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Climate change and the demand for recreational ecosystem services on public lands in the continental United States

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ABSTRACT

Cultural ecosystem services represent nonmaterial benefits people derive from the environment; these benefits include outdoor recreation opportunities. Changes in climatic conditions are likely to shift the spatial and temporal demand for recreational ecosystem services. To date, little is known about the magnitude and spatial variability in these shifts across large geographic extents. We use 14 years of geotagged social media data to explore how the climatological mean of maximum temperature affects the demand for recreational ecosystem services by season across public lands in the continental United States. We also investigate how the demand for recreational ecosystem services on public lands may change by 2050 under two climate change scenarios, RCP 4.5 and RCP 8.5. Across all public lands in the continental U.S., demand for recreational ecosystem services is expected to decrease 18% by 2050 under RCP 4.5 in the summer, but increase 12% in the winter and 5% in the spring, with no significant changes in the fall. There is substantial variation in the magnitude of projected changes by region. In the spring and fall, some regions are likely to see an increase in the demand for recreational ecosystem services (e.g., Arkansas-Rio Grande-Texas-Gulf), while others will see declines (e.g., South Atlantic Gulf, California Great Basin). Our findings suggest the total demand for recreational ecosystem services across the continental U.S. is expected to decline under warming temperatures. However, there is a large amount of variation in where, when, and by how much, demand will change. The peak season for visiting public lands is likely to lengthen in the continental U.S. as the climate continues to warm, with demand declining in the summer and growing in the off-season.

1. Introduction

Ecosystem services (ES) represent all direct and indirect benefits humans receive from the environment. These include provisioning services (e.g., food), regulating services (e.g., water purification), supporting services (e.g., nutrient cycling), and cultural services. Cultural ES are defined as “the nonmaterial benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences” (Millennium Ecosystem Assessment, 2005, p. 40). Cultural ES reflect the social and psychological values ascribed to an environment. Outdoor recreation opportunities are a particular type of cultural ES defined by the opportunity provided by a particular environment for individuals to engage in an outdoor recreation activity. Recreational ES are intractably intertwined with other cultural ES like spiritual, educational, and aesthetic values, making them a good indicator of these broader cultural ES (Hermes et al., 2018).

Quantifying and mapping cultural ES has often depended upon soliciting input from a set of stakeholders, or the broader public, about the types of values they associate with a landscape (Lee et al., 2019). While participatory approaches have proven useful in illustrating possible trade-offs associated with different policies and decisions (Plieninger et al., 2015; Ruckelshaus et al., 2015) and increasing the legitimacy of decision-making processes (McKenzie et al., 2014; Milcu et al., 2013), they can be costly. The process often requires individuals who use a landscape to provide input on how they value that landscape through surveys or interactive exercises. Consequently, maps of cultural ES are often limited to small geographic scales such as municipalities (Brown and Kyttä, 2014; Martínez-Harms and Balvanera, 2012; Van Berkel and Verburg, 2014). While recreational ES are relatively easier to quantify when compared to other types of cultural ES such as spiritual

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ES (Crossman et al., 2013; Egoh et al., 2012), measurement often requires data collection efforts to be tailored to specific environmental contexts. For example, researchers have used data on park visitation and hotel/campsite occupancy to map recreational ES (e.g., Arkema et al., 2015).

Many factors affect both the demand for, and supply of, recreational ES across landscapes (Milcu et al., 2013). 'Demand', in an economic sense, refers to the desire of an individual to use a cultural ES as well as a willingness to pay the costs associated with doing so. For recreational ES, if an individual travels to a destination from one's home, the travel cost indicates the individual's willingness to pay to participate in outdoor recreation (Khan, 2006). Related to demand, is the supply of recreational ES; this is the total potential for a landscape to produce a recreational ES (Tallis et al., 2012). While the term 'demand' in the cultural ES literature has been used to indicate preferences and values as well as direct use, we adopt the stricter definition and use demand to refer specifically to direct use (Wolff et al., 2015).

Previous research has shown climate, as well as weather, impact the demand for outdoor recreational opportunities (Finger and Lehmann, 2012; Paudyal et al., 2019; Smith et al., 2018). Weather is defined as the atmospheric conditions at a specific time and place, whereas climate represents weather averages across long time periods, often 30 years or more (NASA, 2017). Warmer than average temperatures, and increasing variability in weather, are likely to shift the spatial and temporal demand for recreational ES. Additionally, climate change may affect the supply of recreational ES (i.e., the characteristics of natural environments that facilitate specific outdoor recreation activities). For example, spatial and temporal shifts in wildlife distributions limit the ability of individuals to participate in hunting, fishing, and non-consumptive wildlife-dependent recreation (Moreno and Amelung, 2009). Shifts in the demand for, and supply of, recreational ES due to climate change are also likely to be highly variable across space. Climate change may threaten recreational ES in some locations or seasons while bolstering them in other areas or seasons. In this research, we identify how climate affects the demand for recreational ES on public lands across the continental United States. We use geotagged social media posts as a measure of visitation to public lands. Direct use, or visitation, is one measure that has been used to represent the demand for recreational ES (Wolff, Schulp and Verburg, 2015). Understanding potential shifts in the demand for recreational ES can help public land managers plan and prepare for spatial and temporal shifts in demand.

1.1. *Mapping cultural ecosystem services using social media*

Studies that map cultural ES have used a wide variety of data as indicators (Egoh et al., 2012; Kopperoinen et al., 2017). Recently, researchers have used social media to map cultural ES across public lands (Ghermandi and Sinclair, 2019; Rossi et al., 2019; Runge et al., 2020; Vaz et al., 2020; Zhang et al., 2020). Social media often have a fine spatial resolution and are highly correlated with visitation to public lands across many locations around the globe (Fisher et al., 2018; Tenkanen et al., 2017; Wood et al., 2013). Data from social media may be preferable to visitation data collected by other means due to its fine spatial and temporal resolutions (Wilkins et al., 2021b); it also allows for an estimate of visitation in places where visitor data is not collected through other means. The majority of studies mapping cultural ES with social media on public lands tend to use data from Flickr, a photo-sharing application (Wilkins et al., 2021b).

Researchers who use social media to study cultural ES have predominately analyzed photograph content and geotags to understand the spatial distributions of where visitors take photographs and what they are photographing (Wilkins et al., 2021b). For example, studies have manually viewed and classified Flickr photographs taken on public lands based on the specific cultural ES depicted (e.g., aesthetic landscapes, recreation, cultural heritage, spiritual, research/education) (e.g., Clemente et al., 2019; Retka et al., 2019). The most common cultural ES present in Flickr photographs include aesthetic and recreational services; these ES are often represented through images of natural landscapes, trails, or individuals participating in an activity (Clemente et al., 2019; Retka et al., 2019; Rossi et al., 2019). Other cultural ES (e.g., spiritual values) may also be present in Flickr photographs, however they are often underrepresented because they are harder to photograph and identify (Clemente et al., 2019).

Previous research has also used other aspects of social media, beyond photograph content, to analyze cultural ES. For example, Johnson et al. (2019) found all categories of cultural ES mentioned in the Millennium Ecosystem Assessment were present in geotagged tweets within an urban park. Other studies have used geotagged Flickr photographs and viewsheds to map the demand for, and the supply of, cultural ES across a landscape (Van Berkel et al., 2018; Yoshimura and Hiura, 2017). Social media can also be used to quantify aesthetic and recreational ES at large geographic scales (van Zanten et al., 2016). Collectively, this growing body of literature has demonstrated the potential utility of using geotagged social media to map cultural ES across large landscapes. There remains a need to better understand how the demand for cultural ES across large geographic extents will change across both space and time in response to climate change (Monz et al., 2021).

1.2. *The effect of weather and climate change on visitors to public lands*

Individuals often consider the climate of a destination when choosing where and when to visit an outdoor recreation or tourism destination (Scott and Lemieux, 2010). Once on-site, the daily weather impacts where visitors go, what activities they choose, and how long they stay (Hewer et al., 2017; Wilkins et al., 2021a). Visitors' sensitivity to weather conditions, as well as their behavioral responses, varies based on the location, climate, and topographic features of the area (Scott et al., 2008; Verbos et al., 2018).

Visitation to public lands in North America generally increases with a warming climate, but there is a threshold that visitors tend to consider too hot, and visitation declines (Brice et al., 2020; Fisichelli et al., 2015). Previous research has found this threshold to be between 25 and 33 °C, although this varies based on the climate and topography of the outdoor recreation setting, as well as the season, and the recreational activity of interest (Fisichelli et al., 2015; Hewer, Scott and Gough, 2018; Hewer et al., 2016; Smith et al., 2018). Studies suggests maximum daily temperature affects outdoor recreationists more than mean or minimum daily temperature, likely because visitors tend to be outside in the afternoons, when temperatures tend to be the hottest (Jones and Scott, 2006a; Smith et al., 2018).

Climate change has already expanded the length of the peak visitation season for some public lands (Buckley and Foushee, 2012; Monahan et al., 2016). For example, it is expected to change total visitation at nearly all (95%) U.S. National Park Service units (Fisichelli et al., 2015). However, the effects of climate change on visitation to public lands may vary by season, location, and activity (Hewer and Gough, 2018; Hewer and Gough, 2019). Some places may see an increase in visitation in the shoulder seasons, but a decrease in summer visitation (Scott et al., 2007). In a recent study, visitation to a Canadian park was most sensitive to climate anomalies in the fall, with unusually warm fall temperatures causing an increase in visitation (Hewer and Gough, 2019). Warmer winters may decrease outdoor recreation opportunities in places that traditionally provided snow-dependent recreation (e.g., skiing, snowmobiling), but may increase opportunities for warm-weather activities (Askew and Bowker, 2018; Hand et al., 2018).

Climate may also indirectly impact the demand for recreational ES. For instance, people may have less desire to recreate on landscapes with melted glaciers (Stewart et al., 2016), or in places that recently experienced wildfire (Kim and Jakus, 2019; Duffield et al., 2013). The demand for recreational ES may also shift spatially or temporally depending on changing distributions of plants, fish, and other wildlife (Lamborn and Smith, 2019; Moreno and Amelung, 2009). For example, snow melting earlier than usual may change the timing of wildflower blooms, which in turn may decrease visitor satisfaction, or change the timing of trips (Breckheimer et al., 2020). However, most studies investigating the impacts of climate change on visitors to public lands tend to focus on one agency and often one public land unit (e.g., a particular national park); there is a need for research across multiple agencies and types of public lands (Brice et al., 2017; Hand et al., 2018).

Given the need to understand how climate and climate change may impact visitors to multiple types of public lands (e.g., national parks, national forests, state parks, state wildlife management areas, etc.), our research is guided by two related research questions:

(1) How does the climatological mean of maximum temperature influence the seasonal demand for recreational ES across public lands in the continental U.S.?; and
(2) How might the seasonal demand for recreational ES across public lands in the continental U.S. change in the future as the climate warms?

2. Methods

2.1. Study sites

Our study sites include public lands managed by state or federal agencies within the continental U.S. We restricted this to public lands that can be accessed by the general public for outdoor recreation; we did not include easements. Specifically, this includes lands managed by state agencies, and by the Bureau of Land Management, Fish and Wildlife Service, National Park Service, U.S. Army Corps of Engineers, and the USDA Forest Service. Table 1 shows the types of lands managed by each of these agencies, and Fig. 1 shows the distribution of these lands across the continental U.S. We downloaded the boundaries for all public lands from the Protected Areas Database of the United States (U.S. Geological Survey Gap Analysis Project, 2018). After inspection of the state lands in this database, we found that Missouri state lands were missing, and added them from a state-specific database (Missouri Department of Natural Resources Land Boundaries, 2020).

Table 1
Land management agencies included in this study, as well as the types of lands they manage.

Land management agency	Type(s) of lands
Federal agencies:	
Bureau of Land Management (BLM)	BLM lands
	National monuments
Fish and Wildlife Service (FWS)	National monuments
	National wildlife refuges
	Resource management areas
	Conservation areas
National Park Service (NPS)	National parks
	National monuments
	National recreation areas
	National seashores
	National historic sites
	Wild and scenic rivers
Army Corps of Engineers (USACE)	Recreation management areas
	State recreation areas
USDA Forest Service (USFS)	National forests
	National monuments
	National grasslands
State Agencies:	
State Department of Conservation (SDC)	State parks
State Department of Natural Resources (SDNR)	State recreation areas
State Department of Land (SDOL)	State conservation areas
State Fish and Wildlife (SFW)	State resource management areas
State Land Board (SLB)	State cultural or historic areas
State Park and Recreation (SPR)	
Other state agency (OTHS)	

Note: All states have state-managed public lands (e.g., state parks), but the managing agency varies by state.

We grouped public lands by the U.S. Department of Interior (DOI) regional boundaries (U.S. Department of the Interior, no date). The DOI oversees the majority (67%) of federal land managed by agencies included in this study. These boundaries are used to help manage public lands across different agencies and are based off of state lines and watersheds (U.S. Department of the Interior, no date). These DOI regions are shown in Fig. 1; hereafter, we just refer to these as "regions."

2.2. Data collection and processing

2.2.1. Flickr data

We downloaded all Flickr data within the study sites from 2006 to 2019 directly from the Flickr Application Programing Interface (API) using a Python script. These data were downloaded in March 2020 and included geotagged coordinates, time stamps, user IDs, photograph IDs, URLs to photographs, and spatial accuracies. We only retained posts that had a spatial accuracy assigned by Flickr of 15 – 16 (on a scale from 1 to 16, with 16 being the highest spatial accuracy). We only retained one post per user, per day, within the same grid cell (described below). This represents the concept of a Photo-User-Day (PUD), which has been previously used to avoid oversampling users who post many pictures (Wood et al., 2013; Wilkins et al., 2021b). We used Flickr PUDs as an indicator of visitation to public lands, and thus the demand for recreational ES. PUDs have been used as a common indicator of cultural ES broadly, and particularly recreational ES (e.g., Sinclair, Ghermandi and Sheela, 2018; Hermes et al., 2018; Zhang et al., 2020). Although one agency in this study collects monthly visitation estimates (NPS), the others do not collect monthly or seasonal estimates, instead collecting visitor data across broader timescales (e.g., annual), if at all. Additionally, each agency measures visitation in different ways that are not consistent, and estimates are often across large areas (e.g., visitation for a whole forest rather than specific locations within the forest). Therefore, we used Flickr as an indicator of visitation rather than agency-reported visitation estimates.

We aggregated PUDs across all years, by season, at a 30 km hexagonal grid. Given that climate affects visitors differently in different seasons, we separated PUDs based on the season when the photographs were taken: summer (June, July, August); fall (September, October, November); winter (December, January, February); or spring (March, April, May). We aggregated data at these spatial and temporal scales so there was enough Flickr data to make statistical inferences without substantial counts of zero PUDs. A 30 km grid size was chosen after analyzing the proportion of cells with zero PUDs at different scales following Zhang et al. (2021) (see supplementary material, Figure A.1.)

2.2.2. Climate data and other control variables

For the location of each photograph, we found the climatological mean of maximum temperatures from 1990 to 2019, for the specific season the photograph was taken, using data from Daymet (Thornton et al., 2016) downloaded directly in R using the package daymetr (Hufkens, 2019). Daymet provides spatially continuous modeled weather and climate data at a 1 km scale; we used 30 years of monthly climate summary rasters (Thornton et al., 2016). For instance, if a photograph was taken on July 1, 2018 (or June 15, 2006, etc.), we found the climatological mean in daily maximum temperature across June, July, and August, from 1990 to 2019, at that location.

We then calculated the climatological mean in maximum temperature by grid cell, for each season, by taking the average of the climatological mean in maximum temperature at all Flickr points within the grid cell. We analyzed temperature at the Flickr points rather than the average across entire grid cells to account for the fact that some areas may not be easily accessible (e.g., steep slopes, road-less areas) or have much less demand for recreational ES. If a grid cell had 0 PUDs, we found the climatological mean in seasonal maximum temperature from 1990 to 2019 at the cell centroid. We used maximum temperature as this

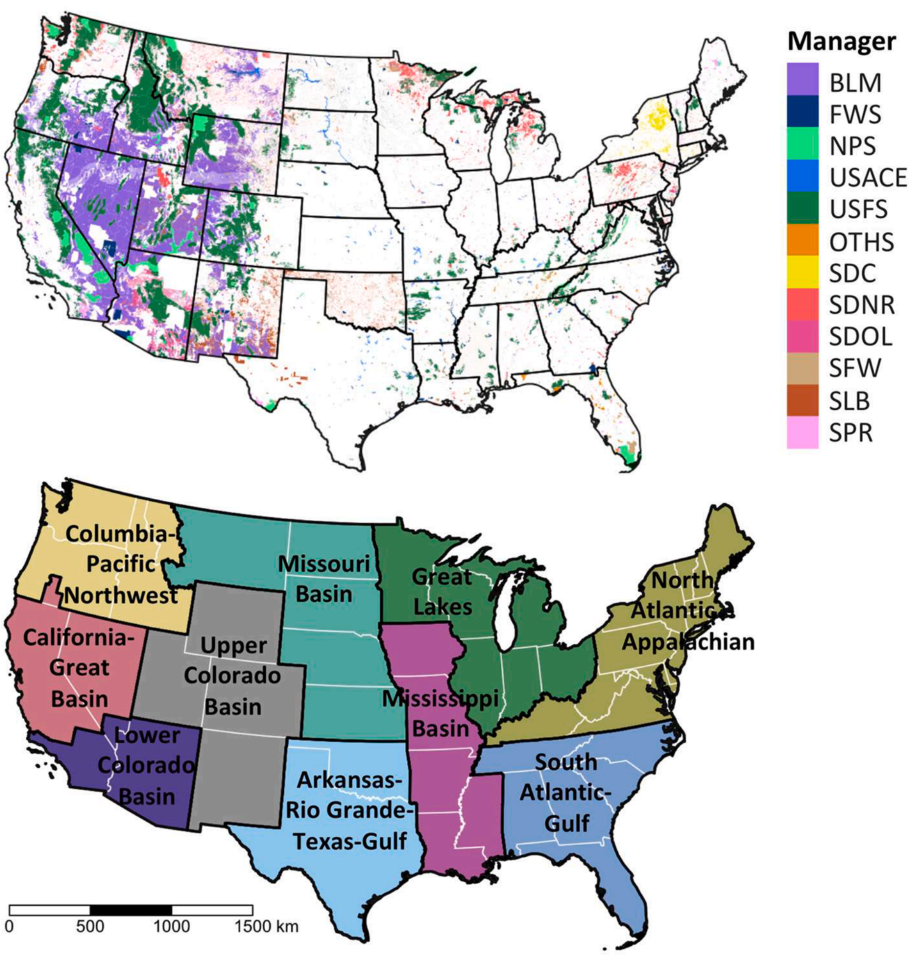

Fig. 1. Public lands managed by federal and state agencies in the continental U.S. where public access is commonly allowed (top), and Department of Interior (DOI) regions (bottom). BLM = Bureau of Land Management, FWS = U.S. Fish and Wildlife Service, NPS = U.S. National Park Service, USACE = U.S. Army Corps of Engineers, USFS = USDA Forest Service, OTHS = Other state lands, SDC = State Department of Conservation, SDNR = State Department of Natural Resources, SDOL = State Department of Land, SFW = State Fish and Wildlife, SLB = State Land Board, and SPR = State Parks and Recreation.

can be a more influential predictor of visitation to parks than minimum or mean temperature (Smith et al., 2018). Maximum temperature often occurs in the afternoon, which is when public lands visitation is the highest. Additionally, visitors are also more likely to see forecasts for maximum temperature than for averaged or minimum temperatures.

We calculated the population residing within 50 km and 500 km of each grid cell using 2010 population data from the NASA Socioeconomic Data and Applications Center (Center for International Earth Science Information Network, 2017). We used population within 50 km to control for local population and more frequent visits by locals, and 500 km to control for the population that could potentially make a weekend trip to the destination. However, we do not assume that the population within 500 km is the only source of demand for recreational ES. We also calculated the total km of roads within public lands for each cell using road data from OpenStreetMap; road data were downloaded directly in R using the package osmdata (OpenStreetMap Contributors, 2019; Padgham et al., 2017). We used road density to control for the fact that many visitors to U.S. public lands stay close to roads, so places with more roads are more likely to see higher demand for recreational ES (Wilkins et al., 2021a).

We also calculated the area of each grid cell that was public lands, as well as the area that was managed by the National Park Service. Lands managed by the National Park Service have substantially more concentrated visitation relative to other land management agencies (Leggett et al., 2017). Therefore, this is likely an important predictor of the demand for recreational ES. Additionally, we found the area of each cell that is designated Wilderness (U.S. Geological Survey, no date). Wilderness areas tend to be harder to access and may have lower visitation; again, a useful piece of information to include in a model estimating the demand for recreational ES. Fig. 2 provides a visual example of what the Flickr PUDs and control variables (public lands, NPS lands, roads, Wilderness, and population data) look like for one cell.

2.2.3. Climate projection data

We downloaded maximum temperature projection data for Representative Concentration Pathway (RCP) scenarios 4.5 and 8.5 using the multi-model ensemble mean from the Coupled Model Intercomparison Project Phase 5 (CMIP5) model experiments (World Meteorological Organization, 2020). RCP 4.5 represents an intermediate greenhouse gas emissions scenario, while 8.5 represents a high emissions scenario (IPCC, 2014). We downloaded monthly projections for maximum temperature in all ten regions. For each region, we drew a bounding box to cover the majority of land grid-cells in each region (2.5° x 2.5° latitude-longitude grid). We calculated the monthly anomalies of maximum temperature projections for the 2045–2055 average compared to the 1990 – 2019 average and then took the seasonal mean of those anomalies in each region. We refer to these projections as the seasonal maximum temperature in 2050.

2.3. Data analysis

2.3.1. Regression models to estimate the impact of climate on the demand for recreational ES

We first examined the spatial autocorrelation of Flickr PUDs using Moran's I to understand how clustered PUDs on public lands were across the U.S. We used Monte-Carlo simulation of Moran's I (using 999 simulations) to obtain p-values for the significance of autocorrelation. We ran season-specific negative binomial regression models for the entire

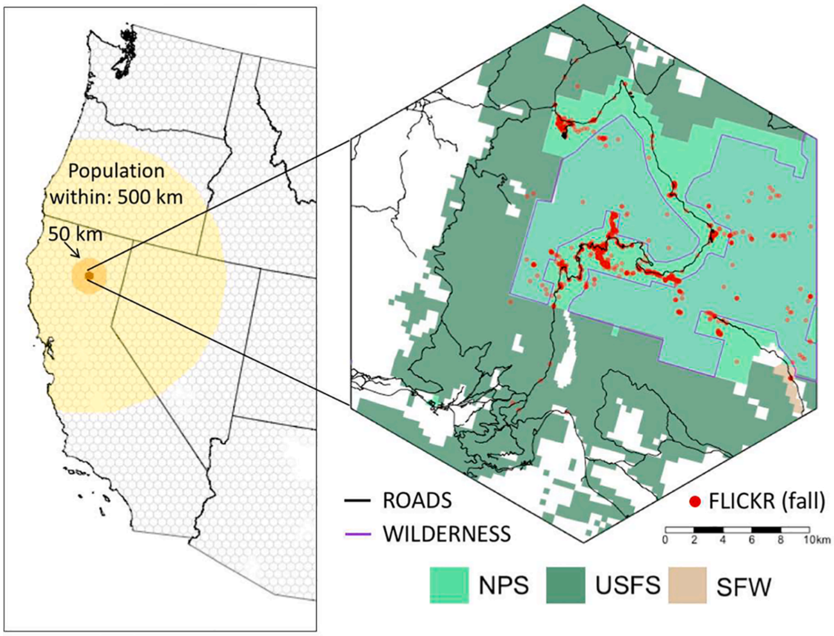

Fig. 2. An example of what these data look like for one grid cell. Red dots represent Flickr photo-user-days (PUDs) in the fall (n = 314). This cell has 689.7 km^2 of total public lands, 309.7 km^2 of land managed by the National Park Service, 206.8 km^2 of designated Wilderness, 73,894 people within 50 km, 16.5 million people within 500 km, and 273 km of roads within public lands. NPS = National Park Service; USFS = USDA Forest Service; SFW = State Fish and Wildlife. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

continental U.S. to estimate global coefficients and baseline model fit estimates. We then ran ten separate negative binomial regression models, one for each region. Global model fit was assessed using Nagelkerke R^2, a pseudo-R^2 measure that is appropriate for regression models using count data (Nagelkerke, 1991).

The season-specific negative binomial regressions allowed us to estimate the relationship between the recent climate of an area and the demand for recreational ES in that area, while controlling for other factors known (or believed to) affect the demand for recreational ES. These variables are not exhaustive of all factors that might affect the demand for recreational ES; they represent factors that are known to be important and are quantifiable across all public lands in this study. The negative binomial regression model for each season and for each region can be generally expressed using Eq. (1).

$$PUD_i = exp(\alpha + \beta_0 + \beta_1 TEMP_i + \beta_2 POP50_i + \beta_3 POP500_i + \beta_4 RD_i + \beta_5 PL_i + \beta_6 NPS_i + \beta_7 WILD_i) + \varepsilon. \quad (1)$$

where the subscript i refers to each cell, and PUD_i represents the cell-specific Photo-User-Days, following a negative binomial distribution. α is the overdispersion parameter. B_0 refers to the intercept, and *TEMP* refers to the climatological mean in maximum temperature. *POP50* refers to the population within 50 km (in millions), *POP500* refers to the population within 500 km (in millions), *RD* refers to the total length of roads (100 km) within public lands, *PL* is the total area (km^2) of all public lands, *NPS* refers to the total area (km^2) of National Park Service lands, and *WILD* refers to the total area (km^2) of designated wilderness. ε denotes random error.

For each model, we assessed if the residuals exhibited substantial spatial autocorrelation through maps and Moran's *I*. If residuals are significantly spatially autocorrelated, this indicates non-spatial statistical models likely violate assumptions of random error terms (Griffith, 1987). If a model exhibited problematic spatial autocorrelation of the residuals, a negative binomial regression with eigenvector spatial filtering to account for the spatial patterns would be appropriate (e.g., van Zanten et al., 2016). We analyzed deviance residuals, given this is a more common measure for negative binomial regression models compared to raw residuals (Hilbe, 2011; Pierce and Schafer, 1986). Deviance residuals represent how much each observation contributes to the overall model deviance (Pierce and Schafer, 1986). All analyses were conducted in *R* version 4.0.3; the code and data are publicly available (Wilkins and Smith, 2021).

2.3.2. Projecting the change in demand under climate change scenarios

We used the incidence rate ratios (IRRs) from the negative binomial regression models to understand how increasing temperatures may impact the seasonal demand for recreational ES in each region. We used IRR instead of raw coefficients since IRR represents a non-logged interpretation (Hilbe, 2011). For instance, an IRR of 1.15 indicates that for every increase in 1 °C, the demand for recreational ES on public lands increases by 15%, holding the other variables constant. We calculated standard errors on the IRRs using the delta method (Eq. (2)), which is customary for negative binomial regression (Hilbe, 2011).

$$SE_{delta} = exp(\beta) * SE(\beta) \quad (2)$$

We used the IRRs for historical temperature, coupled with the maximum temperature anomaly projection data for 2050, to infer the expected percent change in the seasonal demand for recreational ES by 2050. We calculated these estimates for each region, season, and both RCP scenarios using Eq. (3). The IRR is specific to each region and season, and temperature anomaly is specific to each region, season, and RCP scenario.

$$PUDchange\ (\%) = (IRR^{TempAnomaly} - 1) * 100 \quad (3)$$

These projected changes only represent changing demand due to rising maximum temperatures; they do not include other societal changes (e.g., population growth, increased development), or other climate-related changes (e.g., precipitation patterns, melting glaciers, increasing wildfires).

3. Results

3.1. Descriptive statistics and spatial autocorrelation

Across public lands in the continental U.S., the demand for recreational ES was highest in the summer and lowest in the winter, as would be expected (Table 2). Flickr PUDs by season, aggregated from 2006 to 2019 at a 30 km grid, ranged from 159,052 to 325,183 posts. The mean PUDs per cell had a very high standard deviation; this indicates the data is over-dispersed and follows a negative binomial distribution. Between 24.5 and 36.7% of cells had public lands but no Flickr posts over this

Table 2
Total posts and PUDs by cell and by season (data aggregated from 2006 to 2019). Numbers only represent Flickr posts within study sites shown in Fig. 1. There were 8,097 grid cells that had federal or state public lands (1,045 cells had no federal or state public lands included in this study).

Season	Total posts	PUD (30 km grid)	Cells with 0 PUDs (%)	Mean PUDs per cell* (SD)	Median PUDs per cell*	Moran's *I*	Moran's *I*: *p*-value
Summer	2,187,355	325,183	2,240 (24.5%)	40.2 (236.1)	4	0.263	0.001
Fall	1,645,887	257,545	2,645 (28.9%)	31.8 (202.8)	3	0.256	0.001
Winter	879,950	159,052	3,356 (36.7%)	19.6 (152.4)	1	0.248	0.001
Spring	1,618,287	248,181	2,599 (28.4%)	30.7 (235.6)	3	0.230	0.001

* Does not include cells that have 0 PUDs.

time period. The spatial distributions of PUDs on public lands can be found in the supplementary material, Figure A.2. Additionally, PUDs per cell are spatially correlated (Moran's $I = 0.230 - 0.263$, $p < 0.001$; Queen's case to define neighbors and weights with row standardization). If using distance measures to define neighbors, Moran's *I* of PUDs drops below 0.10 (see supplementary material, Figure A.3).

3.2. Models of the demand for recreational ES

Results from the seasonal negative binomial regression models fit to all data across the continental U.S. indicate the climatological mean of maximum temperature has a positive relationship with the demand for recreational ES on public lands in the winter and spring, a negative relationship in the summer, and an insignificant relationship in the fall (Table 3). The coefficient is the largest in the summer, indicating the relationship between the climatological mean in maximum temperature and the demand for recreational ES is the strongest in the summer. The population within 50 km and 500 km, total road length, amount of public land, amount of National Park Service land, and amount of Wilderness all have positive and significant relationships with the demand for recreational ES in every season. Notably, the amount of land managed by the National Park Service per cell has a much higher influence on PUDs compared to the total areas of all public lands.

The seasonal models fit to all data across the continental U.S. exhibited statistically significant, but fairly minor, spatial autocorrelation of the residuals. Moran's *I* of the deviance residuals, for Queen's case with row standardization weighting, are: 0.312 (summer), 0.351 (fall), 0.329 (winter), and 0.354 (spring). The spatial autocorrelation drops further when considering distance measures to define neighbors (supplementary material, Figure A.3). Maps of residuals can be found in the supplementary material, Figure A.4.

Model results differ by region (Table 4). Although general trends were the same as the seasonal models fit to all data across the continental U.S., there were differences between the regions. For instance, the area of National Park Service lands was positively associated with PUDs in all regions, but this effect was substantially larger in the Mississippi Basin and North Atlantic-Appalachian regions. Similarly, the climatological mean in maximum temperature had varying effects on the demand for recreational ES differently by region. This is to be expected, given the regions have different climates.

Overall, the Lower Colorado Basin and South Atlantic-Gulf regions have the warmest climates across all seasons. The Great Lakes, Missouri Basin, and North Atlantic-Appalachian regions tend to be coldest in the winter, but parts of the Rocky Mountains (mostly in the Upper Colorado Basin region) are colder in the spring and summer. Figures showing the spatial distribution of mean seasonal maximum temperature can be found in the supplementary material, Figure A.5.

In the summer, the climatological mean in maximum temperature was consistently negatively correlated with demand for recreational ES on public lands, across eight of the ten regions. This suggests cells with warmer climates had fewer summer visitors. This effect was strongest in the South Atlantic-Gulf region, one of the warmest regions. In the fall, mean maximum temperature was negatively correlated with demand for recreational ES in most (seven of ten) regions; however, there was a positive and significant correlation in the Arkansas-Rio Grande-Texas-Gulf region. In the winter, mean maximum temperature was positively correlated with demand for recreational ES in four of the ten regions, with the biggest effects in the Arkansas-Rio Grande-Texas-Gulf, Great Lakes, and Missouri Basin regions. The only region where we observed a negative and significant correlation between the climatological mean in maximum winter temperatures and the demand for recreational ES was in the Lower Colorado Basin; the negative correlation was small. In the spring, mean maximum temperatures had a positive and significant correlation with demand for recreational ES in two regions (the Missouri Basin and the Arkansas-Rio Grande-Texas-Gulf region), and a negative correlation in four others (North Atlantic-Appalachian, South Atlantic-Gulf, Mississippi Basin, and Lower Colorado Basin). For each season, mean maximum temperature exhibited an insignificant influence on the demand for recreational ES in some regions. To summarize the findings, Fig. 3 shows the differences in IRRs by season and region.

As shown by the Nagelkerke R^2 values in Table 4, the models fit better in some regions than others (Table 4). For instance, Nagelkerke R^2 ranged from 0.51 to 0.64 in the North Atlantic-Appalachian region, but 0.20 – 0.29 for the Arkansas-Rio Grande-Texas-Gulf region. Full model results by region, as well as the spatial autocorrelation of the residuals, can be found in the supplementary material, Appendix B. Overall, the spatial autocorrelation of the residuals for each model were relatively small (see supplementary material, Table B.1), so did not require any spatial filtering in the models.

3.3. Projected changes to the demand for recreational ES under climate change

To assess climate change impacts on the demand for recreational ES, we analyzed the future climate projections in CMIP5 products. Overall, maximum temperature projections by 2050 show the greatest amount of warming during the summer in the continental U.S., followed by the fall, across both RCP scenarios (Table 5). Maximum temperature projections by region can be found in the supplementary material, Table C.1. The South Atlantic-Gulf region has the lowest rates of warming by 2050 across all seasons and RCP scenarios, while the Missouri Basin, Upper Colorado Basin, and Great Lakes regions generally have the highest projected rates of warming by 2050 (with some variation by season and scenario). The continental U.S. has already warmed by about 1 °C from 1900 to 2016, with the Southeast having the least warming (U.S. Global Change Research Program, 2018).

Across all public lands in this study, demand for recreational ES by 2050 is expected to decrease by 18% in the summer under RCP 4.5, and by 28% in the summer under RCP 8.5 (Table 5). These estimated changes only account for warming temperatures, and do not include other potential changes due to climate change (e.g., changing species distributions) or other factors, such as population growth. In the winter, demand is projected to increase by 12% under RCP 4.5, and 20% under RCP 8.5, by 2050. Changes in the spring are smaller, with a 5% increase in demand for recreational ES under RCP 4.5, and a 9% increase under RCP 8.5, by 2050. There was no significant relationship between mean maximum temperature and the demand for recreational ES across the continental U.S. in the fall. However, there are substantial differences by region across the four seasons. Fig. 3 shows the expected percent change in PUDs for each region under 1° C warming, and by 2050 under RCP 4.5

Table 3
Results by season for continental U.S. negative binomial regression models. Coefficients are not standardized and represent the change in the log PUDs for every one-unit change in the predictor variable, with the other variables held constant. IRR is the incidence rate ratio, expressed as a percentage.

		Coef	S.E.	p-value	IRR (%)	S.E. (IRR %)
Summer	Intercept	4.483	0.146	<0.001		
	Mean maximum temp. *(°C)*	−0.105	0.005	<0.001	−9.969	0.435
	Population within 50 km *(millions)*	0.625	0.018	<0.001	86.856	3.416
	Population within 500 km *(millions)*	0.017	0.001	<0.001	1.738	0.122
	Roads within PPAs *(100 km)*	0.328	0.022	<0.001	38.767	3.083
	Area PPAs *(100 km^2)*	0.146	0.009	<0.001	15.729	1.087
	Area NPS *(100 km^2)*	0.660	0.027	<0.001	93.562	5.143
	Area wilderness *(100 km^2)*	0.066	0.024	0.005	6.836	2.531
Fall	Intercept	1.223	0.089	<0.001		
	Mean maximum temp. *(°C)*	−0.006	0.004	0.178	−0.563	0.417
	Population within 50 km *(millions)*	0.688	0.020	<0.001	99.029	3.919
	Population within 500 km *(millions)*	0.022	0.001	<0.001	2.250	0.133
	Roads within PPAs *(100 km)*	0.326	0.024	<0.001	38.583	3.309
	Area PPAs *(100 km^2)*	0.146	0.010	<0.001	15.727	1.173
	Area NPS *(100 km^2)*	0.657	0.029	<0.001	92.958	5.513
	Area wilderness *(100 km^2)*	0.151	0.025	<0.001	16.255	2.949
Winter	Intercept	0.027	0.054	0.593		
	Mean maximum temp. *(°C)*	0.067	0.003	<0.001	6.971	0.344
	Population within 50 km *(millions)*	0.801	0.021	<0.001	122.829	4.581
	Population within 500 km *(millions)*	0.019	0.001	<0.001	1.954	0.139
	Roads within PPAs *(100 km)*	0.431	0.025	<0.001	53.902	3.839
	Area PPAs *(100 km^2)*	0.109	0.011	<0.001	11.548	1.187
	Area NPS *(100 km^2)*	0.441	0.030	<0.001	55.420	4.616
	Area wilderness *(100 km^2)*	0.303	0.026	<0.001	35.386	3.580
Spring	Intercept	0.604	0.080	<0.001		
	Mean maximum temp. *(°C)*	0.031	0.004	<0.001	3.168	0.400
	Population within 50 km *(millions)*	0.745	0.019	<0.001	110.695	4.064
	Population within 500 km *(millions)*	0.019	0.001	<0.001	1.926	0.130
	Roads within PPAs *(100 km)*	0.345	0.023	<0.001	41.262	3.310
	Area PPAs *(100 km^2)*	0.122	0.010	<0.001	12.988	1.128
	Area NPS *(100 km^2)*	0.622	0.028	<0.001	86.202	5.222
	Area wilderness *(100 km^2)*	0.133	0.025	<0.001	14.188	2.846

Nagelkerke R^2: 0.416 (summer), 0.347 (fall), 0.383 (winter), 0.366 (spring). PPA = Parks and protected areas (in this study); NPS = National Park Service; S.E. = Standard error.

and 8.5. The estimated percent change in PUDs for each region and scenario can be found in the supplementary material, Table C.2.

In the summer, most regions are expected to see a decline in the demand for recreational ES on public lands. In the South Atlantic-Appalachian region, this decline is projected to be 61% under RCP 4.5, and 79% under RCP 8.5. Most regions are projected to have smaller, but still substantial, declines in summer demand. For instance, the Columbia-Pacific Northwest region could see a 23% decline in the demand for recreational ES under RCP 4.5, or a 36% decline under RCP 8.5. There is no projected change in summer demand due to a warming climate in the Missouri Basin and Arkansas-Rio Grande-Texas-Gulf regions.

In the winter, increases in the demand for recreational ES on public lands by 2050 are largest in the Great Lakes (42% increase under RCP 4.5), Arkansas-Rio Grande-Texas-Gulf (41%), and Missouri Basin (27%). The Upper Colorado Basin is the only region expected to see a decline in winter demand, and the decline is small (6% decrease under RCP 4.5, and 9% decrease under RCP 8.5). This could be because this region is known for many ski resorts located at higher, colder elevations, which make winter recreational demand in this region high, even in colder areas.

Projected changes to the demand for recreational ES by 2050 vary more across regions in the fall and spring. One of the warmest regions, the South Atlantic-Appalachian region, is expected to see the largest declines in the demand for recreational ES, with a 34% decline in the fall, and a 26% decline in the spring under RCP 4.5. In the fall, the only projected increase is in the Arkansas-Rio Grande-Texas-Gulf region, with a possible 48% increase in demand under RCP 4.5, and 96% increase under RCP 8.5. However, the negative binomial regression model fit was lowest for this region, so there may be other factors that affect the demand for recreational ES on public lands in this region that we did not account for. The only region that is not projected to have changes to demand in both the fall and the spring is the Great Lakes region.

4. Discussion

This study is the first we are aware of to look at how the demand for recreational ES on public lands may change across a country due to climate change. Our results suggest there will likely be a greater overall demand for recreational ES on U.S. public lands in the winter and spring, and a lower demand for recreational ES in the summer, compared to past visitation patterns. However, there is substantial variation by region. No region is expected to see increases in summer demand for recreational ES under a warming climate. However, these regions are large, and it is possible that certain recreational sites within a region (e.g., higher elevation locations or places with water-based recreation) may still see increased demand in the summer (Wilkins et al., 2021a). In the fall and spring, the Missouri Basin and the Arkansas-Rio Grande-Texas-Gulf regions are expected to see an increase in demand, while others are expected to experience declines. The larger declines in both spring and fall demand are expected in the warmest regions, such as the South-Atlantic Gulf. Across the whole U.S., we expect to see a slight increase in spring demand for recreational ES (5% under RCP 4.5 by 2050), and no change in the fall.

The relationship between the climatological mean in maximum temperature and demand for recreational ES was strongest in the summer, suggesting that climate change is likely to have the largest effect on summer demand. Across all public lands in the continental U.S., the demand is expected to decrease 18% under RCP 4.5 in the summer, or 28% under RCP 8.5, by 2050. However, demand is projected to increase in the winter by 12% under RCP 4.5, and 20% under RCP 8.5, by 2050. The demand for recreational ES on public lands between 2006 and 2019

Table 4
Results for the seasonal negative binomial regression models, by region. Values represent the IRRs, expressed as a percentage (this represents the percent change in PUDs for every one-unit change in the predictor variable). Bolded values are significant at $\alpha \leq 0.05$.

	North Atlantic-Appalachian	South Atlantic-Gulf	Great Lakes	Mississippi Basin	Missouri Basin	AR-Rio Grande TX Gulf	Upper Colorado Basin	Lower Colorado Basin	Columbia-Pacific NW	California Great Basin
Sample sizes (30 km grid)	867	845	1015	700	1064	560	1134	462	809	641
Summer										
Mean maximum temp.	**−13.8**	**−44.4**	**−16.3**	**−18.2**	−0.2	2.6	**−10.6**	**−7.6**	**−12.5**	**−15.1**
Population within 50 km	**48.6**	**60.7**	**79.0**	**966.4**	**1277.4**	**104.6**	**324.3**	**22.5**	**116.5**	**83.4**
Population within 500 km	**1.8**	**−7.0**	0.7	0.8	−1.6	**−2.4**	**9.4**	**1.6**	**7.6**	**4.0**
Roads within PPAs	**82.0**	**123.5**	**176.7**	**134.9**	**450.3**	**83.0**	**−6.7**	**131.0**	**14.3**	**35.1**
Area PPAs	1.2	−0.9	**−21.6**	4.5	1.9	−8.5	**27.0**	−4.1	1.0	2.2
Area NPS	**1054.9**	**23.2**	**335.0**	**3924.9**	**276.8**	**54.0**	**128.0**	**44.9**	**43.0**	**37.9**
Area Wilderness	75.0	−8.4	**46.7**	−66.8	**68.7**	**2722.1**	4.9	−2.4	**12.7**	6.9
Nagelkerke R^2	*0.51*	*0.34*	*0.26*	*0.24*	*0.47*	*0.20*	*0.58*	*0.42*	*0.46*	*0.54*
Fall										
Mean maximum temp.	**−7.7**	**−23.5**	2.0	**−8.2**	4.9	**25.7**	**−6.8**	**−7.8**	**−8.7**	**−9.9**
Population within 50 km	**48.9**	**69.6**	**64.6**	**1256.8**	**5305.6**	**77.6**	**467.8**	**27.6**	**157.2**	**105.5**
Population within 500 km	**1.8**	**−8.0**	−0.7	1.3	−2.8	−0.8	**19.7**	**2.7**	**16.2**	**6.3**
Roads within PPAs	**71.9**	**118.1**	**221.4**	**167.2**	**453.8**	**134.6**	−2.9	**114.1**	**14.8**	**26.1**
Area PPAs	5.8	14.0	**−23.1**	−4.0	8.0	−7.5	**27.2**	−3.8	−3.7	**−9.0**
Area NPS	**1219.5**	**36.5**	**252.1**	**2464.2**	**225.3**	**56.1**	**133.8**	**38.6**	**46.5**	**35.5**
Area Wilderness	**166.8**	−16.6	**37.7**	36.9	**52.5**	**5794.9**	**12.6**	2.8	**17.8**	11.3
Nagelkerke R^2	*0.52*	*0.26*	*0.24*	*0.24*	*0.39*	*0.24*	*0.53*	*0.37*	*0.35*	*0.42*
Winter										
Mean maximum temp.	−2.0	2.5	**20.0**	0.0	**14.2**	**25.6**	**−3.6**	2.4	**7.6**	0.6
Population within 50 km	**61.1**	**81.9**	**74.7**	**1793.8**	**8852.8**	**81.3**	**1165.8**	**37.9**	**242.3**	**111.4**
Population within 500 km	**1.7**	**−3.3**	**−2.2**	1.1	−3.1	−1.8	**24.6**	**2.6**	**10.9**	**5.1**
Roads within PPAs	**66.1**	**134.9**	**188.2**	**240.1**	**383.5**	**226.6**	7.6	**141.1**	**38.3**	**72.5**
Area PPAs	5.9	**21.7**	**−26.0**	−21.9	9.7	−15.9	**21.9**	−5.1	−4.9	**−20.2**
Area NPS	**569.5**	**24.7**	**212.8**	**865.6**	**111.8**	**57.4**	**94.6**	**37.8**	**29.3**	**24.3**
Area Wilderness	**178.6**	−10.2	**46.4**	189.4	**37.1**	**6799.8**	**38.6**	5.9	**37.9**	**40.7**
Nagelkerke R^2	*0.55*	*0.22*	*0.32*	*0.30*	*0.32*	*0.29*	*0.44*	*0.35*	*0.28*	*0.57*
Spring										
Mean maximum temp.	**−6.2**	**−19.0**	0.2	**−5.9**	**17.6**	**28.0**	−2.1	**−4.0**	−0.7	**−7.7**
Population within 50 km	**55.0**	**73.7**	**80.1**	**1368.1**	**4978.1**	**90.1**	**503.5**	**29.4**	**175.4**	**106.4**
Population within 500 km	**2.8**	**−7.6**	0.8	1.3	−3.7	0.7	**20.1**	**2.3**	**17.1**	**7.2**
Roads within PPAs	**88.1**	**97.5**	**210.6**	**158.3**	**523.8**	**112.9**	−6.0	**108.9**	**16.3**	**58.4**
Area PPAs	−0.5	**21.4**	**−30.4**	−5.6	3.7	−10.4	**24.7**	−2.0	**−6.4**	**−19.4**
Area NPS	**900.7**	**24.5**	**221.0**	**1641.0**	**171.0**	**57.4**	**123.1**	**38.9**	**45.7**	**40.2**
Area Wilderness	128.9	−8.5	**59.9**	59.7	**56.2**	**7620.2**	3.9	4.0	**13.9**	**22.1**
Nagelkerke R^2	*0.64*	*0.24*	*0.32*	*0.24*	*0.32*	*0.26*	*0.47*	*0.34*	*0.30*	*0.62*

Units for each variable: Mean maximum temperature (°C); population (millions); roads within PPAs (100 km); Area PPAs, NPS, and Wilderness (100 km^2)

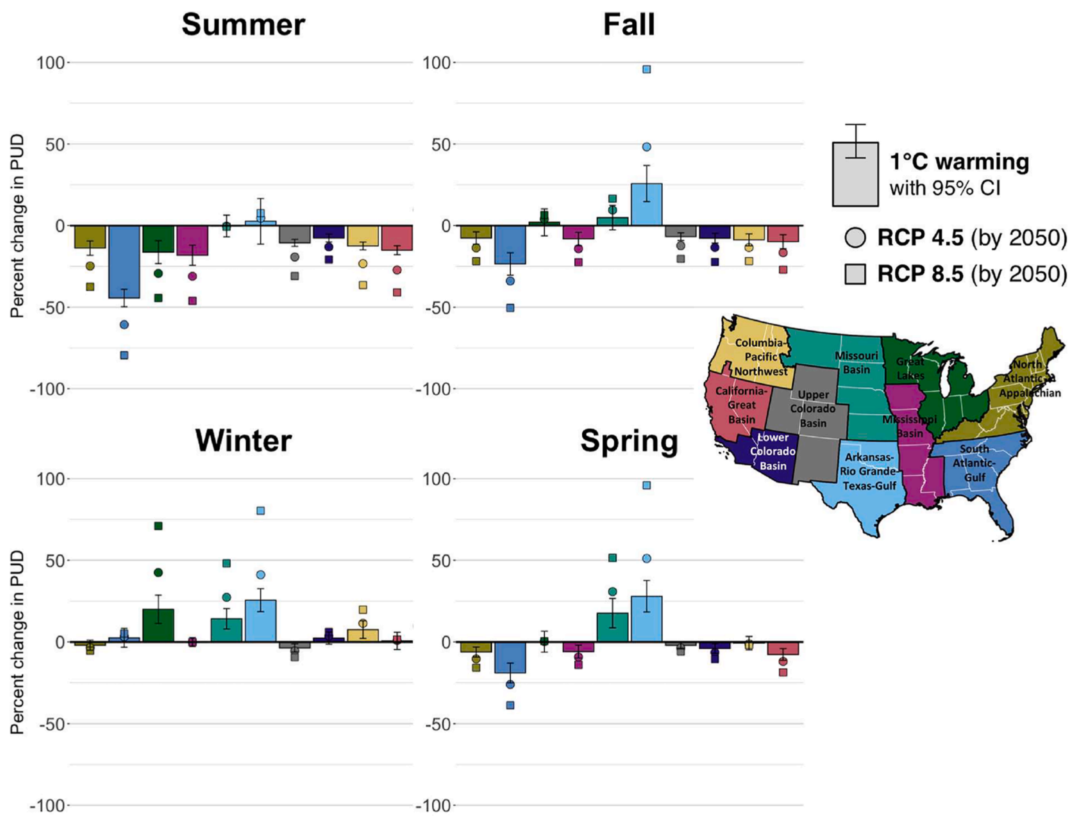

Fig. 3. Projected change in PUDs by region under different levels of warming. Bars and standard errors are directly from the negative binomial model results; if error bars cross zero, the change is not statistically significant at $\alpha \leq 0.05$. Point estimates represent extrapolations of model results out to 2050, based on the projected temperature anomalies under RCP 4.5 and 8.5.

Table 5
Projected maximum temperature anomaly (°C) by 2050 in the continental U.S., compared to 1990–2019, and the estimated shift in demand for recreational ES by 2050 under increased temperature scenarios.

	Maximum temperature anomaly (by 2050)		Estimated percentage change in demand for recreational ES	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Summer	1.863	3.142	−17.77	−28.12
Fall	1.790	3.032	NA	NA
Winter	1.666	2.710	11.88	20.04
Spring	1.694	2.694	5.43	8.77

NA indicates the relationship between maximum temperature and PUDs was not statistically significant in the negative binomial regression models. Region-specific estimates are shown in Fig. 3 and the supplementary material, Table C.2.

was twice as high in the summer compared to the winter, so declines in summer demand would have the largest impact on the total annual demand. It is important to note that these projected changes are a result of projected temperature increases only, and do not include other factors.

Our results support other findings suggesting peak season demand for recreational ES will plateau and shoulder season demand will increase as the climate warms (Buckley and Foushee, 2012; Jones and Scott, 2006b; Monahan et al., 2016; Smith et al., 2018). Rather than have high demand for recreational ES during only a few months (often in the summer), the demand may be either spread out more or be elevated for a longer period of time (i.e., expanding shoulder seasons and off-season). Interestingly, the demand for recreational ES on public lands in the winter is only projected to decline in one region (Upper Colorado Basin), and this region has many ski resorts on public lands. Ski resorts are particularly vulnerable to warming temperatures, given less precipitation falls as snow in warmer years (Steiger et al., 2019). Although warmer winters often decrease opportunities for snow-dependent recreation, there will likely be more opportunities for recreationists to participate in activities such as hiking and biking in the winter (Askew and Bowker, 2018), thus causing an overall increase in demand for recreational ES in the winter for most regions.

Our results have implications for managing public lands and surrounding communities. Demand that plateaus or decreases in the summer and increases in the shoulder seasons may require public land management agencies to provide more visitor services (e.g., visitors centers, bathrooms, and campgrounds) for longer durations throughout the year. Increased staffing in support of visitor services in the winter may also be needed to help accommodate the increased demand likely to be seen over those months. Rising demand in the shoulder seasons may also increase the operating costs associated with providing visitor services; this could require increased fees or increased public investment (Smith, Wilkins and Leung, 2019). Because summer usually sees the most visitation to public lands in the U.S., some places that are struggling with overcrowding may find the mid- to long-term projected decline in summer visitation welcome news. In these places, park managers could provide more information about the best activities and trails in the other seasons to further encourage spreading demand out temporally. For this to be effective, local businesses (e.g., hotels, restaurants) should remain open across a longer season (or year-round) to accommodate increasing demand in the off-season.

4.1. Limitations and future research

Our study does have limitations that need to be considered when interpreting the findings. Only a small portion of visitors post images to Flickr, so these data may not be representative of all public lands users and may be biased towards some user groups. Flickr users may also be more likely to take and share photos during certain times of the year (e.g., wildflower blooms, fall foliage changes). In addition, the pseudo-R^2 values from the regional models varied, indicating the models fit better in some regions than others. There are likely other variables that impact the demand for recreational ES on public lands that we were not able to account for. We were not aiming to create the best possible model to explain PUD counts; rather, our models show the impact of mean maximum temperature on PUDs, while holding other known and important predictors constant. The area of National Park Service land was much more influential in the models than the area of all public lands, indicating that although we modeled demand for recreational ES across all public lands, the demand tends to be much higher on lands managed by the National Park Service.

When projecting the change in demand for recreational ES under a warming climate, our projections only account for warming temperatures and should be interpreted as such. Some of the other factors in the models also had substantial effects, such as local population size, indicating that demand would likely increase in the future as the population grows. A study in Canada found that park visitation is expected to increase under climate change, but that other factors, such as demographic change and population growth, were likely to have an even larger influence on visitation (Jones and Scott, 2006b). Over the last decade in the U.S., there has been an overall increase in the demand for recreational ES on state and federal lands (National Park Service, 2020; Smith, Wilkins and Leung, 2019). Other factors related to climate change, such as precipitation amount, more extreme weather events, melting glaciers, shifting species distributions, and increasingly common wildfires, are all likely to have an effect on the demand for recreational ES as well (Kim and Jakus, 2019; Monz et al., 2021; Stewart et al., 2016).

Future studies could explore the direct versus indirect influence of climate on the demand for recreational ES. For example, some of the trends found in this study may be due to indirect factors, such as the timing of seasonal blooms or foliage changes, rather than temperature alone. Additional research at smaller geographical scales would be useful to explore the nuances of how climate affects visitors and what other variables (beyond temperature) may be regionally important. Finally, visitor surveys would be useful to further understand if and how warming temperatures would affect the amount, location, and timing of visits to public lands. Our study found the demand for recreational ES is likely to shift seasonally and regionally, but it is still unknown how the demand may shift at other spatial and temporal scales. For instance, we found that overall demand is likely to decline in the summer, but visitors may also adapt by visiting public lands on cooler summer days, at cooler times of the day (e.g., earlier in the morning), or by visiting comparatively colder locations in the same region (e.g., higher elevations) (Wilkins et al., 2021a).

5. Conclusion

This study is an exploration into how average maximum temperatures, and increasing temperatures under climate change scenarios, may impact the demand for recreational ES in different seasons across U.S. public lands. We found the demand for recreational ES on public lands was positively related to the climatological mean in maximum temperature in the winter, but negatively related in the summer. As the climate continues to warm, demand for recreational ES on public lands is expected to increase in the winter, but decrease in the summer. The relationship in the fall and spring varied across the U.S., with demand being negatively correlated with the climatological mean in maximum temperature in some regions, but positively correlated in others. Across the whole U.S., the demand for recreational ES is expected to increase in the spring under climate change, but some regions will likely see declines when considering changing temperatures. In many locations, land managers may want to consider preparing for an increased peak season length, and more visitors in the winter compared to levels observed in the past. Our work shows the climate has an impact on the demand for recreational ES across public lands, and that demand is likely to shift temporally (across seasons) and spatially (across regions) across the continental U.S.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2021.102365.

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