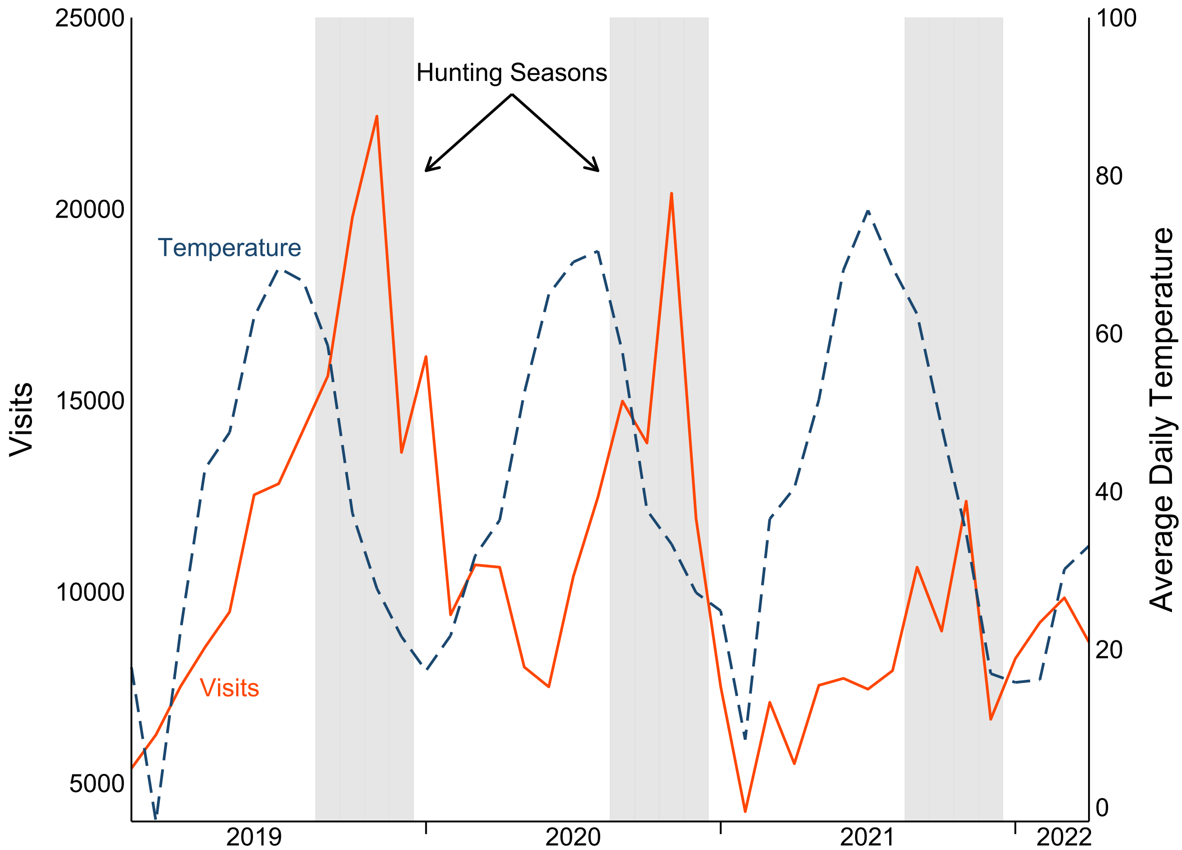
Note. Rainfall estimates include snow melt. There are
Source. gridMet, PRISM, and U.S. National Weather Service

Figure 5. Average daily temperature distribution for 16 nationally notable grasslands (January 2019 - April 2022) by 30-year cooling degree day (CDD) normals



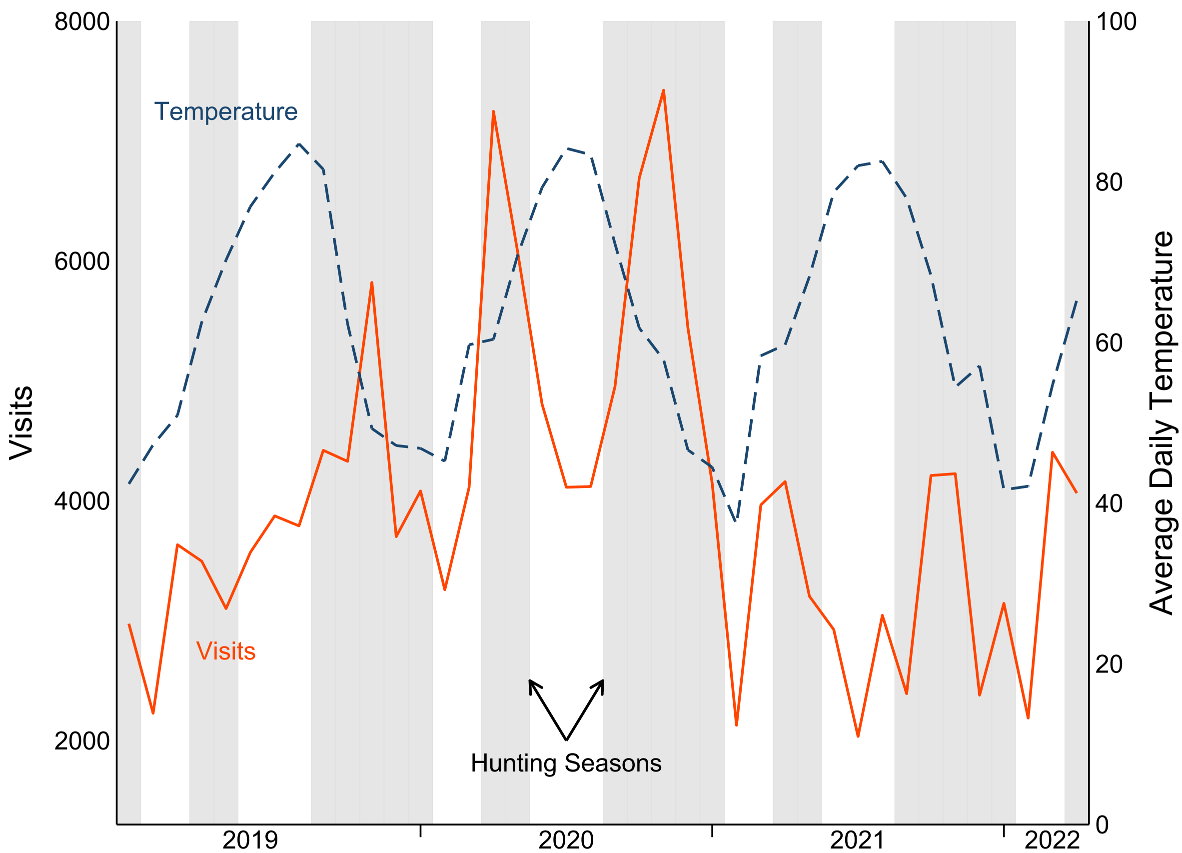
Note. All sites are national grasslands unless otherwise noted. CDD 30-year normals are the average number of annual CDDs between 1992 and 2021 for each grassland. A CDD represents a one-degree positive difference between the average daily temperature and 65 °F. The number of CDDs per day increases linearly as average daily temperature increases and is zero for average daily temperatures below 65 °F. TPNP = Tallgrass Prairie National Preserve.
Source. Author calculations (PRISM)

Figure 6. Monthly visits and average maximum daily temperature - Little Missouri National Grassland (January 2019 – April 2022)



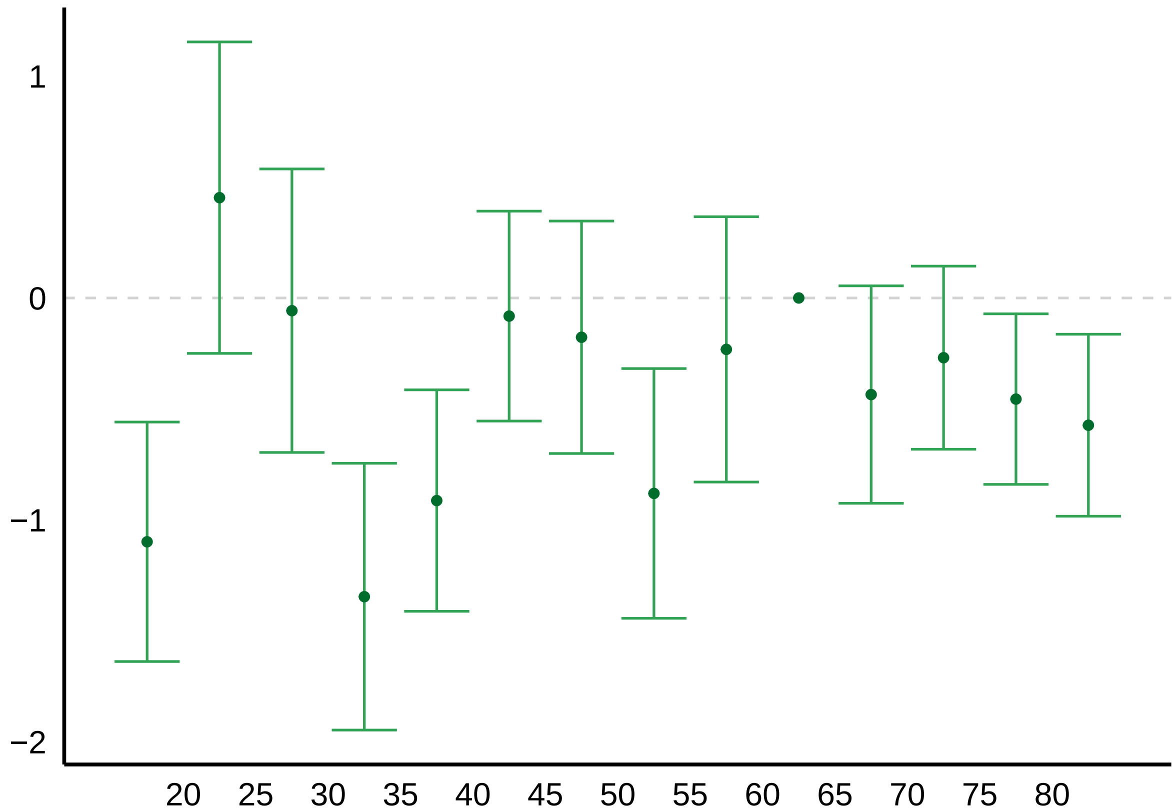
Note. The dashed line represents the average daily temperature in each month at Little Missouri National Grassland. The solid line is the total number of visits to the grassland in that month. The shaded regions show months in which it was legal for visitors to hunt big game or fowl on the grassland (see Footnote 3). Source. Author calculations (PRISM and StreetLight Data)

Figure 7. Monthly visits and average maximum daily temperature - Lyndon B. Johnson National Grassland (January 2019 – April 2022)



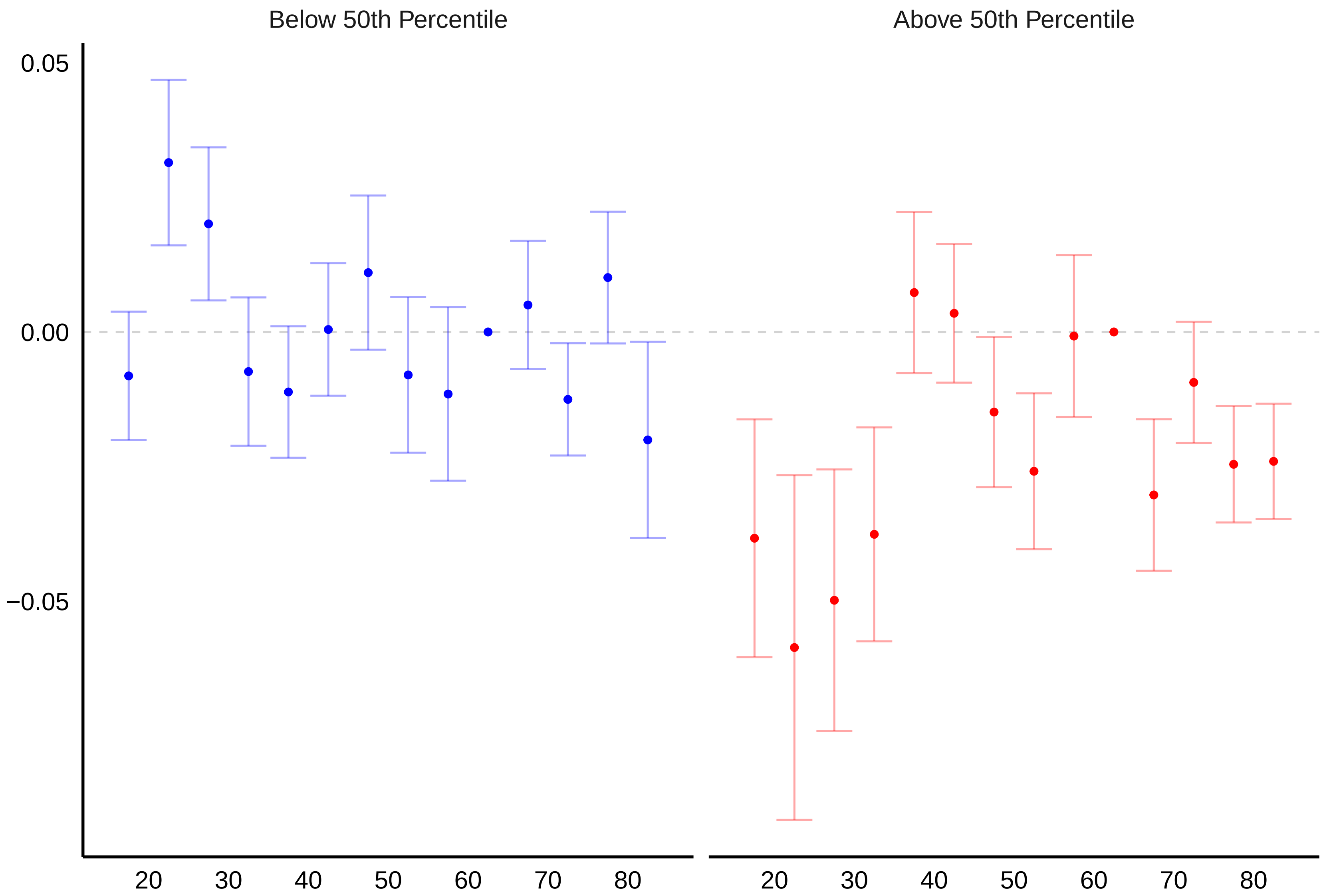
Note. The dashed line represents the average daily temperature in each month at Lyndon B. Johnson National Grassland. The solid line is the total number of visits to the grassland in that month. The shaded regions show months in which it was legal for visitors to hunt big game or fowl on the grassland (see Footnote 3).
Source. Author calculations (PRISM and StreetLight Data)

Figure 8. Marginal impacts on willingness to pay per grassland visit of changes in average daily temperature from the reference bin (60 - 65 °F)



Note. Willingness to pay (WTP) estimates based on results from the model with site, month-of-year, and hunting season fixed effects. Values should be interpreted as the loss (gain) in use value if the temperature distribution changed such that a day in the 60 - 65 °F bin was replaced by a day in one of the other bins. Average WTP for a grassland visit is $53.60. I calculated the 95% confidence intervals using the delta method.

Figure 9. Marginal impacts on willingness to pay per grassland visit of changes in average daily temperature from the reference bin (60 - 65 °F) by 30-year CDD normal percentile



Note. Willingness to pay (WTP) estimates based on results from the model with site and month-of-year fixed effects. Values should be interpreted as the loss (gain) in use value if the temperature distribution changed such that a day in the 60 - 65 °F bin was replaced by a day in one of the other bins. I calculated the 95% confidence intervals using the delta method. CDD = cooling degree day.