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Contingent behavior modeling for dark skies valuation at Great Sand Dunes National Park

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Abstract

Dark sky conservation is increasingly popular, requiring facility upgrades and community cooperation. This study assesses its economic benefits at Great Sand Dunes National Park and Preserve, a Gold Tier International Dark Sky Park. Through on-site surveys, we collected data on visitor behaviors, expenditures, and night sky perceptions. We introduced a continuum of contingent night sky brightness levels based on visitors' home locations and measured changes in visitation. Our Travel Cost-Contingent Behavior analysis shows that each unit increase in nightlight decreases visitation by 0.05 days over 5 years. Using a weighted Latent Class Negative Binomial (LCNB) model, we estimate consumer welfare losses under escalating nightlight pollution scenarios. If the park's night skies matched an average rural, suburban, or urban area, visitors' consumer surplus would fall by about 3%, 23–24%, and 42–44%, respectively. These results underscore the substantial economic value of preserving dark skies.

KEYWORDS

contingent behavior model, dark sky conservation, ecotourism, latent class, national park, negative binomial, nightlight pollution, survey methods, tourism, travel cost model, willingness-to-pay

JEL CLASSIFICATION

Q26, Q51, Q56

1 | INTRODUCTION

Preserving dark skies has emerged as a significant aspect of nature conservation, recognized for its ecological and health benefits such as maintaining biodiversity and protecting circadian rhythms (e.g., Argys et al., 2021; Boslett et al., 2021; Cao et al., 2023; Karan et al., 2023; Seewagen & Adams, 2021; Wang et al., 2023). Concurrently, dark sky tourism is gaining popularity as people seek out pristine night skies for stargazing and astronomical experiences. In 2022, the Governor of Colorado signed the "Support Dark Sky Designation and Promotion in Colorado" Act, highlighting the state's commitment to dark sky preservation and its potential for tourism (Colorado General Assembly, 2022). The 2023 Conservation in the West Poll conducted by the State of the Rockies Project revealed that 69% of the respondents consider dark sky preservation a key conservation goal (State of the Rockies, 2023). Despite the increasing popularity of dark sky tourism, there is still a gap in research on its economic value. Understanding this economic value can inform the development of policies for dark sky preservation and offer a new perspective on nature conservation.

Great Sand Dunes National Park and Preserve (hereafter the "park") is located in southern Colorado and covers approximately 149,000 acres (National Park Service, 2024). The park draws over half a million visitors annually, contributing more than $30 million to the local economy in 2022 (Flyr & Koontz, 2023). Its high elevation, dry air, remote location, and low light and noise pollution create an ideal environment for stargazing (Underwood, 2015). In 2019, the park earned the Gold Tier International Dark Sky Park designation from DarkSky International (formerly the International Dark-Sky Association, IDA). While this recognition attracts visitors, achieving and maintaining it involves significant costs, such as monitoring and updating lighting, creating dark sky education programs for the public, and working with nearby Alamosa and Saguache Counties to minimize nightlight pollution (DarkSky International, 2024). Given the investment needed to preserve dark skies, gaining a better understanding of the benefits specifically derived from dark sky tourism is essential.

Our project quantifies the consumer surplus associated with dark sky conservation at the Great Sand Dunes. To support such estimation, we conducted on-site, in-person surveys with visitors at the park between October 20, 2023 and October 22, 2023. Our survey collected comprehensive information on the visitors, including their points of origin, trip-taking behavior, expenditures during travel and in the local area, and perceptions of the night sky quality at the park. We asked whether they had spent time observing the night sky and requested them to compare its quality at the park to that at their residences. Importantly, we inquired how changes in the night sky at the park might affect their future visitation behavior.

The primary finding of this project is that dark skies significantly enhance the tourism value of the park. Our main results are threefold. First, for each unit measure increase in nightlight at the site, a tourist's visitation decreases by 0.05 days over a 5-year period. Second, while each day spent at the park yields substantial positive consumer welfare, we observe that the marginal consumer welfare diminishes rapidly as the number of visitation days increases. Third, we quantify the decrease in consumer welfare due to changes in night sky brightness, by combining our estimate of baseline consumer surplus with the estimated change in visitor behavior under a brighter night sky scenario. Specifically, our estimates indicate that if the night sky at the park were to become as bright as an average rural, suburban, or urban area, an average visitor would experience percent decreases in annual consumer surplus ranging from about 3% for rural brightness, 23–24% for suburban brightness, and 42–44% for urban brightness.[1]

Methodologically, our project contributes to the literature on public goods valuation. We design a survey that provides tangible and discrete contingent scenarios for a public good—night sky quality—that is continuous in scale. Nightlight pollution is continuous by nature, and the impression of whether a dark sky exists varies subjectively across individuals. To address this, we ask each respondent to compare the actual night sky at the park, a common baseline for all respondents, to the night sky at their home base. This provides an individual-specific counterfactual state. Then, we examine whether their visitation days would change if the park's night sky became the same as at their home, while all other park attributes remained unchanged. This design creates a discrete and

[1]These percent decreases correspond to declines in annual consumer surplus for the average visitor of $4–$18 for a transformation to average rural brightness, $39–$159 for suburban brightness, and $72–$291 for urban brightness.

exact comparison for each respondent on an otherwise continuous matter. It also makes the comparison of actual and contingent states accessible and understandable to each respondent.

In our analysis, we convert each respondent's home base night sky, the contingent state, into a numerical measure of darkness using cloudless nightlight data captured by the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite, produced by the Earth Observation Group (Elvidge et al., 2013). The park had a baseline nightlight value of 0.28 in October 2023. For comparison, rural areas where our tourists originate had an average nightlight value of 1.82 in 2022, while urban areas averaged 32.08.[2]

By anchoring each respondent's contingent scenario to their personally experienced baseline conditions (i.e., their home location's sky brightness), we generate a continuum of respondent-specific contingent scenarios. Pooling these individualized responses creates a rich, continuous gradient of contingent states reflecting different potential levels of nightlight pollution. Traditional contingent behavior studies often rely on binary or a limited set of discrete scenarios, which constrains the nuance and policy relevance of the resulting valuation estimates. To our knowledge, ours is the first study to employ such a continuum of personalized contingent states, rather than a small set of discrete alternatives, extending contingent behavior methods (CBMs) to continuous and potentially non-measurable environmental attributes.

This methodological innovation has implications beyond dark-sky valuation and tourism. It is particularly suited to evaluating policy-relevant incremental changes across other continuous environmental gradients. For example, policymakers working to comply with the European Union's Water Framework Directive could use our approach to quantify how incremental improvements in water quality influence recreational visitation and welfare. Similarly, recreation area managers dealing with wildfire risks could apply our framework to quantify visitor responses to incremental changes in wildfire probabilities. The method could also assess the incremental impacts of noise pollution from sources such as aircraft, road, or off-road traffic in or around natural recreation settings.

We employ a fixed-effect regression to remove unobserved biases that may correlate with both visitation behavior and nightlight levels at respondents' home bases. This unobserved bias is a unique endogeneity issue arising from our survey design, where contingent scenarios are respondent-dependent. Such an issue typically does not occur when studying contingent behaviors with only exogenous and discrete scenarios. By creating a panel of individuals across their historical and contingent states, we utilize individual fixed effects to control for person-specific unobserved biases. We do not find further significant demographic-based group-specific effects in robustness tests after controlling for individual fixed effects.

Finally, we address the challenges of truncation and endogenous stratification inherent in on-site data collection. On-site surveys typically capture responses only from visitors who have spent at least 1 day at the site, and frequent visitors are more likely to participate. Our survey design introduces a contingent scenario of night sky deterioration, allowing respondents to report zero visitation days under this counterfactual condition. By combining historical visitation data with contingent data, we create an individual-level panel that effectively mitigates the issue of truncation at zero.

Our on-site survey inherently oversamples frequent visitors, creating endogenous stratification that could bias our estimates of the sensitivity of consumer surplus to environmental quality changes. Frequent visitors typically have lower marginal responses to quality changes compared to infrequent visitors (Englin & Shonkwiler, 1995; Haab & McConnell, 2002; Parsons, 2017). To correct for this bias, we employed an inverse visitation-day weighting procedure, following Shi and Huang

[2]It is important to clarify that the park's Gold Tier International Dark Sky Park designation is not contingent upon any specific satellite-derived threshold such as VIIRS nightlight radiance. Rather, Gold Tier status is based on compliance with rigorous qualitative and quantitative criteria established by IDA, reflecting exceptionally dark skies, strict lighting policies, and active community engagement. Gold Tier parks are described as having "pristine or near-pristine" night skies, approaching natural darkness levels. Our measured VIIRS radiance of 0.28 (October 2023) is consistent with very low artificial lighting environments. We selected VIIRS radiance rather than ground-based mag/arcsec^2 measures because comprehensive mag/arcsec^2 data at the ZIP code level are not available nationwide, whereas VIIRS offers a continuous and comparable dataset across all locations.

(2018), which assigns each respondent a weight inversely proportional to their historical visitation frequency. Without weighting, our estimated impact of night-sky deterioration on visitation was substantially biased downward. After applying inverse weighting, the *nightlight* coefficient became more negative and statistically significant, accurately reflecting the higher sensitivity of infrequent visitors who were initially underrepresented. Similarly, weighted models produced significantly higher marginal consumer surplus estimates per visit, aligning with economic theory: frequent visitors typically derive lower marginal utility from each additional visit, whereas infrequent visitors place a substantially higher marginal value on each visit.

Furthermore, to capture respondent heterogeneity in preferences, we employ a Latent Class Negative Binomial (LCNB) regression model, as recommended by Hynes and Greene (2013, 2016). The combination of inverse visitation weighting with the latent class (LC) structure addresses both on-site sampling biases and respondent heterogeneity, a combination of approaches not applied previously in this context to our knowledge. This methodological combination ensures unbiased and nuanced estimation of visitor behavior and consumer welfare related to dark-sky quality.

The rest of the paper proceeds as follows. Section 2 overviews literature on night sky tourism, CBMs, and on-site sampling. Section 3 describes the survey methodology, empirical methods, and our collected data. Section 4 presents estimation results. Section 5 concludes the paper.

2 | LITERATURE

The body of literature examining the implications of nightlight pollution has predominantly focused on human health and biodiversity (e.g., Argys et al., 2021; Boslett et al., 2021; Cao et al., 2023; Karan et al., 2023; Seewagen & Adams, 2021; Wang et al., 2023). Research specifically addressing the economics of dark sky tourism is considerably limited. Some studies have provided preliminary insights. Collison and Poe (2013) conducted research in Bryce Canyon National Park and found that up to 10% of park visitors engaged in either formal dark sky programs or informal dark sky-related activities. Additionally, Mitchell and Gallaway (2019) projected that tourists prioritizing dark skies would contribute \$5.8 billion to the Colorado Plateau region over a decade, generating higher wages and creating over 10,000 jobs annually. Rodrigues, Rodrigues, and Peroff (2015) highlighted the role of dark sky areas as distinctive tourism destinations, potentially attracting visitors over comparable sites without dark sky designations. Hvenegaard and Banack (2024) surveyed 31 visitors at the Jasper Dark Sky Festival in Alberta, Canada, to investigate visitor outcomes such as attitudes, satisfaction, learning, and behavior changes. They found that, while visitors reported high levels of satisfaction, learning, and the importance of protecting dark skies, only 42% intended to change any of their behaviors to help protect dark skies. Simpson and Hanna (2010) used contingent valuation to estimate willingness-to-pay for improved night skies, but faced limitations due to small and specific student samples and hypothetical inflation.

The ecotourism literature emphasizes the importance of perceived environmental value in influencing tourist behavior (e.g., Carvache-Franco et al., 2021; Donici & Dumitras, 2024). Carvache-Franco et al. (2021) find that functional and emotional values are significant predictors of tourist satisfaction and intentions to recommend destinations. Although not focused on dark sky tourism specifically, these findings underscore the broader significance of environmental quality in nature-based tourism. Additionally, studies suggest that the benefits associated with ecotourism can increase local support for conservation efforts (Lindberg et al., 1996).

To our knowledge, only one other study, Heberling and Templeton (2009), has conducted a rigorous statistical analysis to estimate the consumer welfare of trips to our study site. They employed a travel cost model (TCM) using only revealed preference (RP) data, utilizing secondary data collected by the National Park Service to enhance understanding of visitor patterns. Their contribution augmented the limited literature on the valuation of national parks in the United States and demonstrated the potential for using secondary survey data not specifically designed to support a TCM. In contrast, our survey is specifically designed to support both a TCM as well as a model combining TCM and the CBM. By incorporating both stated and RP data, our research extends previous studies focused on recreation on federal lands.

There exists a broad range of previous studies in the literature that have used the CBM to estimate the effects of potential changes in various environmental attributes (e.g., Bhat, 2003; Börger et al., 2024; Cameron et al., 1996; Egan & Herriges, 2006; Eiswerth et al., 2000, 2008; Hesseln et al., 2004; Hynes & Greene, 2013, 2016; Loomis, 1993, 2002; Mathews et al., 2002; Voltaire & Koutchade, 2020). Such applications in recreation demand modeling generally focus on use values associated with activities, including hiking, hunting, recreational fishing, boating, and beach recreation. In these studies, contingent scenarios typically involve changes in site access, environmental quality, congestion, catch rates, wildfire damage, or other measurable attributes that directly affect a specific recreational activity. The CBM framework is therefore most commonly applied to settings in which the environmental attribute under study is closely linked to a defined recreational use and where quality changes can be described in terms of discrete site characteristics.

The present study extends this line of research by applying the CBM framework to night sky quality at a national park. Unlike many previously examined attributes, night sky brightness is spatially diffuse, perceptual, and not tied to a single activity in that it may affect a visitor's overall experience of the site. By situating changes in artificial light pollution within a revealed-preference-anchored contingent behavior structure, this study broadens the range of environmental attributes evaluated using CBM in recreation demand contexts.

One of the advantages of CBM lies in its combining of revealed and stated preference (SP) methods, an approach suggested and used by Cameron (1992), Adamowicz et al. (1994), and Kling (1997), and assessed by Whitehead et al. (2008). CBM can be less prone to hypothetical response bias compared to contingent valuation methods (CVM) because it anchors respondents' stated preferences directly to their actual visitation behavior. By combining actual (revealed) visitation data with hypothetical scenarios, CBM reduces incentives for respondents to engage in hypothetical or strategic overstatement, thus producing more reliable valuation estimates (e.g., Adamowicz et al., 1994; Cameron et al., 1996; Meyer & Yang, 2016; Whitehead et al., 2008).

A CBM is an extension of the TCM, with RP data supplemented by stated preference observations for the same set of recreators. In CBM, as in TCM, count data models are generally preferred. Their application to consumers is grounded in micro theory (Hellerstein & Mendelsohn, 1993), and their employment in recreation demand modeling is pervasive, with early examples in the literature including but not limited to Shaw (1988), Creel and Loomis (1990), Englin and Shonkwiler (1995), Shonkwiler and Shaw (1996), and Englin et al. (1998). Count data models are suitable if a dependent variable of interest assumes nonnegative integer values and the measures to be estimated involve baseline levels and changes in measures, such as aggregate recreation days and consumer surplus.

Contingent scenarios designed for CBM may be based on either objective or subjective indications of an environmental attribute. While contingent scenarios in the literature are often based partly or entirely on objective and numerical metrics, researchers have pointed out that numerical measures of environmental attributes may be difficult for many people to comprehend. Furthermore, it may be challenging to compare two different quantitative measures of an attribute and assess what the differences might mean for recreation, aesthetic benefits, and overall satisfaction. For example, researchers have noted the difficulty that consumers have in assessing the differences among and implications of alternative pollutant loading levels or ambient pollution concentrations (e.g., Smith & Desvousges, 1985; Whitehead et al., 2000). Our CBM design relies on subjective references to the condition of the night sky at the location where each respondent resides.

Our CBM design further differs from much of the prior literature in how the contingent scenarios are constructed. We anchor each contingent scenario to the respondent's reported home night sky conditions. This approach generates a continuum of individualized contingent states, reflecting heterogeneity in respondents' reference environments.

In contrast, many previous CBM applications have relied on a single or a small set of common discrete and uniform hypothetical changes in environmental quality, presented identically to all respondents. By incorporating respondent-specific reference points, our approach preserves the internal consistency between revealed and contingent observations while allowing quality changes to vary continuously across individuals. Beyond the construction of contingent scenarios, CBM applications must also address econometric issues arising from on-site sampling and the integration of revealed and contingent data, issues to which we now turn.

In both CBM and the broader context of TCM, the issues of truncation and endogenous stratification resulting from on-site sampling are well-known. The literature has addressed these concerns through various methods. Initial approaches involved corrections for count data models using Poisson (Shaw, 1988) and negative binomial (NB) (Englin & Shonkwiler, 1995) distributions. Subsequent studies have employed panel data techniques to account for on-site sampling effects (e.g., Beaumais & Appéré, 2010; Egan & Herriges, 2006; Moeltner & Shonkwiler, 2010). Similar to our approach described below, Egan and Herriges (2006) allow for zero trips in the contingent trips portion of their data, though their contingent scenarios involve price increases rather than decreases in site quality. Allowing zero trips addresses incidental truncation in their on-site data, treats zero hypothetical trips as simply one possible outcome in the count distribution, and avoids the necessity of a separate participation model. Similarly, though using a different type of panel model, Beaumais and Appéré (2010) accommodate zero trips in the contingent trips portion of their data under a scenario of diminished water quality. Their inclusion of zero trips is essential for measuring the welfare effects of the contingent scenario, and their on-site survey approach means that every respondent has positive revealed trips while zero trips are allowed under the contingent scenario of environmental deterioration.

In a different approach, LC models have been utilized in CBM to correct for on-site sampling and account for correlations between revealed (actual) and contingent trip data (e.g., Hynes & Greene, 2013, 2016). Unlike the present application and those of Egan and Herriges (2006) and Beaumais and Appéré (2010), however, Hynes and Greene (2013, 2016) deal with a scenario of improved environmental quality and therefore expect no contingent trip observations equal to zero.

At the same time, empirical evidence on comparing TCM models correcting and not correcting for stratification has been mixed. For example, Ovaskainen et al. (2001) concluded that a model not adjusted for stratification could be acceptable for estimating the aggregate benefits of a recreation site. In contrast, other studies have found significant differences between corrected and uncorrected models in per-person baseline consumer surplus and changes in consumer surplus due to attribute changes (e.g., Hynes & Greene, 2013). Some research indicates that while correcting for on-site sampling significantly affects trip demand estimation, it has a relatively small impact on estimated per-person consumer surplus (e.g., Egan & Herriges, 2006; Shi & Huang, 2018). With respect specifically to CBM models, Hynes and Greene (2013) and Voltaire and Koutchade (2020) have noted that the failure to fully correct such models for endogenous stratification and correlation between revealed and contingent observations is quite common, specifically regarding CBM scenarios involving a deterioration in environmental quality. In our models, we address potential on-site sampling issues.

Shi and Huang (2018) employ a TCM using only actual trips rather than a CBM with combined actual and contingent trips. They observe the limitations in standard corrections for on-site sampling in the literature. Specifically, the effectiveness of such adjustments heavily depends on the accuracy of the population distribution assumptions. If the true population distribution is incorrectly specified, the corrections embedded in the assumed probability density function can be fallacious. Instead, Shi and Huang (2018) propose an alternative method to account for on-site sampling bias: they use the sample distribution of the collected data to reweigh the observations. Instead of scaling up the assumed population distribution to match the on-site sample, they empirically downscale the observed on-site sample to estimate the unknown population distribution more accurately. They conclude that this reweighting approach performs better than the standard corrections when the underlying population distribution differs from the assumed distribution, and performs comparably well even in the absence of such differences. This technique is illustrated elsewhere in the literature (e.g., Wooldridge, 2002). Our methods adopt the inverse reweighting approach to account for potential on-site sampling bias.

Other important issues in CBM applications include accounting for unobserved respondent heterogeneity and possible correlation between revealed and contingent trip data collected from individual respondents. Hynes and Greene (2013) note that simply pooling revealed and contingent trip observations, though a common practice, does not account for potential correlations between these observations. To address these methodological concerns, Hynes and Greene (2013, 2016) propose an innovative panel data model that utilizes a LC structure, capturing both response heterogeneity and correlations between revealed and contingent observations. LC approaches are widely recognized in the literature on recreation demand and environmental valuation for capturing discrete preference heterogeneity without relying on continuous distribution assumptions, thereby enhancing interpretability (Boxall & Adamowicz, 2002; Greene & Hensher, 2003; Hynes & Greene, 2013, 2016).

In our analysis, we initially adopt a fixed-effects model to control for respondent-specific heterogeneity when estimating contingent behaviors. However, a fixed-effects approach inherently absorbs all time-invariant attributes, including *travel cost*, which is essential for welfare calculations. Consequently, we also employ a LC model, following Hynes and Greene (2013, 2016), to estimate *travel cost* parameters and effectively capture preference heterogeneity through discrete latent segments.

3 | METHODS AND DATA

3.1 | Contingent behavior scenario and survey design

We design a survey and research methodology that utilizes and integrates techniques from both the TCM and CBM methods.[3] Our survey design supports the TCM framework by collecting data on the number of trips and days per trip that visitors take and the round-trip cost of traveling to the recreation site. To implement the CBM, we present respondents with a hypothetical scenario in which the night sky at the park differs from its current condition. We then inquire about how this change might influence their visitation behavior. Furthermore, it enables us to examine how consumers might react to environmental conditions that are outside their prior experiences at the site.

In designing our contingent behavior scenario, we aim to describe a simple and familiar alternative night sky at the park to which each respondent can directly relate. The specific scenario offered to each respondent is shown in Figure 1.

If a respondent replies “Yes” to the initial question regarding the contingent behavior scenario, they are asked to provide details about how they think they would change their behavior over the next 5 years. Specifically, we ask how many fewer trips they would take and the degree to which trips in the future might be of a different duration.

One of the major innovations in our research design is how we measure and present the quality of the park's dark sky (and potential changes to it) to respondents. Dark sky quality is inherently subjective, and its deterioration through nightlight pollution is continuous. Scientific measurements of night sky darkness are not intuitive for the average visitor. To make the concept accessible, we asked respondents to compare the night sky at the park to the night sky they experience at home. This creates a discrete and familiar scenario for each person. Then, by pooling all responses and their associated scenarios, we create a synthetic continuous set of contingent nightlight pollution scenarios for our study. This method allows us to analyze a wide range of potential night sky conditions as a continuous variable.

We acknowledge the possibility of hypothetical bias in stated preference approaches of any type. This issue is of concern when using the CVM. For example, a meta-analysis by Murphy et al. (2005)

[3]The full survey is included in the Supporting Information Appendix.

6a. Specifically, if the night sky at *the Great Sand Dunes* looked identical to the sky at your home base *(where you live for most of the year)*, that is, you could see about the same amount of stars here as at your home base, do you think you would change your visiting plans *(that is, either the number of visits or the length of those visits)* to *the Great Sand Dunes* over the next 5 years? *Assume that, even if we had more or fewer stars to see at night at the Great Sand Dunes, the nature of the other amenities and qualities of the Great Sand Dunes would stay the same.*

FIGURE 1 Contingent behavior scenario offered to respondents.

concluded that hypothetical willingness-to-pay derived from the CVM often surpasses real payments, a finding also reported by Champ and Bishop (2001). Our use of the CBM, rather than CVM, is aimed in part at reducing such hypothetical bias. However, we also acknowledge the potential for hypothetical bias in stated behavior (visitation) responses. For example, Whitehead et al. (2000) found that stated contingent visitation (stated trips) for an environmental improvement was significantly higher than respondents' actual trip counts.

In light of these findings, we designed our survey questions to mitigate bias. First, the scenario is anchored in each respondent's personal experience, asking them to compare the quality of the night sky at the park with that at their home residence. This scenario is understandable and personalized. Second, our contingent scenario is framed as a loss in environmental quality (a deterioration of night-sky viewing) rather than a gain in quality, as in Whitehead et al. (2000) and many other studies. This framing may reduce both the likelihood and magnitude of hypothetical bias. Additional steps to minimize potential hypothetical bias are discussed in the empirical methods sections below. Nevertheless, the possibility of overstatement in stated behavioral changes remains in this and any CBM study. Future research could incorporate additional elements, such as a follow-up certainty scale or a "cheap talk" script cautioning respondents about hypothetical bias (Boyle, 2017; Champ et al., 1997). While such methods have been developed for and typically apply to the CVM, their adaptation can also be considered for CBM applications.

Data collected from the seven follow-up questions after the contingent behavior scenario were used to estimate changes in the number of trips and the average trip length for each respondent. These measures were then combined to calculate each respondent's total number of visits and visit-days over the next 5 years under the contingent scenario, holding all other factors constant. Important here is the concept of baseline visitation as used in models that combine RP and stated preference data in one model (e.g., Cameron et al., 1996; Börger et al., 2024; Egan & Herriges, 2006; Eiswerth et al., 2000; Hynes & Greene, 2013, 2016; Loomis, 1993, 2002; Voltaire & Koutchade, 2020). Specifically, the RP observations are used to estimate future visitation that would occur in the absence of a change in environmental quality. Then, data collected from the contingent scenario provides the stated differences in future visitation due to the change in the environmental attribute of interest, ceteris paribus. Note that, in the same way the researcher assumes (and informs the respondent) that site attributes other than the one(s) of interest will remain the same in the scenario, they also assume that visitor characteristics (e.g., income) that might shift the demand curve remain the same as well.

In addition to actual past and contingent future trip-taking behavior, our survey asks a number of other questions to support our analyses. This includes a question about the location of the visitor's home base and questions about expenses, both during travel to and from the site and during the visitors' time spent in the area. Our survey also includes questions about demographics (e.g., age, education, occupation, and income), whether the visitor had spent time looking at the night sky at the park, and the visitor's impressions of the quality of the night sky and stars there. These questions allow us to characterize visitors' attitudes, backgrounds, expenses, and tourism behavior.

3.2 | Survey implementation

We collected our data employing a hardcopy visitor intercept survey. Visitors were intercepted at two locations within the park: (1) the approach paths from the Visitor Center parking lot to the Visitor Center and (2) the primary and largest parking lot that feeds the main access points to the dunes. The survey was implemented over 3 days: October 20–22, 2023. Visitors were intercepted, provided a brief background on the survey, and assisted with survey completion as necessary.

We used an intercept format (rather than, for example, a mail survey format) due to financial constraints. In addition, the characteristics of our site and our research objectives recommend an intercept survey. First, visitors to the park typically originate from most states in the United States as well as many other nations (Le & Littlejohn, 2003). However, as a percentage of the overall population, very few recreators have ever visited the park, with annual visits in recent years at about half a million (Flyr & Koontz, 2023). Therefore, for the study of recreation and perceptions of night sky quality at the park, implementing a mail survey was not feasible with the budget available.

Second, our primary aim was to contact individuals who visit the park in its present, recently bestowed capacity as a Gold Tier International Dark Sky Park. We then assess how visitors might change their trip-taking behavior in the future if the night sky at the park were to become less dark. Therefore, in addition to the fiscal constraints present for our study's implementation, our methods and objectives suggest intercept contact with current visitors rather than a sample of participants and nonparticipants via a mail or telephone survey.

Third, since our contingent scenario involves a diminishment rather than an improvement in an environmental attribute, the issue of new recreation potentially engendered by enhanced quality is not present. Thus, the study differs from many previous CBM studies, and it is not necessary to survey nonparticipants.

Five survey takers worked as a team to intercept visitors and guide them through the survey. The number of completed surveys collected was similar across the five survey takers. Subsequent empirical tests do not find appreciable differences in visitor responses as a function of the survey worker's identity.

3.3 | Empirical methods

As described in the literature review section, our method uses a count data model similar to approaches employed in numerous previous studies of the value of outdoor recreation. The Poisson and NB are commonly used. We favor the application of the NB a priori as it does not assume equidispersion. Subsequent analysis also confirms overdispersion in this particular data set. The general form of the model follows that of Hynes and Greene (2013, 2016), and is described by Equation (1):

$$P\left(days_{it} | days_{it} \geq 0, s_i, c_i, nl_{it}\right) = F\left(days_{it} | s_i, c_i, nl_{it}; \gamma\right), \tag{1}$$

where $days_{it}$ is the number of visit days that visitor i takes in the last 5 years ($t =$ actual) or in the next 5 years ($t =$ counterfactual); s_i is a vector of individual demographic characteristics; c_i is the visitor's round-trip *travel cost* to the site divided by the average number of days the visitor spends on site each trip; nl_{it} is the *nightlight* feature of the site; and γ is a vector of unknown parameters.[4] While all other variables are collected through the survey, we use the cloudless nightlights reported by VIIRS to approximate the darkness of each area.

The individual demographic factors are important control variables for the NB regression because of potential unobserved individual differences. However, *travel cost* and counterfactual *nightlight* tend to strongly correlate with most of the demographic variables we surveyed. For instance, individuals living in urban centers are often associated with brighter nightlights. There are often systematic correlations between home base *nightlight* and income and education levels. To avoid multicollinearity with our main variables nl_{it} and c_i, we only include age_i and age_i^2. The inclusion of age_i^2 in trip demand models is common in order to accommodate potential nonlinearity in the influence of *age*. To facilitate hypothesis testing even under model misspecification, we use White's standard errors (White, 1982).

Our survey design establishes a continuum of counterfactual states that are dependent on the home base of each respondent. However, this also introduces unobserved biases if we regress the counterfactual nightlights on the associated contingent visitation behavior. For instance, respondents may have individual-specific preferences that lead to different visitation behaviors, independent of the night sky conditions. Moreover, group-specific biases may exist. For example, respondents living in urban centers with brighter nightlights, a higher value in the counterfactual scenario, may also have group-specific preferences that lead to visitation behavior to dark sky preserves that are systematically different from those visiting from rural areas.

We exploit an individual fixed effect model to tease out individual-specific factors biasing our estimation of the impact of nightlight pollution on contingent visitation behaviors. Specifically, we stack the actual historical visitation behavior associated with the actual nightlight at the site on top of the contingent scenarios and their contingent visitations for each respondent. This creates a panel for each respondent of actual and contingent data. The individual fixed effect regression controls for all factors idiosyncratic to each visitor and returns an estimate of visitation behavior contingent on a marginal change in nightlight at the site that is common to all visitors. Equation (2) describes the fixed-effect NB (FENB) regression. Since the individual fixed effect for visitor i includes all constant individual factors, s_i and c_i drop out.

$$P\left(days_{it} | days_{it} \geq 0, nl_{it}, \alpha_i\right) = F\left(days_{it} | nl_{it}, \alpha_i; \gamma\right). \tag{2}$$

Further, we modify Equation (2) by adding a term that interacts nl_{it} with the respondent's existing demographics to infer whether any group-specific (g) factors further moderate our estimation:

$$P\left(days_{it} | days_{it} \geq 0, nl_{it}, group_g, \alpha_i\right) = F\left(days_{it} | nl_{it}, nl_{it} \times 1\left(group_g\right), \alpha_i; \gamma\right). \tag{3}$$

Equation (3) describes our regression controlling for group-specific effects. We group individuals based on their responses regarding their *home base type* (rural, suburban, urban), whether they are from Colorado or out of state, *age*, *education*, and whether they have seen the night sky at the park. If the coefficients on the interaction terms are statistically significantly different from zero, we can infer that some group-specific variation impacts their contingent behavior in addition to individual-specific factors.

[4]We chose total *visitation days* (the number of trips multiplied by days per trip) as our dependent variable, rather than simply the number of visits. This choice allows us to incorporate both dimensions of visitor response, trip frequency and trip duration, into a single, comprehensive measure. Many visitors to Great Sand Dunes National Park stay multiple days per trip, and our survey allowed respondents to indicate whether they would reduce visitation by taking fewer trips, shortening trips, or both under deteriorating night-sky conditions. Thus, total *visitation days* capture visitor responses more fully than a count of trips alone, aligning our measure directly with the behavioral responses elicited in the survey instrument.

Our research aims to estimate the consumer welfare value associated with a marginal change in nightlight pollution. The FENB effectively controls for all time-invariant individual-specific factors by modeling within-individual variation. However, an inherent limitation of the fixed-effects model is that it absorbs all variables that do not vary within each individual, including *travel cost*, making it impossible to estimate its direct effect. Since the *travel cost* coefficient is critical for welfare estimation, this limitation is significant.

To address this limitation and estimate the *travel cost* effect, we employ a complementary LCNB model following Hynes and Greene (2013, 2016). Unlike the FENB, the LCNB does not use fixed effects but accounts for visitor heterogeneity by segmenting respondents into distinct LCs. By doing so, the LCNB enables estimation of coefficients for time-invariant attributes such as *travel cost*, facilitating direct welfare calculations. We acknowledge that this latent-class approach, while allowing estimation of invariant variables, provides somewhat less precise control over individual-specific unobservable characteristics than the fixed-effects model. We adjust the model by Hynes and Greene (2013, 2016) using our general form in Equation (4):

$$P\left(days_{it} | days_{it} \geq 0, s_i, c_i, nl_{it}, class = \theta\right) = F\left(days_{it} | s_i, c_i, nl_{it}; \gamma_\theta\right). \tag{4}$$

To account for endogenous stratification, we follow Shi and Huang (2018) and weight each observation i by $1/days_{it}$ ($t=$ actual) to correct for the overrepresentation of more frequent trip-takers sampled via the on-site survey. We apply this correction to both Equations (2) and (4). This yields a weighted FENB regression and a weighted LCNB regression. It is worth noting that each respondent's observations, including both historical (revealed) and hypothetical (contingent) visitations, were weighted uniformly by the inverse of their actual historical visit days reported over the previous 5-year period. Thus, if a respondent had historically visited the park for 5 days, all their data (revealed and contingent) were weighted by a factor of 1/5. This consistent application of the weighting scheme across both revealed and contingent data is necessary because the sampling bias (overrepresentation of frequent visitors) inherently impacts both types of responses. Failing to apply weighting uniformly would disproportionately represent frequent visitors' contingent responses, biasing the estimates of how nightlight pollution affects visitation.

As in Egan and Herriges (2006) and Beaumais and Appéré (2010), our model includes zero-trip responses to the contingent scenario (i.e., stated preference data not truncated at zero) in a single NB count framework. That is, in common with these studies, our approach handles on-site samples in a one-step fashion; we do not drop or separately model zero contingent trips but rather include them in an integrated RP-stated preference count model. Our approach relies on the theoretical consistency of a single-count process within a unified demand model and exploits information from zero-trip observations to yield valid welfare estimates in cases of environmental deterioration.

Our estimates of contingent behavior under increased nightlight from the weighted LCNB and the weighted FENB models are largely consistent. This allows us to infer that the weighted LCNB regression effectively accounts for endogenous stratification and respondent heterogeneity.

We use the weighted LCNB to infer the consumer welfare value for a marginal change in nightlight at the park. In a NB count model, consumer surplus per day is calculated as: $CS\,per\,day = -(1/\gamma_c)$, where γ_c is the estimated coefficient for the *travel cost* variable (Haab & McConnell, 2002). Note that $days_{it}$ represents visit days per person (party-days $\times$ party size). This specification has the advantage of adding information as well as variation to the travel demand dependent variable (e.g., Bhat, 2003; Bowker et al., 1996; Heberling & Templeton, 2009; Martinez-Espineira & Amoako-Tuffour, 2008).

After estimating the total consumer welfare for each day of visit at the site, we can combine it with the coefficient of nl_{it}, which represents the marginal visitation change due to nightlight pollution, to estimate the welfare value of a marginal change to nightlight at the site.

It is important to clarify the distinct roles of our modeling approaches in addressing methodological concerns. The LCNB structure primarily accounts for unobserved heterogeneity among visitors by segmenting the respondent population into distinct LCs with different underlying visitation behaviors and preferences (Hynes & Greene, 2013, 2016). This captures differences in visitation rates and responsiveness to night sky quality among distinct visitor groups that a single-class model would obscure.

However, LC modeling alone may not be sufficient to correct for endogenous stratification, which arises from our on-site sampling design, where frequent visitors are disproportionately represented. To correct for this stratification bias, we employ inverse visitation-day weighting (Shi & Huang, 2018), which systematically down-weights responses from high-frequency visitors. By combining inverse weighting with the LC structure, we simultaneously address both endogenous stratification and preference heterogeneity effectively.

3.4 | Data description

The project team collected 367 completed surveys, each corresponding to a visitor party comprising 1 or more individuals. From these responses, we remove those that do not provide an identifiable home location or days of presence at the park. We further exclude international travelers and travelers with a home location in Alaska and Hawaii from the present analysis. This leaves us with 330 visitor parties. Table 1 provides descriptive statistics of the responses that we use for the remaining analysis.

According to our survey data, visitors took an average of 2.66 trips to the park in the last 5 years. On average, visitors spend 2.68 visitation days per person over the last 5-year period.

Next, we ask tourists to rate the quality of the night sky on a scale of 0 to 10, with 10 being the most pristine. The average rating is 8.93, with 90% of tourists rating the sky over 8. Then, we ask tourists if they would take fewer trips and/or stay for fewer days per trip in the next 5 years if the night sky at the park were to resemble the one at their home, while all amenities and other park qualities remained the same. In response, 47% of the respondents indicate that they would spend fewer days at or take fewer trips to the park in the next 5 years. The average visitation days per person over the next 5 years dropped to 1.60 days in this hypothetical scenario.

We estimate each respondent's *travel cost* to and from the park by combining the national park private vehicle access fee of $25 and an estimated round-trip automobile fuel cost between the site and the respondent's home base. In estimating *travel cost* as a per-mile automobile cost times round-trip mileage between the respondent's home base and the destination recreation site, we follow typical practice in TCM (Parsons, 2017). We first estimate the driving distance using the crow-fly distance between the reported home base and adjusting it with a coefficient of 1.417, following Boscoe et al. (2012). We then apply the 2010 US fleetwide mileage per gallon of 17.4 mpg and the average gas price per gallon of $3.613 for regular grade all formulations retail gas in October 2023 (US Energy Information Administration, 2024a, 2024b). As a comparison, the fleetwide mileage per gallon in 2022 is 18.5 mpg. We use the 2010 mpg value because the average age of light motor vehicles in the United States is 12.5 years (Bureau of Transportation Statistics, 2024). Lastly, we divide the estimated total *travel cost* for each visitor party by the number of days each visitor party spent at the site; it gives an average estimated transportation cost per day of $300.89.

Researchers have taken varied approaches to measuring the opportunity cost of time for recreational travel, with no consensus (e.g., Czajkowski et al., 2019; Feather & Shaw, 1999; Parsons, 2017). Parsons (2017) notes that about half of the studies use one-third of the hourly wage, while others use different values, and some suggest travel itself provides positive utility. Czajkowski et al. (2019) observed that the cost of travel time remains a persistent uncertainty, and that assumptions linking travel time to a fixed share of wages are unreliable, as many respondents report no desire for shorter travel. Given these complexities, we exclude travel time costs from round-trip travel costs.

TABLE 1 Descriptive statistics.

Category	Mean	SD	Observations
Number of past days	2.68	3.14	330
Number of contingent days	1.60	2.74	329
Transportation cost per day	300.89	303.30	330
Number of past trips	2.66	1.47	330
Home base light	17.39	18.74	329
Park night sky rating	8.93	1.31	198
Age			
16–24	11.52	31.97	38
25–34	26.36	44.13	87
35–44	22.73	41.97	75
45–54	13.33	34.05	44
55–64	11.21	31.60	37
65+	14.85	35.61	49
Education			
High school or less	8.39	27.76	27
Some college/associate degree	8.07	27.29	26
College degree	44.72	49.80	144
Graduate degree	38.82	48.81	125
Occupation			
Primary and industrial services	5.96	23.72	14
Trade, transportation, retail, and admin services	8.94	28.59	21
Finance, real estate, information, and professional services	51.91	50.07	122
Educational, health, and social services	21.70	41.31	51
Arts, entertainment, recreation, public, and other services	11.49	31.96	27
Home base			
Urban	26.97	44.45	89
Suburban	53.33	49.96	176
Rural	19.70	39.83	65
Home base is in Colorado			
No	43.03	49.59	142
Yes	56.97	49.59	188
First time visiting Great Sand Dunes			
No	54.85	49.84	181
Yes	45.15	49.84	149
Have seen night sky at Great Sand Dunes			
No	42.81	49.56	140
Yes	57.19	49.56	187

Note: This table presents descriptive statistics. *Home base light* is based on the 2022 average monthly cloudless nightlight levels from VIIRS for each respondent's home base. Other variables are derived from survey responses. Except for the first panel, the mean values of all categorical variables are expressed as percentages of responses.

Nightlight is measured using cloud-free composite imagery from the VIIRS Day/Night Band (VIIRS DNB) provided by the National Oceanic and Atmospheric Administration's (NOAA) Earth Observation Group (Elvidge et al., 2013). These data have a spatial resolution of approximately

15 arc-seconds (~500 m). For each respondent's home base, we matched their ZIP code to the average monthly cloudless *nightlight* VIIRS radiance values from 2022, providing a stable, representative baseline that averages out short-term anomalies, as respondents likely perceive home sky brightness in general rather than as a specific monthly snapshot. For the Great Sand Dunes National Park area, we specifically used the VIIRS radiance measured in October 2023 (0.28 $nW/cm^2/sr$) to reflect the actual night-sky conditions visitors experienced during our survey period.

The VIIRS sensor measures upward radiance rather than direct perceived sky brightness. Due to its spectral sensitivity range (~ 500–900 nm), VIIRS may systematically underestimate brightness from blue-rich LED lighting, increasingly common in urban areas (Gibson et al., 2020; Kyba et al., 2015, 2017). Thus, our reported VIIRS radiance values for urban home locations (averaging approximately 17.39 $nW/cm^2/sr$ across respondents, with individual urban areas as high as 32.08 $nW/cm^2/sr$) could represent conservative estimates of actual sky brightness perceived visually by human observers. Additionally, the extremely low radiance at Great Sand Dunes (0.28 $nW/cm^2/sr$) approaches the VIIRS detection limit. Consequently, while we have confidence that the park's night sky is exceptionally dark relative to typical rural or urban locations, some caution is warranted in interpreting this specific numerical value. Nevertheless, the large magnitude difference between the park's radiance and urban averages provides robust evidence of the park's uniquely dark conditions.

We further collect demographic information from each respondent. Approximately 49% of visitors are aged between 25 and 44. Over 83% of visitors hold at least a college degree. Excluding retirees, students, and full-time homemakers, most visitors are employed in professional fields (Finance, Real Estate, Information, and Professional Services) and public services (Educational, Health, and Social Services). More than 50% of visitors come from suburban areas, while 27% are from urban locations. Fifty-seven percent of respondents are traveling from within Colorado. About 45% of respondents reported that it was their first time at the park, and 43% have yet to see the night sky in the park area. We do not exclude respondents who have not seen the night sky in our survey, as this allows us to maintain a larger sample base and not overlook visitors who may wish to stargaze during their current or future visits to the park. Our surveyors informed visitors about the site's International Dark Sky Park designation and described its dark sky scenery to visitors as they completed the survey. We conduct a robustness check in the following section to show that respondents who have yet to see the night sky neither overstate nor understate their responses to the contingent scenario of a change in night sky quality, compared to other respondents.

In Figure 2, we compare the reported total visitation days per person over the next 5 years if the night sky were to become brighter. The red line near the origin indicates the current level of light at the park, which is a value of 0.28. If the sky were to resemble that of Fort Collins (zip code 80521), tourists state that they would spend 0.81 fewer days on average at the park in the next 5 years. If it were to resemble that of Denver (zip code 80205), tourists state that they would spend 1.51 fewer days on average at the park in the next 5 years.

4 | RESULTS

4.1 | Nightlight pollution impacts on visitation behavior

We first analyze whether an increase in *nightlight* pollution impacts tourist visitation days to the site and present the results in Table 2. Column 1 displays the regression results using a Negative Binomial (NB) model without adjusting for endogenous stratification or individual fixed effects. Columns 2 and 3 show the results using Fixed Effect regression with NB distribution (FENB). We employ the Shi and Huang (2018) method to adjust for endogenous stratification by applying the inverse of visit days as a weight for the weighted FENB regression in Column 3. The estimated coefficient for *nightlight* pollution (*nl*) from the NB regression in Column 1 is negative, as expected, and statistically significant at the 5% level. As discussed in previous sections, the NB model (Column 1) does

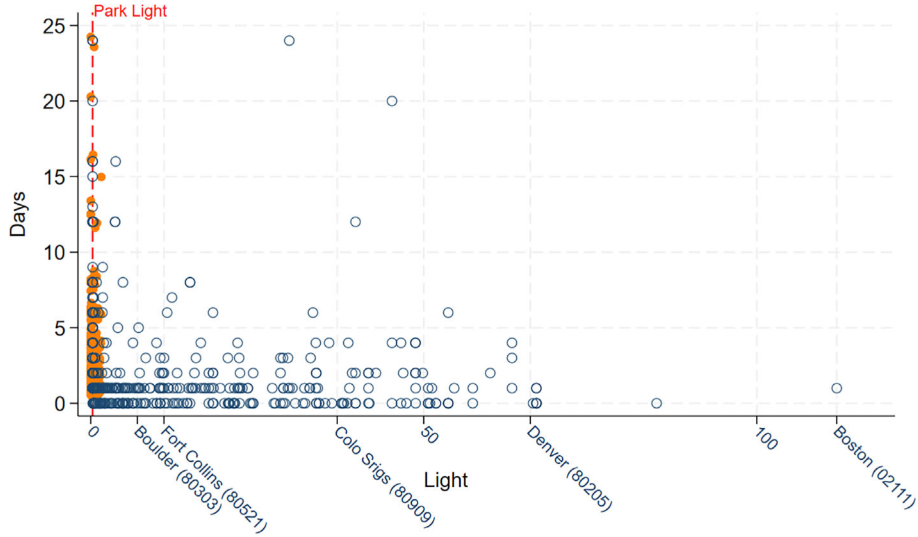

FIGURE 2 Counterfactual *nightlight* levels at the park and reported *visitation days*. This figure compares respondents' reported *visitation days* over the next 5 years under different *nightlight* conditions. The red line marks the park's current *nightlight* level (0.28). The horizontal axis is the counterfactual *nightlight* level, and the vertical axis is the reported *visitation days*.

TABLE 2 Regression results: impact of nightlight pollution on visitation days.

	(1)	(2)	(3)
Variable	**NB**	**FENB**	**Weighted FENB**
nightlight	−0.0145**	−0.0166***	−0.0186***
	(0.0053)	(0.0027)	(0.0039)
travel cost	−0.0019***		
	(0.0002)		
age	−0.0585		
	(0.0311)		
age^2	0.0007*		
	(0.0003)		
Constant	2.6288***	3.2444***	17.3171
	(0.7493)	(0.5601)	(841.9662)
lnalpha	−0.0571		
	(0.1606)		
AIC	2675.5670	772.0926	365.8567
Log likelihood	−1331.7835	−384.0463	−180.9283
Observations	657	662	662

Note: Standard errors in parentheses.
Abbreviations: AIC, Akaike information criterion.
*Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

not account for on-site survey endogenous stratification or individual heterogeneity. Once we address these factors, the estimated coefficient for *nightlight* increases in absolute value and becomes statistically significant at the 1% level.

We consider the weighted FENB regression in Column 3 to be our benchmark estimation of tourists' contingent behavior regarding nightlight pollution. In addition to our preference for it a priori due to its corrections for endogenous stratification and individual heterogeneity, it also has the lowest absolute log-likelihood value and the lowest Akaike Information Criterion (AIC) score, indicating the best fit for our data. Each unit increase in *nightlight* pollution at the site decreases a visitor's visitation by approximately 1.88% (calculated using 1 − exp[0.0186]). Considering that the average per-person visitation days over the past 5 years is 2.68, a 1.88% reduction translates to about 0.05 days lost per person in the next 5 years for each unit of increase in *nightlight* pollution. Respondents from brighter home locations (for whom the personalized contingent scenario represented a larger loss of darkness) reported larger reductions in visitation, a pattern that aligns with economic intuition and suggests the credibility and internal consistency of the responses to the contingent scenario.[5]

4.2 | Robustness check on group-specific factors

As discussed, group-specific factors can bias our estimation of visitation behavior change due to nightlight pollution. Table 3 provides a series of robustness checks based on respondent demographics. Each column is a FENB regression based on Column 2 of Table 2, augmented with interaction terms of each group and *nightlight*.[6] Across Columns 1–5, we do not find statistical significance in the interaction terms; hence, we cannot reject the null hypothesis and infer that group-specific factors do not affect the impact of nightlight pollution on visitation behavior. Importantly, the coefficients on *nightlight* demonstrate consistent statistical significance. Though varying from −0.0155 to −0.0231, they fall within the 95% confidence interval of benchmark estimation in Column 3 of Table 2 without any group interaction terms.[7]

Column 4 investigates potential confounding between respondents' travel distance and home *nightlight* levels. Visitors traveling from greater distances often originate from urban locations with brighter home skies, raising the concern that distance might drive our findings. To test this, we included an interaction term between home *nightlight* and a binary indicator of Colorado residency (Table 3, Column 4). The interaction was statistically insignificant, confirming that the response to changes in night-sky brightness did not differ systematically between Colorado residents (who generally have shorter travel distances) and visitors from other states. Additionally, our LC modeling approach naturally segments respondents into groups that reflect frequent local visitors versus infrequent, more distant tourists, implicitly accounting for any underlying distance-related heterogeneity. Thus, these robustness checks confirm that our key results are not driven solely by long-distance visitors, reinforcing the generalizability and internal validity of our findings.

Column 5 addresses potential differences in contingent behavior responses between visitors who have personally observed the park's night sky and those who have not. Since some respondents had not directly experienced the park's night skies, our surveyors informed all participants about the park's exceptional night-sky quality, emphasizing its Gold Tier International Dark Sky Park status and minimal artificial lighting. Previous contingent behavior studies have shown that respondents without direct personal experience can provide valid responses when adequately informed about relevant environmental attributes (Cameron & Englin, 1997; Kniivilä, 2006; Whitehead et al., 1995).

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[5]We also tested for parameter stability across the revealed preference (RP) and stated preference (SP) data following Englin and Cameron (1996). Specifically, we included two interaction terms in the NB model in Column 1, Table 2: (*CB* × *travel cost*) and (*CB* × *nightlight*), where *CB* is a binary indicator variable denoting the source of the data for each observation ($CB = 1$ for contingent behavior data and $CB = 0$ for revealed preference data). The estimated coefficients for both interaction terms are not statistically significant ($z_{CB\times travel\ cost} = -0.96$ and $z_{CB\times nightlight} = -0.55$). This result indicates that (a) pooling the RP and SP data is appropriate even without including interaction terms, and (b) convergent validity (based on the consistency of results across revealed and stated preference data) (Loomis, 1993; Pearce et al., 1998) holds for this dataset, though this may not necessarily be the case in all applications (Englin & Cameron, 1996). Note that such parameter stability tests are not possible in the fixed-effects regressions in Columns 2 and 3 of Table 2, since the cost variable is absorbed into the individual fixed effects.

[6]Ideally, we would conduct the weighted FENB as in Column 3 of Table 2. Given the limited sample size, the added interaction terms prevent the weighted regression from reaching convergence.

[7]Table 2 Column 3, the 95% confidence interval for light is [−0.0262, −0.0110].

TABLE 3 Robustness check on group-specific effects.

Variable	(1) Home base	(2) Age	(3) Education	(4) Colorado	(5) Have seen
nightlight	−0.0155***	−0.0167***	−0.0226**	−0.0227***	−0.0231***
	(0.0032)	(0.0033)	(0.0093)	(0.0064)	(0.0059)
nightlight × *suburban*	−0.0036				
	(0.0055)				
nightlight × *rural*	0.0016				
	(0.0401)				
nightlight × *age2*		−0.0060			
		(0.0070)			
nightlight × *age3*		0.0055			
		(0.0059)			
nightlight × *somecollege*			0.0034		
			(0.0156)		
nightlight × *college*			0.0099		
			(0.0100)		
nightlight × *grad*			0.0041		
			(0.0100)		
nightlight × *colorado*				0.0074	
				(0.0070)	
nightlight × *seen*					0.0084
					(0.0066)
Constant	3.2096***	3.3732***	3.3111***	3.3331***	3.3866***
	(0.5523)	(0.6657)	(0.5771)	(0.6101)	(0.6428)
Observations	662	662	646	662	656
Individual FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports FENB regressions with group-specific interaction terms. Column 1 groups individuals by *home base* (*rural*, *suburban*, urban—omitted). Column 2 groups by *age* (*age1*—omitted: <36; *age2*: 36–55; *age3*: over 55). Column 3 groups by *education* (high school or below—omitted, *somecollege*, *college*, *grad*). Column 4 groups by residency (*colorado* vs. out-of-state—omitted). Column 5 groups by whether individuals have seen the park's night sky (*seen*). Standard errors in parentheses.
*Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

To test for systematic differences based on prior night-sky experience, we interacted the *nightlight* variable with an indicator variable for whether respondents had previously seen the night sky at the park (Table 3, Column 5). The interaction term was statistically insignificant, confirming that respondents lacking direct night-sky experience provided responses indistinguishable from those who had personally observed the park's night sky. This robustness check demonstrates that including respondents without prior night-sky experience at the park did not bias our results, further confirming the internal validity and robustness of our contingent behavior estimates.

4.3 | Baseline consumer surplus of visits to the park

The advantage of the NB TCM in Column 1 of Table 2 is that it establishes a consumer welfare estimation for each day at the site. However, given endogenous stratification due to on-site sampling and individual heterogeneity, we augment it with a set of LCNB models, following Hynes and Greene (2013, 2016). Moreover, we compare a two-latent-class NB model with one augmented with

TABLE 4 Regression results for latent two-class NB and weighted latent two-class NB models.

	LCNB		Weighted LCNB	
	(1)	(2)	(3)	(4)
Variable	Class 1	Class 2	Class 1	Class 2
nightlight	−0.0180***	−0.0014	−0.0075	−0.0193***
	(0.0030)	(0.0085)	(0.0043)	(0.0047)
travel cost	−0.0011***	−0.0060***	−0.0036***	−0.0003**
	(0.0002)	(0.0013)	(0.0005)	(0.0001)
age	0.0090	−0.3819***	−0.0143	0.0063
	(0.0164)	(0.0597)	(0.0191)	(0.0107)
age^2	−0.0002	0.0035***	0.0003	−0.0001
	(0.0002)	(0.0006)	(0.0002)	(0.0001)
Constant	0.9448**	2.1948***	12.6836***	0.1341
	(0.3413)	(0.3727)	(1.5465)	(0.2397)
lnalpha in latent class	−1.3471***	−1.3471***	−4.6695***	−4.6695***
	(0.1956)	(0.1956)	(1.1451)	(1.1451)
Latent class probability	0.9376	0.0624	0.0510	0.9490
	(0.0159)	(0.0159)	(0.0098)	(0.0098)
Latent class average days	1.764	38.8185	3.729	1.00185
	(0.0817)	(16.7264)	(0.2871)	(0.0302)
AIC	2485.8780		1176.3310	
Log likelihood	−1230.9388		−576.1653	
Observations	657		657	

Note: This table compares the results of a two-class LCNB regression with those of a weighted two-class LCNB regression using Shi and Huang (2018) weight. AIC, Akaike Information Criterion. Standard errors in parentheses.
*Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

inverse visit-day weight, following Shi and Huang (2018). Hynes and Greene (2013, 2016) argue that the LCNB effectively accounts for on-site sampling issues and response heterogeneity. In this section, we show empirically that weighing LCNB with Shi and Huang (2018) weight better accounts for heterogeneity and on-site sampling for our dataset and given our unique survey design.

Column 1 of Table 4 shows that a two-class LCNB without weighting partitions the sample with a 94% probability for Class 1 and a 6% probability for Class 2. Class 1 has an average number of visit days of 1.76, while Class 2 has 38.82. After weighing the sample with inverse visit days, Column 2 reports a Class 1 probability of 5% and a Class 2 of 95%. Weighted LCNB has an average number of visit days of 3.73 for Class 1 and 1.0 for Class 2. This suggests that the Shi and Huang (2018) weight method discounts high visitation observations and allows the LC methods to split the sample based on further heterogeneities in respondents. Overall, the weighted Latent 2 Class NB in Column 2 of Table 4 best fits our on-site sampling data, given its lower absolute value in log-likelihood and AIC score.[8] Therefore, we consider the weighted LCNB as our benchmark to estimate the consumer surplus value.

[8]Following Hynes and Greene (2013, 2016), we determine the optimal number of latent classes in our LCNB model using standard information criteria, specifically the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). We conducted robustness checks comparing the two-class model with one-class, three-class, and four-class models. The two-class model substantially improved its fit relative to a single-class model, reducing the AIC from 1221.6 to 1176.3 and the BIC from 1248.5 to 1230.2. When further expanding to three or four classes, the AIC and the BIC scores indicated no meaningful improvement (AIC increased to 1186.3 and BIC to 1267.1 for three classes, and further worsened to an AIC of 1194.4 and BIC of 1302.1 for four classes), suggesting overfitting and reduced interpretability. Thus, the two-class latent model was the most appropriate specification, balancing statistical fit and parsimony effectively, consistent with established practices in latent class recreation demand modeling (Hynes & Greene, 2013, 2016).

We invert the coefficient for *travel cost* to derive the mean consumer surplus (Haab & McConnell, 2002). Then, since each survey response represents a party (group) visit, we scale the consumer surplus to the individual level by dividing the mean per-party consumer surplus by the average party size (2.59) to obtain consumer surplus per person-day (e.g., Bowker et al., 1996).[9] Both latent classes of Columns 1 and 2 have statistically significant coefficients on *travel cost*. Column 1 suggests a consumer surplus of \$350.83 from Class 1 and \$64.45 from Class 2 per day per person at the site. After weighing the sample towards lower visitation days, Column 2 suggests consumer welfare of \$107.29 from Class 1 and \$1286.38 from Class 2. Following Hynes and Greene (2013, 2016), the unweighted LCNB provides an average consumer surplus of \$323.95 per visitor per day using the respective class probabilities. The weighted LCNB provides an average of \$1226.29 per visitor per day.[10]

The coefficient for *nl* reflects the estimation of the consumer's change in visitation behavior due to nightlight pollution. The unweighted LCNB has an estimated coefficient of −0.018 for Class 1 (significant at the 1% level), while the coefficient is statistically insignificant for Class 2. The weighted LCNB shows −0.0193 for Class 2 (significant at the 1% level), whereas it is statistically insignificant for Class 1. Both coefficients fall within the 95% confidence interval of the estimation in Column 3 of Table 2. Since the estimated coefficient is statistically insignificant for one of the classes in each model, we do not include it in calculating the overall contingent behavior. Following Hynes and Greene (2013, 2016), the overall marginal change in visitation for a one-unit increase in *nightlight* is −0.0169 for the unweighted LCNB and −0.0183 for the weighted LCNB.

In the next section, we link the estimated change in visitation due to nightlight pollution with the calculated daily total consumer surplus at the site to assess the consumer's welfare valuation of nightlight pollution in monetary terms.

4.4 | Welfare valuation of nightlight pollution

An important feature of our approach is that the contingent scenario is a continuous space; therefore, each visitor has a different comparison point. Our regression analysis controls for individual factors and shows the mean behavior change in visitation days due to a marginal increase in nightlight pollution.

To illustrate the implications of the marginal effect and convert it to a welfare valuation in a more accessible way, we present calculations in Table 5 using both the unweighted LCNB and our preferred benchmark, weighted LCNB regressions. We develop three synthesized contingent scenarios: transformation of the park's nightlight to mean rural, suburban, and urban states, by averaging the home base nightlight based on that experienced by visitors from each of those three home base categories (Row 1 of Table 5). We then aggregate the marginal contingent behavior change and welfare value for each synthesized scenario.

Rows 3 and 4 of Table 5 show the days lost if the park's nightlight were as bright as the average rural, suburban, and urban night. Specifically, we use the formula $\Delta days = days_{\text{hist}} - \exp\left(\gamma_{nl} \times \left(nl_{\text{cf}} - nl_{\text{park}}\right)\right) days_{\text{hist}}$, where $days_{\text{hist}}$ is the average historical visit days, nl_{cf} is the counterfactual synthesized nightlight, nl_{park} is the actual park nightlight, and γ_{nl} is the estimated regression

[9]An alternative approach would be to treat each individual as if they incurred a pro-rated share of their party's *travel cost* (e.g., dividing each party's *travel cost* by its size upfront). Doing so in the model or in post-calculation would lead to an almost identical mean consumer surplus figure for the "average visitor." In this paper, we follow standard convention in travel cost modeling and divide the mean per-party consumer surplus, which is derived by inverting the *travel cost* coefficient, by mean party size to estimate mean per-person consumer surplus.

[10]We conducted further heterogeneity analysis, decomposing the sample into small visitation day windows, particularly for days 0–5, 1–5, 2–5, 6–12, 6–16, and 6–20. Given the small sample size, we can only use unweighted NB and weighted NB regressions. Our estimates suggest a diminishing marginal utility for days spent at the park. Visitors who spend fewer days at the park derive the highest marginal utility for each additional day. In comparison, visitors who spend more days derive the lowest marginal utility for each additional day. Weighing the sample towards low visitation days using the Shi and Huang (2018) weighting method adjusts the estimated consumer welfare towards the origin of the utility curve, hence the higher marginal value.

TABLE 5 Estimates of losses in recreation days and consumer surplus from potential increases in nightlight pollution at the park.

	Synthesized scenarios		
	(1)	(2)	(3)
Measure	**Rural**	**Suburban**	**Urban**
Average nightlight	1.8173	15.3257	32.0768
Days lost per visitor in the next 5 years:			
LCNB	0.075	0.647	1.186
Weighted LCNB	0.069	0.602	1.115
Equivalent consumer surplus loss per visitor per year:			
LCNB	$4.45 (3%)	$39.02 (23%)	$72.27 (42%)
Weighted LCNB	$18.27 (3%)	$158.66 (24%)	$290.79 (44%)
Equivalent aggregate consumer surplus loss per year:			
LCNB	$2,226,521	$19,510,272	$36,132,641
Weighted LCNB	$9,137,341	$79,330,106	$145,395,875

Note: This table presents estimates from unweighted and weighted LCNB regressions under three synthesized *nightlight* scenarios (rural, suburban, urban). It reports the average synthesized *nightlight* levels, the estimated reduction in *visitation days* per visitor over 5 years, the corresponding annual consumer surplus loss per visitor, and the aggregate annual consumer surplus loss (assuming 500,000 visitors).

coefficient for *nl*. Using the unweighted LCNB estimation, each visitor would reduce their days at the site in the next 5 years by 0.08, 0.65, and 1.19 days if the park night were to become as bright as the mean rural, suburban, and urban nightlight, respectively. With the weighted LCNB estimation, the reductions are 0.07, 0.60, and 1.12 days, respectively.

Rows 6 and 7 of Table 5 calculate the average consumer surplus loss for each synthesized contingent scenario. The unweighted LCNB estimates $323.95 for consumer surplus per visitor per day at the park, while the weighted LCNB estimates $1226.29. We multiply the estimated consumer surplus per day by the visitation days lost due to increased nightlight pollution and adjust the time frame to yearly to estimate the equivalent consumer surplus loss per year. On average, visitors incur a welfare loss valued at $4.45, $39.02, and $72.27 per year using unweighted LCNB estimation, and $18.27, $158.66, and $290.79 per year using the weighted LCNB, for park nightlight transformations to mean rural, suburban, and urban home base nightlight, respectively.

To provide perspective on these monetary losses, we express them as percentage decreases relative to a baseline annual consumer surplus per visitor. For instance, using the unweighted LCNB for the suburban scenario: visitors averaged 2.68 visit days over 5 years, which equates to approximately 0.536 days per year (2.68 divided by 5). Multiplying the daily consumer surplus of $323.95 (as reported in the previous section from Table 4) by 0.536 results in a baseline annual consumer surplus of $173.64 per visitor. In the suburban scenario, the estimated annual loss amounts to $39.02 per visitor, which represents about 22.5% (rounded to 23%, as shown in Table 5). Similar calculations indicate losses of approximately 3% for a transformation to a rural brightness and 42% for an urban brightness with the unweighted model, as well as 3%, 24%, and 44% with the weighted model, respectively.

Finally, we augment the individual visitor behavior and losses with total visitation numbers to calculate aggregate consumer surplus losses per year (Rows 9 and 10). In 2022, there were 493,428 total recreation visits to Great Sand Dunes National Park and Preserve (Flyr & Koontz, 2023). For estimation purposes, we conservatively assume that the baseline average number of total recreation visits to the park over the next 5 years would be 500,000 annually. For our site, a transformation to mean rural home base nightlight seems to be the most plausible of the three scenarios in the immediate future. However, we include the suburban and urban scenarios for completeness and to show how losses would likely increase if the night sky became brighter.

5 | CONCLUSION

This study estimates consumer surplus losses from potential increases in nightlight pollution at the Great Sand Dunes National Park and Preserve, a Gold Tier International Dark Sky Park. Using on-site intercept surveys and the CBM, our analysis indicates that even modest increases in nightlight pollution, comparable to nearby rural levels, would reduce visitation by 3% and lower consumer surplus. Larger increases would further decrease visitation, spending, and overall consumer surplus.

A substantial innovation in our research is measuring and presenting the quality of a site's dark sky and potential future changes in darkness to respondents. Dark sky quality is subjective, and the damage that nightlight pollution does is a continuous phenomenon. To make the concept accessible, we asked respondents to compare the night sky at the park to the night sky they experience at home. This creates a discrete and familiar scenario for each respondent and a synthetic continuous set of contingent nightlight pollution scenarios for the researcher. This method allows us to analyze a wide range of potential night sky conditions as a continuous variable. In other contingent behavior work of which we are aware, scenarios are discrete and typically few (often, one) in number.

Our approach of anchoring contingent behavior responses to respondents' own baseline conditions could also prove valuable in other environmental policy contexts involving continuous gradients of environmental quality. For instance, the European Union's Water Framework Directive aims to achieve "good ecological status" (GES) in water bodies. Policymakers could employ a continuous contingent behavior approach similar to ours, asking residents how their recreational activities (e.g., swimming, fishing, or boating trips) might change with incremental improvements towards GES in their local water quality conditions. Such a method could provide policymakers with detailed insight into the welfare benefits of achieving specific, measurable water-quality targets.

Similarly, continuous contingent behavior modeling could quantify the economic impacts of incremental increases in wildfire risk, a topic of growing relevance. Respondents could indicate how visitation or recreation patterns might shift in response to gradual increases in wildfire risk probability or area burned. Managers could then directly evaluate the incremental benefits of fire management policies or risk-reduction programs on recreational visitation, as opposed to simply comparing extreme scenarios (e.g., no wildfire versus complete closure).

Additionally, our method could effectively assess the recreational impacts of incremental increases in noise pollution (such as from aircraft, automobile, or off-road vehicle traffic) in or around natural areas. Visitors could report how their park visitation frequency or duration would change in response to increasing noise levels, measured continuously in decibels above natural ambient conditions. This would facilitate marginal damage analyses of noise pollution, providing guidance on acceptable noise thresholds for recreation management. In each case—water quality, wildfire risk, and noise pollution—anchoring respondents' contingent responses to their individual baseline conditions provides richer data than traditional binary or categorical contingent scenarios. By capturing nuanced behavioral responses across a continuum of environmental quality changes, this approach can significantly enhance the precision and policy relevance of nonmarket valuation studies.

Moreover, we use a combination of models to estimate baseline trip demand and consumer surplus, assess the impact of changes in nightlight pollution on visitor behavior, and evaluate the declines in consumer surplus caused by a brighter night sky. This combination of model approaches includes a combined revealed and stated preference NB trip demand model, augmented by a fixed-effect panel approach estimated within a LC framework, with checks for robustness concerning group-specific effects. Furthermore, the analysis incorporates inverse visit-day weights from Shi and Huang (2018). This combination of methods addresses on-site sampling issues, response heterogeneity, and the correlation among revealed and stated trip observations. The use of the inverse weights within a LC framework in this context is new to our knowledge.

It is important to acknowledge possible omissions, biases, and uncertainties in our estimation of prospective changes in consumer surplus under brighter-sky scenarios. For instance, this analysis conservatively uses recent visitation levels at the park to scale per-visitor impacts and yield aggregate consumer surplus losses. Visitation numbers typically increase over time, driven by population growth and rising income levels. Our contingent behavior scenario surveyed visitors regarding their anticipated changes in visiting habits over the next 5 years. Therefore, if one were to use projections of likely increased visitation in future years, the aggregate estimates of losses would be greater. Similarly, some respondents who visited only once in the past 5 years may not plan to visit again in the subsequent 5-year period under either unchanged or changed night sky conditions, even if they place value on maintaining pristine night skies at the site. To the extent that this is the case, scaling stated behavioral responses by recent visitation could overstate aggregate consumer surplus losses, holding other factors constant. This could lead to an upward bias in the opposite direction from the downward bias yielded by using historical data on aggregate visitation to estimate aggregate welfare changes. In addition, some respondents who do not anticipate future visits under either scenario may nonetheless experience reduced utility under increased night light pollution simply from knowing that conditions have deteriorated or that future visitors may be affected. Such effects reflect existence or bequest values, and their omission tends to understate the total values that would be foregone under a diminishment of night sky quality. Our combined RP/SP framework is designed to capture active use values conditional on observed visitation behavior, rather than broader passive or nonuse values. Capturing those additional components of total value would require a different valuation approach, such as a contingent valuation design rather than a TCM/CB framework.

Places like the Great Sand Dunes have heavily invested in updated lighting, educational programs, and community partnerships to preserve their dark skies. Our analysis indicates that these investments generate substantial economic benefits. While the park's night sky is unlikely to reach the brightness of suburban or urban areas in the near future, our estimates suggest that consumer surplus losses could exceed 25% under those circumstances. As the first rigorous study of its kind, our findings may inform the design of future research studies related to other dark-sky sites, including those with less protection from future nightlight pollution. Overall, our study provides strong evidence that dark sky preservation enhances recreation and tourism and supports incorporating dark sky conservation into broader nature preservation strategies.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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