Leveraging big data for outdoor recreation management: A case study from the York River in Virginia

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Abstract

Outdoor recreation is important for improving quality of life, well-being, and local economies, but quantifying its value without direct monetary transactions can be challenging. This study explores combining non-market valuation techniques with emerging big data sources to estimate the value of recreation for the York River and surrounding parks in Virginia. By applying the travel cost method to anonymous human mobility data, we gain deeper insights into the significance of recreational experiences for visitors and the local economy. Results of a zero-inflated Negative Binomial model show a mean consumer surplus value of $26.91 per trip, totaling $15.5 million across nearly 600,000 trips observed in 2022. Further, weekends, holidays, and the summer and fall months are found to be peak visitation times, whereas those with young children and who are Hispanic or over 64 years old are less likely to visit. These findings shed light on various factors influencing visitation patterns and recreation values, including temporal effects and socio-demographics, revealing disparities that warrant targeted efforts for inclusivity and accessibility. Policymakers can use these insights to make informed and sustainable choices in outdoor recreation management, fostering the preservation of natural resources for the benefit of both visitors and the environment.

Key words: Outdoor recreation; Big data; Human mobility data; Travel cost method; Valuation

1. Introduction

Outdoor recreation plays a crucial role in enhancing quality of life, well-being, and local economies. Resource managers are often interested in understanding the value generated by recreation at their sites, but quantifying it can be challenging without direct monetary transactions. To address this issue, non-market valuation techniques are used to assess the benefits derived from nature, which are frequently overlooked by conventional market data.

The travel cost method is a widely adopted approach that estimates visitor consumer surplus based on travel expenses (Ward and Beal, 2000; Parsons, 2017, Freeman et al., 2014). Analyzing costs to reach outdoor destinations reveals the economic value visitors place on recreational experiences. Consequently, resource managers can gain a more comprehensive understanding of the significance of outdoor recreation to both the visitors and the local economy. This holistic approach ensures that decision-makers have access to comprehensive data when managing and preserving natural resources, leading to more informed and sustainable practices.

While surveys have traditionally been a popular means of data collection for such approaches, big data is emerging as an alternative solution. Big data offers advantages in spatial and temporal scale, cost-efficiency (Jiang et al., 2017), and reduced behavioral alteration risk (Salganik, 2017). However, big data can come with limitations. Since the data was not specifically generated for research purposes, it may contain insufficient research-oriented information (Ghermandi and Sinclair, 2019, Salganik, 2017), which can introduce "aggregation bias" and lead to inaccurate parameter estimates (e.g., Stoker, 1993; Hellerstein, 1991). Nevertheless, research by Hellerstein (1995) has shown that aggregate models can outperform individual-level models if there is low average per-capita demand and are less sensitive to model misspecification. Additionally, big data may suffer from selection bias and measurement errors as it is often aggregated from multiple sources with potentially different data-generating schemes.

This study uses a novel approach of applying anonymous human mobility data to the travel cost method. This data has been used in a variety of applications from modeling disease transmission (Wang et al., 2021, Milusheva, 2020) to large-scale mapping of population movements (Kraemer, 2020). However, only a few studies have used human mobility data to assess recreation patterns (Kim et al., 2023, Tsai et al., 2023) or estimate recreation values (Kubo et al., 2020; Jaung and Carrasco, 2020). Several studies have used social media and crowdsourced data, such as geotagged photographs from Flickr (Sinclair et al., 2022; Sinclair et al., 2020; Fisher et al., 2018; Ghermandi, 2018; Sinclair et al., 2018; Spalding et al., 2017; Sessions et al., 2016; Sonter et al., 2016; Keeler et al., 2015); however, these sources of big data are often prone to issues of representation (Martí et al., 2019; Li et al., 2018; Di Minin et al., 2015; Li et al., 2013; Elwood et al., 2012), a lack of quality controls and data provenance (Ricciato et al., 2017; Goodchild et al., 2013; Kim et al., 2023; Li et al., 2018), intentional deception by social media users (Tsikerdekis and Zeadally, 2014; Hajli et al., 2022), and a lack of accurate or precise spatial or temporal information (Fox et al., 2021; Li et al., 2016).

Human mobility data is not only more spatially and temporally resolute compared to social media and crowdsourced data due to being GPS-derived and continuously logged, but it is also anonymous and readily available for rapid and timely assessments (Kim et al., 2023; Tsai et al., 2023). Human mobility data has also been found to provide comparable visitation estimates to traditional observation counts (Merrill et al., 2020; Fisher et al., 2019; Monz et al., 2019).

By combining non-market valuation techniques like the travel cost method with emerging data sources like human mobility data, resource managers can gain deeper insights into the multifaceted benefits of outdoor recreation. This comprehensive understanding is vital for effective decision-making in managing and preserving natural resources and promoting sustainability. By leveraging big data, decision-makers gain a holistic understanding crucial for sustainable practices in outdoor recreation management, benefiting both visitors and the environment.

2. Methods

2.1 Study Area

This study focuses on the York River in coastal Virginia. The York River is a significant waterway in the eastern part of Virginia, flowing approximately 34 miles from its headwaters to the Chesapeake Bay. It serves as a natural boundary between the Middle Peninsula and the Virginia Peninsula, offering both historical and recreational value to the region. It is known for its scenic beauty and diverse ecosystems, including forests, marshes, and wetlands, creating a habitat for a variety of wildlife species. The York River is home to fish such as striped bass, bluefish, and flounder, making it a popular destination for anglers. Boating and sailing are popular recreational activities, with marinas and boat ramps available for launching watercraft. The river's calm waters also make it suitable for kayaking and canoeing, allowing visitors to explore its scenic beauty at a leisurely pace. Fishing charters and boat rentals provide opportunities for both experienced anglers and those new to the sport.

For the purpose of this analysis, the recreation area was defined as a 500-meter buffer surrounding the York River (Figure 1) to capture access points and to include land that may derive value from being near the river. Several parks and natural areas are captured within the 500-meter buffer, including Cumberland Marsh Natural Area Preserve, York River State Park, New Quarter Park, Machicomoco State Park, Yorktown, and Gloucester Point. These spaces encompass a diverse range of habitats, including open fields, marshes, tidal wetlands, forests, and upland areas, and offer a range of recreational activities, such as wildlife watching, picnicking, hiking, biking, and fishing.

Four additional buffers were tested within a robustness analysis: a 0-meter buffer (on the York River), a 250-meter buffer, a 750-meter buffer, and a 1,000-meter buffer and include all trips with records within the respective buffer. Smaller buffers are likely to include fewer observations, and these observations will be closer to or on the water. Alternatively, larger buffers are likely to include more observations, including observations further from the water. The 1,000-meter buffer was chosen as the largest buffer to exclude the residential and tourism areas surrounding Highway 64, and the additional buffers were chosen to at equal distance intervals.

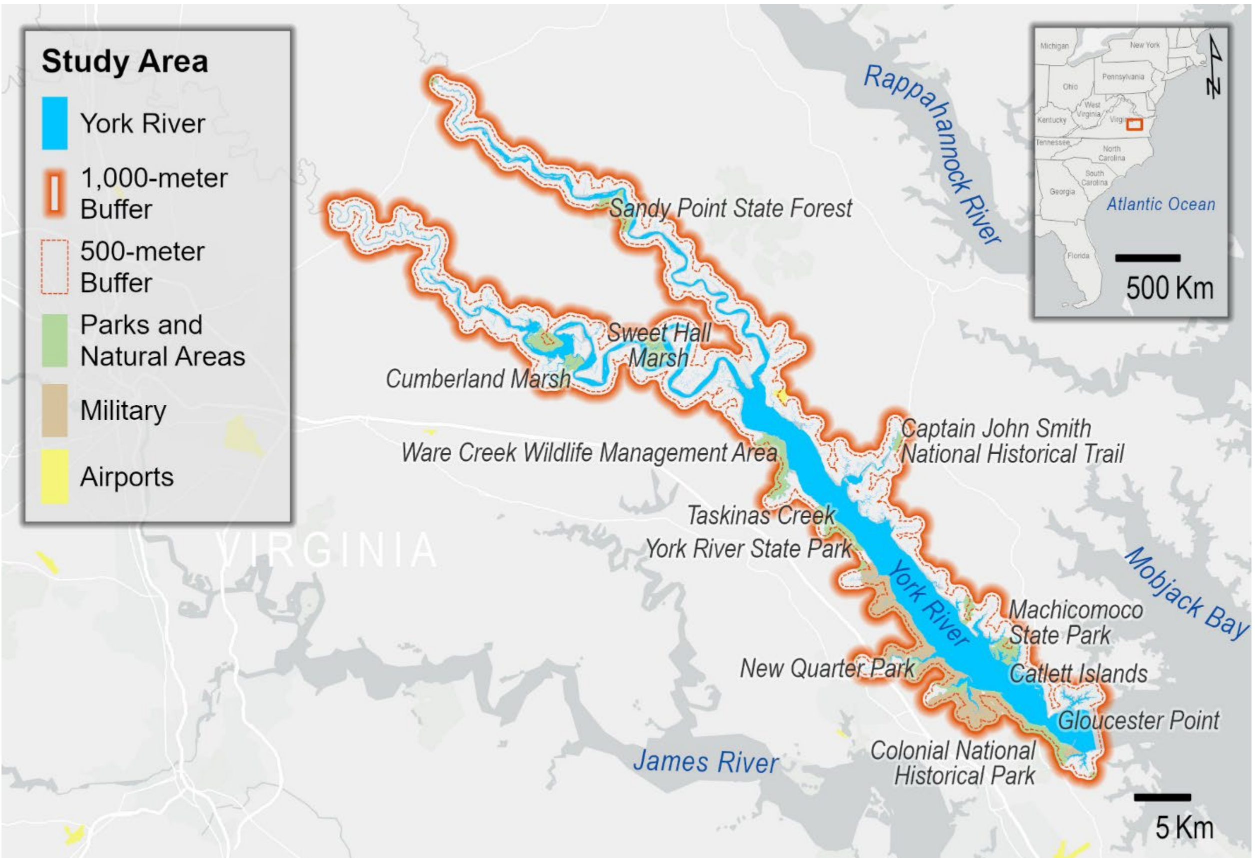

Figure 1. Study area surrounding the York River.

2.2 Data preparation

Human mobility data used in this study was provided by Unacast. This dataset comprises geolocated data collected from millions of smart devices and mobile apps, with users providing opt-in consent. Unacast used machine learning techniques to detect patterns, or classifications, in device activity based on spatial and temporal patterns and to aggregate the information. These classifications included “travel,” “area dwell,” and “potential area dwell” and were determined based on the number of pings within a buffered area of up to 100 meters within a specified amount of time. For example, a consecutive cluster of pings that occurred within a 10-minute period and were at least 100 meters apart were classified as “travel.” Due to the high volume of noise in the data classifications for “travel” and “potential area dwell,” this study used the classification “area dwell,” which indicates a consecutive cluster of pings within 150 meters.

Data was prepared using a combination of ArcGIS Pro (version 3.0) and R (version 4.2.2). The travel distances and times between each home zone and visitation area were estimated using the Origin-Destination Cost Matrix tool in the Network Analyst package of ArcGIS Pro (version 3.0). The street network data source (ArcGIS StreetMap Premium) includes parameters that define speed limits for various road types; while traffic information is available for this data source, it was not used for these travel time estimates. This tool has a constraint on the number of records that can be processed, so working with big data required additional steps to reduce processing time. First, a four-square-kilometer hexagon grid was tessellated over the study area to define all possible generalized visitation areas (Figure 2). Next, centroid points were created for each possible visitation area grid cell and home zone. Travel times and distances were then calculated between all possible combinations of visitation area and home zone centroids.

Data was first prepared for the largest recreation area buffer of 1,000 meters, then subset for each of the four tested recreation buffers. This full dataset included just under 8 million records for the study area in 2022 and was filtered to capture only the “area dwell” records that included “point of origin” Zip Code Tabulation Area, or home zone, information. Thirty-five percent of the records were classified as “area dwell” (n = 2,793,581), and 74% (n = 2,066,283) of the area dwell records contained “point of origin” information (Figure 3).

As the focus of this study is on local visitors, only records with estimated travel times of up to two hours (n = 1,953,157; 95% of records) were retained. Two additional home zone cutoffs (1.5-hours and 2.5-hours) were tested within a robustness analysis: 1.5 hours and 2.5 hours. A fundamental assumption of the travel cost model is that all travel costs are incurred exclusively to obtain access to the single recreation site (Haspel and Johnson, 1982), as including multiple sites in a single trip can lead to an overestimation of the value of each site. Consequently, these additional home zone cut-offs are tested as the recreation area is more likely to be the primary reason for the trip as the travel distance decreases.

These records were then grouped by unique identifier and date to create individual trips. Almost 50% of observed trips occurred on consecutive days with a travel time of 30 minutes or less for 90% of these trips (Figure 2). Additionally, travel time appears to increase as the number of days between trips increases, which suggests that people who live closer to the recreation area visit more frequently than those who live further away. Therefore, trips occurring on consecutive days were treated as multiple, single-day trips rather than multi-day trips.

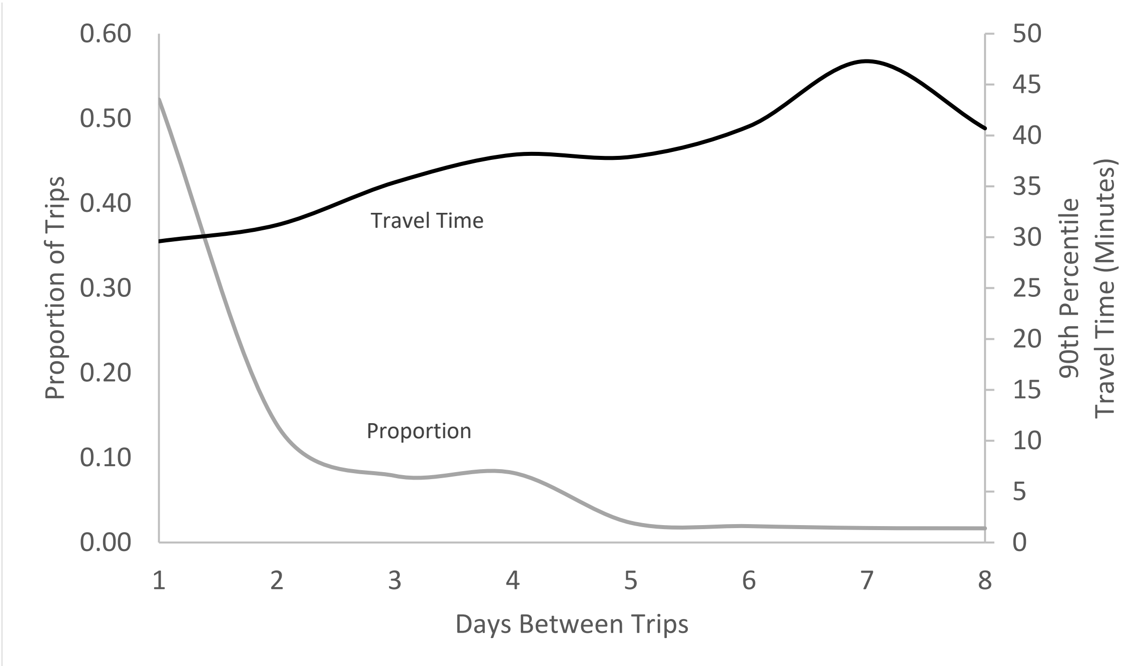

Figure 2. Proportion of Trips and 90th Percentile of Travel Time by the Number of Days Between Trips

Finally, trips that occurred entirely within either the Middle Peninsula Regional Airport or a Department of Defense location (Yorktown Fuel Depot, Naval Weapons Station Yorktown, and Cheatham Annex) were excluded (2.1% of trips) as these were unlikely made for outdoor recreation purposes. The final number of observed trips included in the analysis was 576,065.

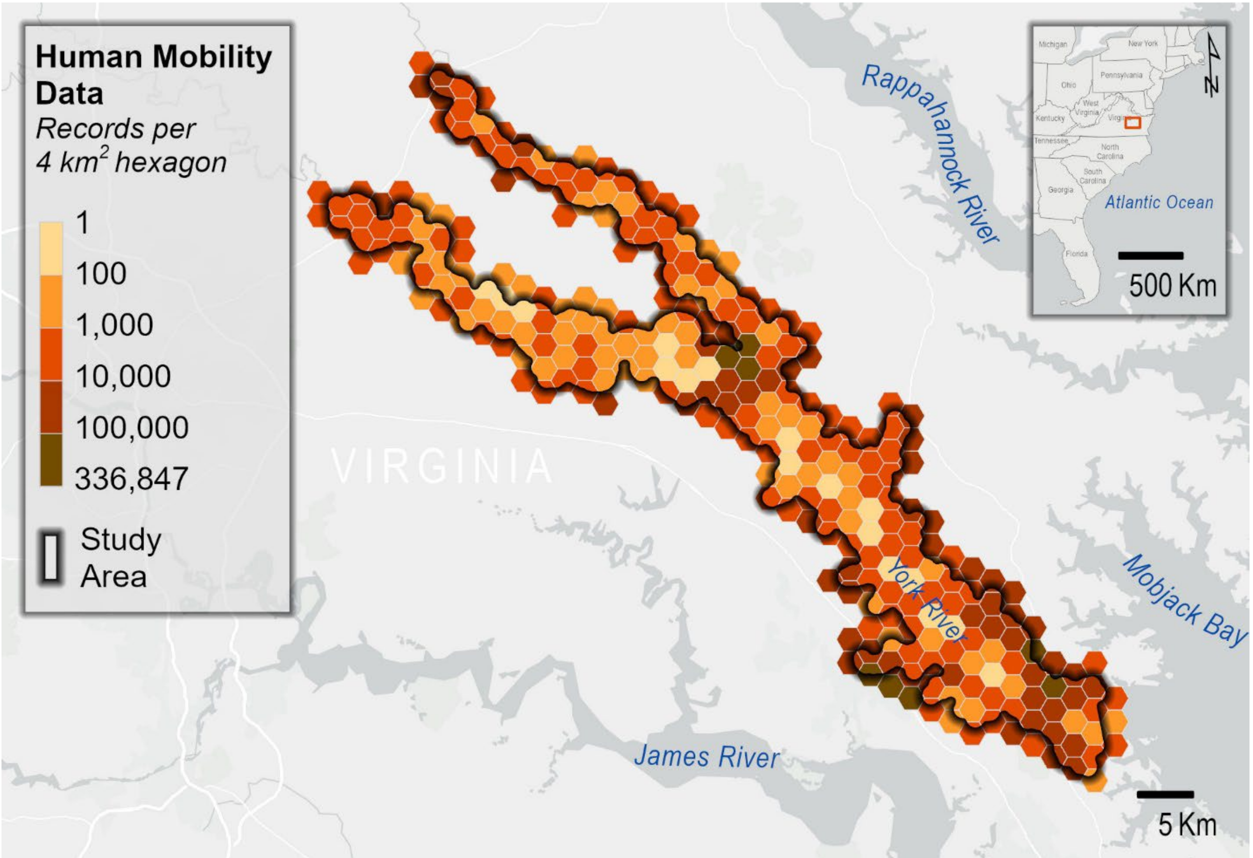

Figure 3. Total number of human mobility data records per visitation area (4-km^2 hexagon grid cell) within the York River study area in 2022.

Trips to the study area were not made every day from every home zone. In fact, almost 90% of the combinations of home zones and days in 2022 did not involve any trips to the study area. For these combinations, mean travel distance and time over the year for each home zone were used as proxies.

Socio-demographic data from the American Community Survey 5-year (2016–2020) estimates were then joined to the trip data in R. Table 1 shows key characteristics for the home zones within a two-hour drive of the study area, which are fairly similar to national averages. Two exceptions are that the Black population is nearly double the national average and the Hispanic population is almost half the national average.

Table 1. Comparison of socio-demographic data between study area home zones and national averages

Characteristic		Proportion	
		Home zones	US
Sex	Female	0.51	0.51
Age (years)	Under 5	0.06	0.06
	5 to 17	0.16	0.17
	18 to 34	0.23	0.23
	35 to 54	0.26	0.25
	55 to 64	0.13	0.13
	Over 64	0.16	0.16
Race	White	0.64	0.68
	Black	0.23	0.13
Ethnicity	Hispanic	0.10	0.18
Household Income ($)	Less than $10,000	0.06	0.06
	$10,000 to $49,999	0.30	0.31
	$50,000 to $99,999	0.30	0.30
	$100,000 to $199,999	0.25	0.24
	$200,000 or more	0.10	0.09

2.3 Zonal Travel Cost Model

To establish the trip-generating function, a regression analysis was conducted, with daily zonal visitation ($trips_{i,t}$) as the dependent variable and average zonal travel cost ($\overline{tc}_i$) whether the trip took place on a holiday ($holiday_t$) or weekend ($weekend_t$), the season the trip took place ($season_t$), and the proportions of the population within each home zone that were under five years old ($under\ 5_i$), over 64 years old ($over\ 64_i$), White ($White_i$) and Hispanic ($Hispanic_i$):

$$trips_{i,t} = \beta_0 + \beta_1 \overline{tc}_i + \beta_2 holiday_t + \beta_3 weekend_t + \beta_4 season_t + \beta_5 under\ 5_i + \beta_6 over\ 64_i + \beta_7 White_i + \beta_8 Hispanic_i \tag{1}$$

Consumer surplus, a widely accepted measure of net social benefit (Pearse and Holmes 1993), represents the difference between an individual's willingness to pay and the actual expenditure for a good or service. Aggregate consumer surplus is obtained by summing this value across the entire population.

When using travel cost models, consumer surplus is derived by calculating the integral above the average trip expenditure and below the estimated demand function. Per-trip consumer surplus is most often used with count data (Creel and Loomis 1990) and can be multiplied by the estimated number of trips in a year to obtain the aggregate consumer surplus of access to a given site or sites. Following Yen and Adamowicz (1993), the formula to estimate per-trip consumer surplus is:

$$CS = -1 \Big/ \beta_1 \tag{2}$$

Travel costs were calculated as a function of roundtrip driving distance and time. The 2022 IRS business standard mileage rates, which provide an estimation of the out-of-pocket driving cost per mile, were used to assign a cost value to the travel distance. These mileage rates encompassed both variable costs (e.g., gas, oil, tires, maintenance, and repairs) and fixed costs (e.g., insurance, registration, depreciation, or lease payments) associated with operating a vehicle. However, the rates do not encompass parking and toll expenses and are not geographically adjusted. For the first six months of 2022, the IRS business standard mileage rate was 58.5 cents per mile, while for the latter half of the year, the rate increased to 62.5 cents per mile to account for increases in fuel prices.

As the time spent traveling could have been used for other purposes, it incurs an "opportunity cost." Failure to include this opportunity cost in the travel cost calculation can result in an underestimation of the value of the site. Various approaches have been proposed to account for the value of time, including assigning a fraction of the wage rate to the time cost (Hagerty and Moeltner 2005; Zawacki et al., 2000; Liston-Heyes and Heyes 1999; Sarker and Surry, 1998; Bowker et al., 1996). However, there is no strong consensus on the appropriate approach. In this analysis, the opportunity cost of time was set to one-third the hourly wage rate for the given home zone, a practice adopted in several previous studies (e.g., Huhtala and Lankia, 2012; Edwards et al., 2011; Egan et al., 2009; Gürlük and Rehber, 2008; Hagerty and Moeltner, 2005; Liston-Heyes and Heyes, 1999).

Two additional wage rate fractions were tested within a robustness analysis: one-fourth (e.g., Bowker et al., 2007; Zawacki et al., 2000; Sarker and Surry, 1998; Bowker et al., 1996) and one-half (e.g., Sarker and Surry, 1998; Bowker et al., 1996). Larger fractions suggest that people consider their time to be more valuable and may be more likely to choose faster or more convenient transportation options. Alternatively, lower fractions suggest that people consider their time to be less valuable and may be more likely to choose more cost-effective, but time consuming, transportation options.

Holidays and weekends are included as time is often a constraint to participating in leisure activities (e.g., Shores et al., 2007; Nyaupane et al., 2004; Herridge et al., 2003), and previous research has found that holidays and weekends are more popular times for leisure travel (e.g., Liu and Sharma, 2006; Lockwood et al., 2005; O’Fallon and Sullivan, 2005) and recreation (e.g., Paudyal et al., 2019; Finger and Lehmann, 2012; Vaara and Matero, 2011; Scott et al., 2007) compared with weekdays.

Seasonality is included as a proxy for climate and weather variables, such as temperature, precipitation, and daylight. Only daily information for rainfall and temperature are available for the study area and, as significant variations in weather can occur within a single day, these daily values may not accurately represent the weather expected or experienced during day trips. Additionally, previous studies have found that temperature might not be the most important climate variable (Hewer et al., 2015; de Freitas et al., 2008; Scott et al., 2008; King et al., 2000). Therefore, seasonal trends may be more appropriate for incorporating weather and climate impacts, as well as other seasonal effects relevant to recreational activities that are popular in the area, such as fishing and viewing fall foliage. A model including rainfall and temperature instead of seasonality was tested within a sensitivity analysis.

Age, race, and ethnicity are included to account for different constraints to outdoor recreation experienced by different socio-demographic groups (Rushing et al., 2022; Zanon et al., 2013; Bustam et al., 2011; Powers et al., 2010; Kindal et al., 2007). For example, research suggests engagement in outdoor activities tends to decline as individuals age (Payne et al., 2002). Older individuals often face constraints linked to transportation, health, disabilities, safety concerns, and a lack of companionship (Green et al., 2009; Shores et al., 2007; Mowen et al., 2005; Johnson et al., 2001). Moreover, family responsibilities can pose obstacles for those with young children (Stodolska et al., 2019; Covelli et al., 2007; Mowen et al., 2005), while concerns about crime can limit outdoor physical activity for the youth (Shinew et al., 2013; Zhu & Lee, 2008; Molnar et al., 2004; Gordon-Larsen et al., 2000).

Additionally, minority groups may experience constraints due to lack of transportation, lack of adequate facilities, expense of participation, fear of crime, discrimination, and social acceptance by peers for engagement in exclusive race/ethnic sanctioned activities (Xiao et al., 2022; Stodolska et al., 2019; Shinew et al., 2013; Johnson et al., 2001; Stodolska et al., 2011; Taylor et al., 2011; Green et al., 2009; Stanis et al., 2009; Shores et al., 2007; Covelli et al., 2007; Stodolska and Livengood, 2006; Mowen et al., 2005; Gobster, 2002; Hibbler and Shinew, 2002; Tierney et al., 2001; Phillipp, 2000; Phillipp, 1999). Further, different socio-demographic groups may have different preferences for outdoor recreation. Previous studies have found that White populations tend to prefer nature-based activities (Payne et al., 2002) and active individual sports (Gobster, 2002), whereas minorities prefer more developed settings (Ho et al., 2005; Gobster, 2002), organized recreation activities (Payne et al., 2002), and passive social-oriented activities (Gobster, 2002).

3. Results

3.1 Summary statistics

Figure 4 shows the total number of observed trips to the study area in 2022 from each home zone within a two-hour driving time. The vast majority of trips are from home zones close to the study area, with an average travel distance of 22.4 kilometers (standard deviation: 22.4 kilometers) and an average travel time of 19.95 minutes (standard deviation: 14.8 minutes). An average of 4.8 daily trips (standard deviation: 26.6 trips) were observed. On days that trips were observed, an average of 14 trips (standard deviation: 43.9 trips) were observed with an average trip cost of $25.91 (standard deviation: $24.33).

The proportion of trips observed on holidays (3.4%) or over the weekend (29.3%) is similar to the proportion of holidays (3.3%) and weekends (28.8%) in the year, but slightly more trips were observed in the summer (28.1%) and winter (27.1%).

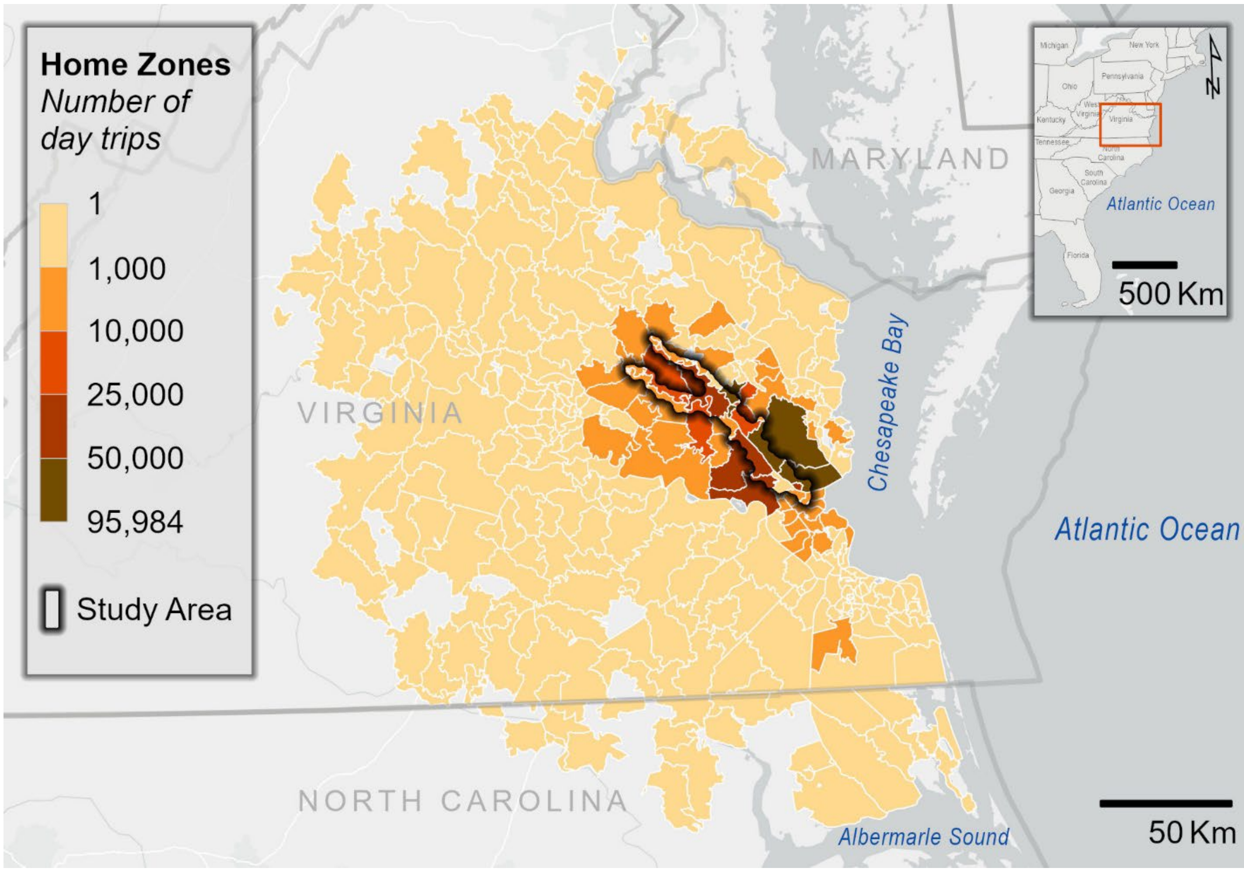

Figure 4. Total number of observed day trips from each home zone (zip code tabulation area) to the York River study area in 2022.

3.2 Zonal Travel Cost Model

A zero-inflated negative binomial distribution was used as the trip count data is overdispersed and has excess zeros. The data distribution combines the negative binomial distribution (count model) and the logit distribution (zero-inflated model). This distribution is suitable when there are both structural (i.e., outcomes that can only be zero) and sampling zeros (i.e., outcomes that were zero, but could have been non-zero). Total zonal population was used as an offset to account for the fact that home zones with larger populations may inherently have greater visitation (i.e., greater exposure).

Table 2 shows the results of the regression analysis as estimated using Stata SE/16.1. The likelihood ratio test for alpha is significant ($\bar{\chi}^2$= 6.0E5, p<0.01), indicating that a zero-inflated negative binomial model is preferred to a zero-inflated Poisson model. The number of observations refers to the combination of days and home zones included in the analysis. The total number of trips is also included for reference. Finally, to interpret the results of the count model, the coefficients (change log odds) can be exponentiated to estimate the change in odds.

A Variance Inflation Factor (VIF) was conducted to assess the presence of multicollinearity between independent variables. The VIF values for each variable ranged from 1 to 1.5, with an average VIF of 1.23, which suggests that multicollinearity is not a significant issue in this model.

Table 2. Regression results

	Coef.	Robust Std. Err.	Sig.
Count Model			
Travel costs	−0.04	0.00	***
Holiday	0.12	0.04	***
Weekend	0.13	0.01	***
Summer	0.15	0.02	***
Fall	0.04	0.02	***
Winter	−0.01	0.02	***
Under 5	−1.74	0.30	***
Over 64	−4.53	0.08	***
White	2.51	0.04	***
Hispanic	−0.81	0.16	***
Intercept	−83.44	1.03	***
Zero-inflation Model			
Intercept	−81.85	0.08	***
N = 117,895 Non-zero N = 40,985 Trips = 576,065 Significance: *** 0.001 ** 0.01 * 0.05			

As expected, visits to the recreation area decrease as travel costs increase. This allows us to derive an ordinary demand function for visits and estimate an average trip value of $26.76 (95% CI: $26.54–$26.99), which translates to a total recreation value of $15.75 million (95% CI: $15.62 million–$15.88 million).

Additionally, visitation is more likely to occur on holidays ($e^{0.12} = 1.12$, or 12% more likely), weekends (17%), and during the summer (16%). Finally, visits are less likely to occur from home zones with a greater proportion of the population that is less than five years old (−84%), over 64 years old (−99%), and Hispanic (−66%) and more likely to occur from home zones with a greater proportion of the population that is White (1,227%).

3.3 Sensitivity/Robustness Analysis

Several assumptions were made on the dataset and model specification (Tables 3 and 4). Robustness analyses were used to test if changes to the dataset impact the results; sensitivity analyses were used to test if changes to the model specification impact the results.

Specifically, three main assumptions were made on the dataset: 1) the buffer used in defining the recreation area, 2) the home zone travel time cut-off, and 3) the wage rate fraction used in calculating the opportunity cost of time. Four alternate buffer definitions of the creation area were tested: a 0-meter buffer (on the York River), a 250-meter buffer, a 750-meter buffer, and a 1,000-meter buffer and include all trips with records within the respective buffer. Two additional home zone cutoffs were tested: 1.5 hours and 2.5 hours. Finally, two additional wage rate fractions were tested: one-fourth and one-half.

One main assumption was made on model specification: seasonality as a proxy for weather, and a model including rainfall (inches) and maximum air temperature (Fahrenheit) instead of seasonality was tested. Roughly 15% of days experienced rain in 2022 with an average rainfall of 0.44 inches on those days, and the maximum temperature ranged from 24F to 97F with an average maximum temperature of 70F. Many specifications for temperature were tested (e.g., linear, quadratic, square root, piecewise). For simplicity, a binary specification indicating whether the maximum air temperature is 60F or above is provided.

Table 3. Robustness/sensitivity analysis regression results

	0-m Buffer			250-m Buffer			750-m Buffer			1,000-m Buffer		
	Coef.	Robust Std. Err.	Sig.	Coef.	Robust Std. Err.	Sig.	Coef.	Robust Std. Err.	Sig.	Coef.	Robust Std. Err.	Sig.
Count Model												
Travel costs	−0.04	0.00	***	−0.04	0.00	***	−0.04	0.00	***	−0.04	0.00	***
Holiday	0.24	0.07	***	0.12	0.04	**	0.11	0.04	**	0.11	0.04	**
Weekend	0.29	0.03	***	0.20	0.02	***	0.13	0.01	***	0.14	0.01	***
Summer	0.19	0.03	***	0.15	0.02	***	0.16	0.02	***	0.11	0.02	***
Fall	−0.19	0.04	***	0.00	0.02		0.06	0.02	**	0.02	0.02	
Winter	−0.16	0.04	***	−0.05	0.02	**	0.02	0.02		−0.03	0.02	
Under 5	−1.24	0.47	**	−2.51	0.31	***	−1.81	0.29	***	−2.28	0.29	***
Over 64	−3.10	0.15	***	−4.35	0.08	***	−4.52	0.07	***	−4.51	0.07	***
White	4.24	0.09	***	2.62	0.04	***	2.62	0.04	***	2.61	0.04	***
Hispanic	−1.40	0.27	***	−1.21	0.17	***	−0.45	0.16	**	0.11	0.15	
Intercept	−1.23	0.09	***	2.23	0.04	***	2.89	0.04	***	3.10	0.04	***
Intercept Model												
Intercept	−77.43	0.57	***	−81.43	0.87	***	−83.25	0.74	***	−82.83	0.46	***
N	75,920			113,880			120,815			123,370		
Non-zero N	9,790			34,684			44,406			47,082		
Trips	45,179			355,774			730,270			871,982		
Significance: *** 0.01 ** 0.05 * 0.1												

Table 4. Robustness/sensitivity analysis regression results continued

	1.5-hr Cutoff			2.5-hr Cutoff			¼ Wage Rate			½ Wage Rate			Weather		
	Coef.	Robust Std. Err.	Sig.	Coef.	Robust Std. Err.	Sig.	Coef.	Robust Std. Err.	Sig.	Coef.	Robust Std. Err.	Sig.	Coef.	Robust Std. Err.	Sig.
Count Model															
Travel costs	−0.04	0.00	***	−0.03	0.00	***	-0.04	0.00	***	-0.03	0.00	***	-0.04	0.00	***
Holiday	0.12	0.04	**	0.09	0.04	**	0.13	0.04	***	0.12	0.04	***	0.09	0.04	**
Weekend	0.16	0.02	***	0.14	0.01	***	0.16	0.01	***	0.16	0.01	***	0.16	0.01	***
Summer	0.17	0.02	***	0.15	0.02	***	0.38	0.02	***	0.15	0.02	***	--	--	--
Fall	0.06	0.02	**	0.03	0.02		0.29	0.02	***	0.04	0.02	**	--	--	--
Winter	0.01	0.02		0.01	0.02		0.03	0.02		-0.02	0.02		--	--	--
Precipitation	--	--	--	--	--	--	--	--	--	--	--	--	-0.05	0.02	***
60F+	--	--	--	--	--	--	--	--	--	--	--	--	-0.25	0.05	***
Under 5	−1.58	0.32	***	−2.74	0.29	***	-3.13	0.29	***	-1.72	0.31	***	-1.86	0.30	***
Over 64	−4.60	0.08	***	−4.20	0.08	***	-4.30	0.07	***	-4.62	0.08	***	-4.47	0.08	***
White	2.25	0.04	***	2.75	0.04	***	2.45	0.04	***	2.82	0.04	***	2.58	0.04	***
Hispanic	−1.79	0.17	***	0.48	0.16	**	-0.73	0.16	***	-1.05	0.17	***	-1.06	0.17	***
Intercept	3.22	0.04	***	2.27	0.04	***	2.74	0.04	***	2.58	0.04	***	2.79	0.04	***
Intercept Model															
Intercept	−117.24	0.24	***	−98.26	0.19	***	-82.07	0.71	***	-82.87	1.17	***	-82.40	0.86	***
N	86,140			170,455			117,895			117,895			117,895		
Non-zero N	38,194			43,245			40,985			40,985			40,985		
Trips	571,788			578,771			576,065			576,065			576,065		
Significance: *** 0.01 ** 0.05 * 0.1															

The effect of travel costs is fairly stable across the different models, with less than a 1% difference in the odds of visitation. The effects of holidays, weekends, and across the seasons are also similar across models with the exception of the “0-meter buffer” model, where the odds of visitation are 14% higher on holidays and 18% higher on weekends, but 22% lower in the fall and 13% lower in the winter compared with the “baseline” model presented in Table 2. Conversely, the odds of visitation are 30% higher in the summer and fall under the “1/4 wage rate” model. All effects are fairly stable under the “weather” model.

Further, for every 1% increase in the proportion of the population under five years old, the odds of visitation were 13% higher under the “0-meter buffer” model and 9%, 8%, and 6% lower under the “2.5-hour cutoff,” “250-meter buffer,” and “1,000-meter buffer” models, respectively. On the other hand, the effects of the proportion of the population over 64 years old vary minimally across the four models.

The effects of race and ethnicity vary more drastically. For every 1% increase in the White population, the odds of visiting increase from 31% under the “1,000-meter buffer” model to 5,626% under the “0-meter buffer” model, and decrease by 381% under the “1.5-hour cutoff” model. For every 1% increase in the Hispanic population, the odds of visiting increase from 30% under the “750-meter buffer” model to 127% under the “2.5-hour cutoff” model, and the odds of visiting decrease from 4% under the “250-meter buffer” model to 18% under the “1.5-hour cutoff” model.

Figure 5 shows the relative estimated trip values for each model, including 95% confidence intervals. The difference in values is relatively small, ranging from $23.48 when using the 1.5 hour-cutoff definition to $30.95 when using the 2.5-hour cutoff definition. Trip values are effectively the same between the baseline and weather model and greater when using a smaller buffer, larger cut-off definition, and larger fraction of the hourly wage as the opportunity cost of time.

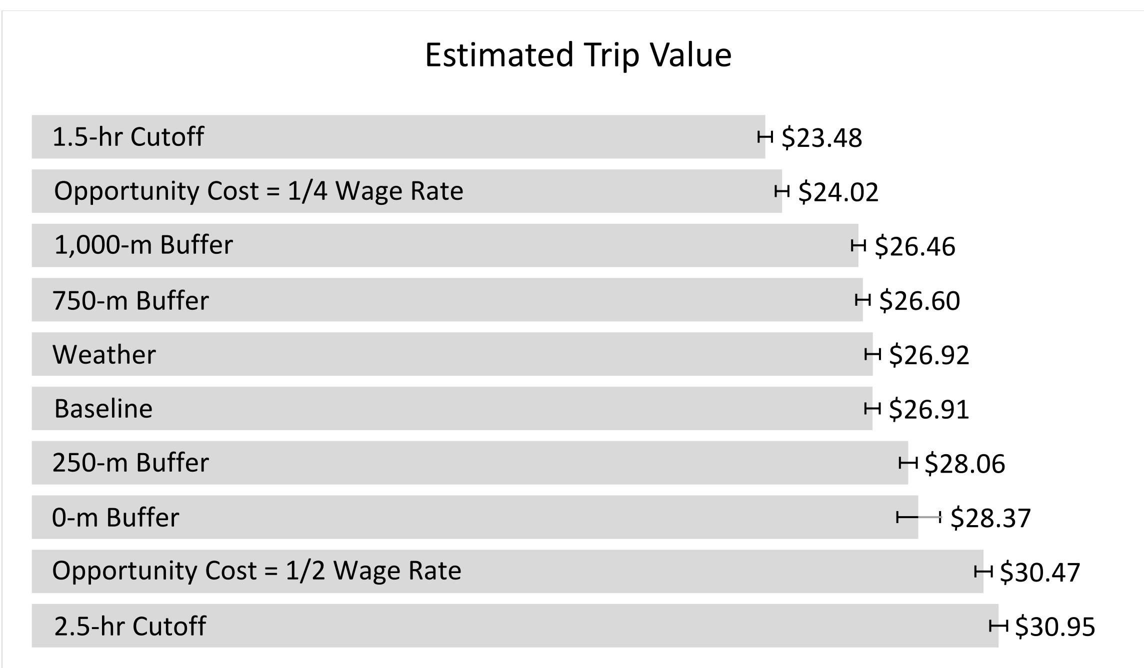

Figure 5. Estimated mean trip values with 95% confidence intervals under each model

4. Discussion

The findings from this study shed light on various factors that influence visitation patterns and recreation values within the study area. Understanding these factors can help in better managing and promoting the recreational opportunities offered by the York River and surrounding parks.

The temporal effects observed in this study align with previous research, indicating that weekends, holidays, and the summer months are the most popular times for visits. This pattern can be attributed to people having more leisure time available during weekends and holidays, while increased visitation during the summer might be influenced by favorable weather conditions such as temperature, daylight, and precipitation. Fall is also popular for land-based recreation, which aligns with the peak fishing seasons for various species and the fall foliage season from mid to late October. Alternatively, visitation is less likely to occur during the fall or winter for water-based recreation, which is likely due to colder water temperatures.

The influence of socio-demographics on visitation is also evident, but nuanced. Results suggest that those with young children and those who are Hispanic or over 64 years old are less likely to visit the York River and surrounding areas. However, those with young children and those who are White are more likely to recreate on the water, which suggests a preference for water-based activities, such as kayaking, canoeing, and fishing. Alternatively, those who are Hispanic are more likely to travel from farther away and spend more time farther away from the water, which may suggest that the York River is not their primary destination.

Finally, the opportunity cost of time appears to influence the relationship between visitation, seasonality, and socio-demographics. As the perceived cost of time decreases (i.e., lower fraction of the wage rate), people generally become more responsive to seasonal factors and those who are Hispanic are more likely to visit the York River and surrounding areas. Alternatively, those with young children and those who are White are less likely to visit, which suggests a preference for destinations further away from home. However, there appear to be a threshold effects (i.e., between one-third and one-half of the wage rate) where the cost of time has already reached a level where seasonal factors, having young children, and ethnicity play a consistent role in recreation decisions.

These findings are supported by earlier studies that have highlighted similar disparities in visitor demographics (e.g., Shinew et al., 2013; Green et al., 2009; Covelli et al., 2007; Shores et al., 2007; Mowen et al., 2005; Gobster, 2002; Payne et al., 2002; Johnson et al., 2001). Several factors may contribute to these observed disparities, such as varying time or income constraints, limited public transportation, and limited options to rent canoes, kayaks, and boats, which might hinder physical access to the York River. These results warrant further investigation and indicate a need for targeted efforts to promote inclusivity and accessibility for a broader range of communities, enhance visitation rates among underrepresented groups, and improve overall access to recreational opportunities in the area.

Three main caveats should be considered when interpreting the findings of this study. First, ancillary access costs, such as parking, entrance fees, and equipment rental, were not incorporated, which could lead to an underestimate of the true value derived from outdoor recreation. Related, only a subset of individuals and trips is captured by anonymous human mobility data (Lu et al., 2017). Finally, the socio-demographic characteristics were based on home zone averages and may not be representative of the visitors, both in terms of which groups are more likely to participate in outdoor recreation and which groups are more likely to use smart devices (Wesolowski et al., 2013).

5. Conclusion

This study demonstrates the value of outdoor recreation and its multifaceted benefits by applying the travel cost method to anonymous human mobility data. The findings shed light on various factors influencing visitation patterns and recreation values, emphasizing the need for targeted efforts to promote inclusivity and accessibility for diverse communities. By leveraging big data and non-market valuation techniques, decision-makers can make informed and sustainable choices in outdoor recreation management, benefiting both visitors and the environment while ensuring effective preservation of natural resources.

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