Spatial and Temporal Responses to Incentives*

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Abstract

Individuals make decisions on location choices and timing of activities in response to changes in environmental conditions and incentives. Examples include restaurant choices, livelihood choices and recreational choices. In economic decision-making, economists focus mostly on location instead of time, thus the behavioral and welfare impacts of the incentives associated with temporal dimensions of choice are largely unknown. We develop a flexible econometric model that combines spatial and temporal choices at intensive and extensive margins to assess individuals' behavioral responses to incentives that offer time flexibility. We estimate the model using data on recreational hunting trips in Alberta, Canada to examine how individuals respond to the incentive of a longer recreation season. We find that individuals substitute activities spatially and temporally, and gain welfare benefits when there is increased flexibility in choosing the time of the activities. Our findings suggest time flexibility could be used as an incentive to change behavior when decisions involve time.

Keywords: Demand system, Substitution behavior, Incentives

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1 Introduction

Location (where to go) and time (when to go) are common components in economic decision-making, such as restaurant visits (Athey et al., 2018), leisure activities (Bhat and Gossen, 2004; Sener et al., 2008), livelihood choices (Barrett et al., 2001), and recreational activities (Dundas and von Haefen, 2019). Accordingly, individuals change behavior spatially and/or temporally in response to external shocks, regulations and incentives. For example, farmers migrate as an adaptation to reduced agricultural productivity caused by climate change (Feng et al., 2010). Commuters adjust their departure time according to different toll regimes (Arnott et al., 1993). Fishers substitute fishing locations seeking economic returns in response to spatial closures (Smith and Wilen, 2003). Recreationists change the location and time of beach visits due to temporary closures of beaches caused by oil spills (English et al., 2018; Glasgow and Train, 2018). In these cases, understanding how individuals choose location and time, and substitute activities spatially and temporally, is important for predicting demand (e.g. restaurants, recreation) and evaluating effectiveness of policy tools (e.g. regulations or incentives).

This study answers the question of how individuals make spatial and temporal decisions involving the natural environment, when receiving non-monetary incentives that allow for time flexibility. People participate in activities to benefit from the natural environment and they choose locations and time periods of these activities to maximize utility (e.g. where and when to hike, where and when to extract minerals). Policy makers can provide incentives to induce behavioral changes for improving environmental conditions (e.g. protect wildlife populations, reserve mineral resources). These behavioral changes may come at the cost of individuals. As a result, individuals' decisions reflect trade-offs among improved environment, incentives and private cost. Environmental economists have widely studied individuals' spatial decisions in response to changes in environmental conditions (e.g. wildfires, "red tide" outbreaks) while relatively few studies have focused on individuals' temporal decisions. Moreover, economists and policy makers have largely examined the behavioral and welfare impacts of direct monetary incentives (e.g. financial incentives increasing the purchase of energy-efficient vehicles in Clinton and Steinberg, 2019). Yet few studies have discussed the impact of incentives that do not offer direct monetary value but allow for a more flexible time period of activities (e.g. a year round fishing season in Abbott et al., 2018, flexible working time in Eriksson and Kristensen, 2014). This study answers this research gap in the context of recreational activities, where individuals consider location and time when receiving incentives with time flexibility.

This study makes two contributions to the environmental valuation and general economics literature. First, from a methodological perspective, this study develops a flexible econometric model to capture individuals' choice behavior by explicitly incorporating spatial and temporal decisions in a demand system. Different from previous studies that capture one dimension of individual decision making (e.g. spatial choices), the proposed model in this study captures multiple dimensions (e.g. spatial and temporal choices). As such, this study presents a more behaviorally consistent model for demand estimation and prediction in terms of individual behavior. The associated welfare measures also derive more accurate values of the natural environment.

Second, from a conceptual perspective, this study provides insights into the use of non-monetary incentives associated with time. Compared to the majority of the economics research that examines monetary incentives (e.g. rewards) or non-monetary incentives (e.g. commodities) that could be converted into monetary values, in this study, we discuss a unique type of incentive: the incentive that offers time flexibility for individuals to obtain utility. For individuals, this type of incentive could increase welfare by increasing the choice set in the temporal dimension (e.g. working, shopping time). For incentive providers such as policy makers or private companies, this type of incentive could be effective in achieving desirable outcomes at a relatively low cost. For example, companies could increase employees' productivity by adding working-time flexibility arrangements without increasing incentive pay (Eriksson and Kristensen, 2014).

The method used in this study is extending the discrete-continuous (often called the Kuhn-Tucker) econometric model, with a focus on spatial and temporal substitution behavior (especially recreation trips), as well as economic benefit measurement. The proposed model captures spatial and temporal choices by recasting choice sets from alternative locations or time periods to alternative locations in each time period. In addition, the proposed model captures decisions at extensive (whether or not to choose a location in a time period) and intensive (trip frequencies) margins. The empirical application of the model is used to study recreational hunters' behavioral responses to the presence of a wildlife disease and the program of season expansions to engage hunters in the disease management. The model is estimated using data from a revealed and stated preference survey of recreational hunters in Alberta, Canada.

Our findings suggest that individuals change recreation location and time when they receive the incentive of the season expansions. We find spatial and temporal substitution behavior caused by the incentives and this behavior is not captured if only the spatial or temporal dimension is examined. An extended season is an effective incentive to engage recreational hunters for disease management because it generates welfare benefits for individuals. Also, we find that the wildlife disease does not appear to affect individuals' behavior which increases the merit of the increase in flexibility as a wildlife conservation policy tool. In general, the findings in this study suggest a time-flexible incentive is effective in encouraging desirable behavioral outcomes when the decision involves location and time.

The remainder of the paper is organized as follows. Section 2 provides a brief review of relevant literature in recreation demand models and welfare measures. Section 3 describes the conceptual model that is used to develop the empirical model. Section 4 introduces the empirical application. Section 5 describes the data used for the empirical analysis. Section 6 provides details on the empirical model and analysis. Section 7 reports results on estimation, spatial and temporal substitution as well as welfare estimates. This is followed with conclusions and the discussion on policy implications.

2 Relevant Literature

Economics literature has applied various choice models to examine individuals' economic decisions such as purchasing decisions. Among these economic decisions, decisions on outdoor recreational activities have motivated environmental economists to model recreation demand to value the natural environment. This section presents a summary of common recreation demand models regarding assumptions on choice, substitution pattern and associated welfare measures.

Recreation demand models apply micro-econometric frameworks to analyze recreation choices in space and time, as well as trip frequencies of recreational activities. Decisions on recreation trips can be divided into the participation decision and the frequency decision. The participation decision is whether to take a trip to a site during one time period and the frequency decision is the number of trips to take based on the participation decision. Two common approaches to model this decision-making process are discrete choice models and the discrete-continuous (often called the Kuhn-Tucker, or corner solution) models. These two approaches explicitly incorporate spatial substitution among multiple sites or temporal substitution across different time periods. However, most studies have focused largely on the spatial dimension while relatively few studies examine the temporal dimension.

Discrete choice models (DCM) that focus on the participation decision are often extended to repeated discrete choice models for the frequency decision. Repeated DCM have been widely applied to examine spatial substitution through different assumptions on error term structures (e.g. nested logit in Morey et al., 1993, random parameter logit in Train, 1998). However, limited studies examine temporal substitution using DCM because the assumptions of the DCM restrict the estimates of seasonal benefits (Phaneuf and Smith, 2005). Herriges and Phaneuf (2002) use repeated logit models (i.e. repeated nested logit and repeated mixed logit) to model spatial and temporal choices through introducing error complexity. They find richer patterns of cross-site (i.e. spatial) correlation and cross-choice occasion (i.e. temporal) correlation compared to a nested logit specification. Swait et al. (2004) incorporate temporal dependence into a multinomial panel data model through a meta-utility framework with consideration of prior behavior and past attribute perceptions. By applying this dynamic model in the context of recreational fishing, they find differences regarding behavioral choices compared to static models.

Repeated discrete choice models are limited in capturing spatial and temporal substitution patterns. First, the researchers have to specify an exogenous number of choice occasions to develop a DCM that captures a full season of trips. As the number of choice occasions for each individual is not observable by the researchers, the common practice is to assume identical choice occasions for all individuals without accounting for the likely heterogeneity of choice occasions among individuals (Bockstael and McConnell, 2007). English et al. (2018) relax this assumption by using different weights according to different reporting periods but the construction of the weights requires more information than the regular trip data. Second, the substitution patterns in DCM are mostly captured through different assumptions of the error term structure. As the error term accounts for all unobserved factors including preference heterogeneity, the substitution patterns captured by the error term are likely to be confounded with all other unobserved factors. Third, as discussed in Phaneuf and Smith (2005) and Bockstael and McConnell (2007), DCM do not introduce diminishing marginal utility from increased consumptions of trips, which can be a key factor in understanding frequency decisions (e.g. number of trips to take) and substitution patterns in response to the incentives that offer alternative time periods.

The Kuhn-Tucker (KT) approach overcomes many of the above limitations of repeated DCM. Combining the participation and frequency decisions, the KT approach is more behaviorally-consistent because it considers multiple discreteness in consumption patterns by modeling which good to consume and how many goods, while allowing for zero consumption levels (i.e. corner solutions). In the KT model, the substitution patterns and satiation effects are explicitly captured in the utility parameters instead of the error term structure. von Haefen and Phaneuf (2005) provide a summary of applications of the KT approach to non-market valuation. They apply the Kuhn-Tucker approach with a Linear Expenditure System (LES) utility specification to estimate recreation demands and welfare estimates for Canadian moose hunting site choices. Another KT specification, the multiple discrete-continuous extreme value (MDCEV) model by Bhat (2008) outperforms the LES Kuhn-Tucker specification regarding weak complementarity, the utility component of the outside good, as well as the structure of the Jacobian in empirical specification (Bhat, 2008). Abbott and Fenichel (2013) apply the MDCEV model to simulate anglers' behavior under alternative policy scenarios by incorporating their adaptive behavior.

Similar to the discrete choice approach, the KT approach has not been largely applied to examine temporal choices in recreational activities. Lloyd-Smith et al. (2019) modify the MDCEV model with a focus on intertemporal substitution by recasting the choice set into when to visit and incorporating time constraints on behavior. By examining anglers' behavioral responses to seasonal closure policy scenarios (i.e. summer versus fall closure), they find different substitution patterns across time periods. Table 1 provides a summary of recreation demand models discussed.

[Table 1]

One purpose of capturing substitution behavior in recreation demand models is to construct a more realistic welfare measure. Studies have found that welfare estimates from models that capture substitution behavior are different from ones without substitution behavior (Swait et al., 2004; Train, 1998). As such, welfare measures could be misleading without accounting for potential substitution.

Welfare measures are usually used to monetize economic gain or loss from external changes (e.g. pollution) and policy programs (e.g. site/season closures). When a recreational site or season is closed, individuals might stop recreational activities that are affected by the closure or have substitution behavior (i.e. recreate in other sites nearby or during other seasons) (Parsons et al., 2009). The associated welfare measures indicate the use value of recreational sites or seasons. The lost values caused by site and season closures is often used to advise damage assessment. Recently, several studies have examined the lost recreational use values due to the 2010 Deepwater Horizon oil spill in the Gulf of Mexico by considering cancelled trips (Whitehead et al., 2018), reduced visitation (Glasgow and Train, 2018; Tourangeau et al., 2017) and lost recreation days (English et al., 2018).

While the welfare loss of site and season closures has been discussed widely, the welfare gain of new recreation seasons or season expansions has not drawn much attention from researchers and policy makers.For recreational activities such as fishing and hunting that are often restricted by shorter seasons, a longer recreation season could generate welfare benefits for hunters and anglers because recreational fishing and hunting activities are likely restricted by short recreation seasons. Abbott et al. (2018) find economic benefits from a flexible fishing management with a longer fishing season than the current management scheme with relatively short seasons. Schwabe et al. (2001) find that hunters benefit from one extra day of deer hunting season in Ohio. Although these two studies show that a longer season could bring potential welfare benefits to recreationists, they do not discuss whether it could serve as an incentive to change recreation behavior for policy use (e.g. fish or wildlife population management).

To evaluate whether policies that add the time flexibility could be used as an incentive to change spatial and temporal choices in the context of recreational activities, we need a more flexible recreation demand model that combines spatial and temporal decisions and assesses welfare gain. This paper uses the Kuhn-Tucker approach with the multiple discrete-continuous extreme value (MDCEV) specification due to its flexibility in incorporating substitution behavior. Deviating from the typical Kuhn-Tucker model that either considers spatial or temporal choices, the modified KT model in this paper combines these two dimensions by modeling both extensive (when and where to take a trip) and intensive (how many trips to take) margins. The model captures temporal and spatial substitution patterns through utility parameters. The associated welfare estimates provide information on the benefits of the season expansion as an incentive to change behavior.

3 Conceptual Model

In order to model when and where to take recreation trips, the choice sets in the proposed model are recast from "what good to consume" (e.g. number of site visits in all time periods as in von Haefen and Phaneuf, 2005) or "when to consume" (e.g. number of recreation days in one site as in Lloyd-Smith et al., 2019) to "what good and when to consume" (e.g. number of site visits in different hunting seasons). Decisions on trip length are ignored for simplification.[1] The modified choice sets allow us to study spatial and temporal substitution in one model. One key assumption is that the location and timing of the trips are decided at the beginning of all recreation periods so that the choice sets are consistent throughout the entire recreational time period.[2]

A conceptual model is developed for the empirical analysis. Each individual is assumed to maximize utility by choosing recreation trips and consumption of a numeraire good subject to a monetary budget constraint and a time constraint. The individual's problem is

$$\max_{x_{km}} \sum_k \sum_m U(x_{km}, Q_{km}, z) \tag{1}$$

$$\text{subject to} \sum_k \sum_m p_{km} x_{km} + z \leq \overline{y} + t_w w \tag{2}$$

$$\sum_k \sum_m t_{km} x_{km} + t_w \leq \overline{T} \tag{3}$$

where:

x_{km} is the number of recreation trips to site k at time m,

Q_{km} is a vector of quality characteristics for recreation at site k at time m,

z is the numeraire good with price normalized to one,

p_{km} is the monetary cost of a recreation trip,

[1] As it is difficulty to model the decisions on trip length, most studies avoid the issue by assuming the exogenous or constant on-site time (Phaneuf and Smith, 2005). This assumption can be relaxed by extending the model to consider single and multiple-day trips as discussed in English et al. (2018).

[2] This assumption is reasonable when the recreation season is within a short period (e.g. hunting season within one to two months). However, the assumption has to be modified if the recreation season is throughout the whole year (e.g. hiking trips).

$\overline{y}$ is exogenous (non-wage) income,
t_w is the time spent working at parametric wage,
w is the parametric wage,
t_{km} is the travel time of a recreation trip,[3]
$\overline{T}$ is total available time to the individual.

As choice sets involve different time periods, we need to decide how to incorporate the time constraint into the model. The common practice in most recreation demand studies is to collapse the time constraint into the money constraint by converting the value of time into a constant fraction of the individual's wage rate with the assumption that the individual can allocate his/her time between work and leisure (Bockstael and McConnell, 2007). There are two other alternatives to incorporate the time constraint into the KT model, depending on the activities and the time horizon considered. Castro et al. (2012) discuss an activity-based approach to incorporate time constraints into the KT model where individuals' decisions on activity/travel patterns are based on their time-use decisions. Lloyd-Smith et al. (2019) include an annual constraint on leisure days to reflect individual valuation of the leisure time. As this study focuses on the time and money allocation of the same type of recreation trips rather than time and money allocation among different activities, the recreational activities in this study fall into the trip-based approach instead of the activity-based approach as discussed in Castro et al. (2012). As this study focuses on the case where individuals allocate recreation time within a relatively short period (i.e. not across the whole year), leisure time constraints are likely to be valued similarly in the time horizon considered. Furthermore, while the value of time is different across time periods, it is relatively difficult to identify the differences within a short period.[4] Therefore, the proposed model follows the common practice and collapses the time constraint into the money constraint, and assume monetary and time costs are the same for each trip to the same alternative location over the time periods. The constraints (2) and (3) can be combined into one and be rewritten as follows:

$$\sum_k \sum_m (p_{km} + t_{km} x_{km}) x_{km} + z = \overline{y} + w\overline{T} \tag{4}$$

Assuming that the consumption of the numeraire z is strictly positive (Phaneuf and Smith, 2005), the final Kuhn-Tucker conditions that define the optimal number of recreation trips

[3] t_{km} does not include on-site time in the empirical analysis due to the results (e.g. issues of endogeneity) of McConnell (1992).

[4] Given the information we collected from the survey, it is difficult to change the value of time for different individuals other than income adjustments when collapsing the time constraint into the money constraint by using the fraction of wage rate. This can be addressed in future work to incorporate individual values of time by asking recreationists willingness-to-accept (WTA) to give up time in different time periods (Lloyd-Smith et al., 2019)

to take at each site k at time m are given as follows:[5]

$$\frac{U_{x_{km}}}{U_z} \leq p_{km} + t_{km}w, \text{ k = 1,...K, m =1,...M} \tag{5}$$

$$x_{km}\left[\frac{U_{x_{km}}}{U_z} - p_{km} - t_{km}w\right] = 0, \text{ k = 1,...K, m =1,...M} \tag{6}$$

In the first equation, the left-hand side is the marginal rate of substitution between recreation trips and the consumption of the numeraire good, or marginal willingness-to-pay (MWTP) for trips to site k at time m. The right-hand side is the corresponding travel cost for x_{km}, which consists of the out-of-pocket monetary expenses and opportunity cost of the time measured in wage rate for each trip. Together with the first equation, the second equation (i.e. complementary slackness condition) represents the conditions for optimal number of recreation trips. The optimal number of recreation trips is positive when MWTP for trips to site k at time m is equal to the travel cost. The optimal number of recreation trip is zero (i.e. no trips are taken) when MWTP for trips to site k at time m is strictly smaller than the travel cost. These two Kuhn-Tucker conditions are used for empirical estimation in Section 6.

4 Empirical Application: Chronic Wasting Disease and Recreational Hunting in Alberta

The empirical application is to study recreational hunters' behavioral responses to the presence of Chronic Wasting Disease (CWD) and its management strategy of season expansions. Chronic Wasting Disease is a fatal wildlife disease that affects free-ranging deer (cervids) such as deer and elk. CWD transmits through direct contact with infected animals and indirect contact with contaminated environments (Williams, 2005). While no direct scientific evidence has found that the disease may be transmitted to humans, the possibility of the transmission is a concern (Williams and Miller, 2002). Therefore, people are recommended to avoid consuming meat from infected animals and to take precautions when handling carcasses.[6] Chronic Wasting Disease has affected cervid species in North America, the Republic of Korea, Norway and Sweden. In addition to some parts of the United States, it has been found in Alberta, Saskatchewan and Quebec in Canada. CWD is difficult to control due to its strong resilience in local environments (e.g. soil) and various transmission routes. According to the latest update in June 2019 from the Government of Alberta, the number of CWD identified cases annually has increased from 4 in 2005 to 579 in 2018, among which the majority were mule deer (87%). CWD prevalence was 12% for mule deer.[7] Furthermore,

[5] Details on the derivation are provided in Appendix A

[6] http://www.inspection.gc.ca/animals/terrestrial-animals/diseases/reportable/cwd/fact-sheet/eng/1330189947852/1330190096558

[7] https://www.alberta.ca/chronic-wasting-disease-updates.aspx?utm_source=redirector

the spatial extent of the known presence of infected animals has increased significantly since the first cases were found. Figure 1 provides a map of CWD prevalence in Alberta in 2018.

[Figure 1]

Since no treatment is available for CWD-infected animals and no vaccine is available to prevent infection, reducing infected deer populations through selective culling and hunter harvests is commonly used to control Chronic Wasting Disease. As selective culling is not widely supported by hunters and the general public (Pybus, 2012), wildlife managers in Alberta are considering changes to recreational hunting policy to engage hunters in the disease control by offering additional harvesting opportunities to maximize hunting satisfaction and remove infected deer.

The expansion of hunting season in areas with high CWD prevalence is under consideration because increasing harvests during or after the breeding season (i.e. outside of the regular hunting season) is likely to reduce prevalence (Western Association of Fish and Wildlife Agencies, 2017). Meanwhile, the expansion of hunting season might increase harvests by providing more options of hunting time periods for hunters and thus be considered as an incentive to hunt more.

Chronic Wasting Disease and extended seasons directly influence recreational hunters in three ways. First, hunting satisfaction likely decreases when wildlife population densities are perceived to be reduced by CWD (Cooney and Holsman, 2010). Second, hunting activities may be influenced by extended seasons that direct harvest towards specific areas for CWD management (Holsman and Petchenik, 2006). Third, Chronic Wasting Disease may affects hunters' risk perceptions on human health from consuming deer meat and wildlife population (Zimmer et al., 2012). These impacts are reflected in hunting behavioral changes regarding trip decisions.

Hunters' behavioral responses include changes in choices of hunting sites and time periods as well as the number of trips. Their behavioral changes are driven by Chronic Wasting Disease levels (and risk perceptions associated with CWD) and/or by the extended season. Most hunters are expected to prefer hunting sites without the presence of CWD as animal health is higher, and the hunter does not have to deal with the submission of wildlife heads for testing.[8] As a result, different prevalence levels are likely to induce hunters to change from hunting sites with high CWD risks to ones with lower or no risks (all else held constant). However, hunters who do not perceive the disease as a risk to wildlife

[8]Since there is no live test for CWD, recreational hunters are required to submit heads for CWD testing if animals are harvested in CWD-infected areas in Alberta (Alberta Environment and Parks, 2018). The process of head submissions decreases hunting satisfaction due to designated locations of head submissions and the waiting time of obtaining testing results.

populations or human health might not change site choices. At the same time, a longer hunting season for CWD management provides extra hunting opportunities for hunters. For example, expansion of hunting seasons in popular hunting sites may cause hunters to change hunting periods from regular hunting seasons to extended ones to avoid congestion. Extended hunting seasons in sites with high CWD prevalence might attract hunters if the perceived benefits are larger than the perceived costs of CWD.

5 Data

Data for the empirical application come from an online survey that collects information on the preferences and behavior of recreational hunters in Alberta, Canada.

5.1 Survey Design and Structure

To ensure the questions were understood and interpreted as expected and for a better development of the structure of the survey, we conducted two focus groups with hunters in Alberta in February 2018. The online version of the survey was pre-tested with a subset of the sample in March 2018 to check for technical issues before the survey was sent to the field.

The survey consists of five sections: background information, hunting trip recall, Chronic Wasting Disease description, contingent behavior and demographic information. The section on background information asked questions about hunting practices and hunting attributes. The section on Chronic Wasting Disease description provided information on CWD and asked questions on hunters' attitudes towards CWD and its management programs, hunters' perceptions of CWD prevalence and wildlife population health risks. The section on demographic information collected information on hunters' socio-demographic background.

The key components of the survey are sections of hunting trip recall and contingent behavior. These two sections collected revealed and stated preference data. Revealed preference data are from the section of hunting trip recall where respondents indicated the sites they went to, the number of trips they took in each site in the previous hunting season (i.e. the whole month in November of 2017). The contingent behavior section collected stated preference data where respondents indicated the number of trips they would have taken in each site in each season under scenarios with the proposed extended season for Chronic Wasting Disease management. The hunting season was proposed to be extended into the last week of October or the first 17 days of December from the current regular hunting season in November (entire month) in mandatory CWD testing zones and adjacent sites.[9] Appendix E provides an example of the contingent behavior scenario.

[9]The extended seasons in October and December were chosen based on the feedback from the focus groups

5.2 Survey Administration

The target population for the survey was recreational hunters in 2017 who held special licenses[10] for mule deer in hunting sites (i.e. Wildlife Management Unit, WMU[11]) from eastern to southeastern Alberta where Chronic Wasting Disease has existed or was likely to spread to.[12] The study area is in grey on the map in Figure 2. The survey was administered online to 5,000 eligible individuals who were randomly drawn from the license database of Wildlife Allocation Policy Branch, Alberta Environment and Parks.[13] A total of 994 respondents completed the online survey for a response rate of 19.8%.[14] We excluded respondents who either disagreed to participate the survey or did not take hunting trips in 2017. As only two policy scenarios included changes of hunting seasons, we use responses from individuals who received at least one of these policy scenarios for this study. A total of 832 observations from 416 respondents are included in the KT estimation because they provided the recall data and contingent behavior responses.

[Figure 2]

5.3 Trip Data

Revealed preference (RP) and stated preference (SP) data include information on trips under different scenarios. Table 2 provides a summary of average number of trips per person. In 2017 hunting season, each respondent took around 10 hunting trips on average. With Chronic Wasting Disease management programs in all SP scenarios, each respondent would have taken around 15 hunting trips on average. With the season expansion program in the SP scenarios, each respondent would have taken around 9 trips on average during the

and the consultations with wildlife managers. The extended season in October was shorter to avoid the overlap with other hunting seasons. Licensed hunters are allowed to have one mule deer tag during the regular season in November. The extended season in December allowed for one additional tag under the existing license while the extended season in October did not allow for it. This is to account for the possibility that recreational hunters would not have taken trips in December after filling the one tag during the regular season in November. The mandatory CWD zone and adjacent sites are designated area of CWD management because it includes sites where CWD exists or is likely to spread to in the next hunting season.

[10] In Alberta, special licenses apply to specific species in designated areas in a certain time period. Recreational hunters must apply for special licenses through a lottery system and can only buy tags to harvest animals once they win the lottery. Recreational hunters who hold mule deer special license are allowed to have one tag to hunt in the hunting season of November (Alberta Environment and Parks, 2018)

[11] As the Government of Alberta manages wildlife resources and hunting activities by Wildlife Management Unit (WMU), hunting site here refers to WMU.

[12] The study area is not limited to only CWD-infected areas for two reasons: (1) Hunters who hunt in sites adjacent to CWD-infected areas are likely to be aware of CWD spread and be affected behaviorally; (2) The purpose of CWD control strategies include reduce the prevalence and spread. Hunters who hunt in CWD surrounding areas are the "targeted" group to help reduce CWD spread by additional harvests.

[13] There were around 18851 eligible licensed hunters in the database for 2017 hunting season.https://www.albertarelm.com/cust.drawsummarymuledeer17.page

[14] The survey was implemented in Qualtrics from March to May 2018 with one invitation email and one reminder.

regular season in November. They would have taken around 6 trips on average during the proposed extended season if the hunting season was extended to either October or December – this is more than half of the trips they actually took in 2017.

[Table 2]

Figure 3 to Figure 5 present maps of trips in percentage aggregated by hunting sites (i.e. WMUs) under different scenarios. Percentage of trips over total number of trips indirectly measures the popularity of a hunting site. Sites in red are most popular, sites in green are least popular. Hunting sites with Chronic Wasting Disease prevalence rates higher than 10% in 2017 are marked with the red boundary.

Figure 3 compares the recalled total number of trips (in percentage) and stated total number of trips (in percentage) with the extended season. The graph on the right has more yellow and red areas than the one on the left, indicating that some hunting sites become more popular with the proposed extended season, especially sites with high Chronic Wasting Disease prevalence. Given that the average number of trips with SP scenarios is larger than RP scenarios in Table 2, Figure 3 indicates people are willing to take more trips with the proposed extended season.[15] Figure 4 compares recalled trips during the regular and stated trips in the extended season in the SP scenarios. Some sites in the interior of the study area become more popular in the extended season. The popularity is not reduced by CWD prevalence. Figure 5 compares trips during the extended season of October and December in SP scenarios. The popularity of sites is different in the two periods. Sites located in the north are more popular in October while sites located south are more popular in December. This pattern could be mainly driven by temperature as it is usually warmer in October than in December. There is no obvious pattern that suggests that people are driven away by the high CWD prevalence.

[Figure 3-5]

6 Empirical Model and Analysis

The Kuhn-Tucker model is applied for empirical estimation because it makes use of the nature of the count data with potential zero trips collected from hunting activities.

[15] This can be explained by two underlying reasons. First, studies have found that individuals take more trips in contingent behavior scenarios than the recall scenario (Lloyd-Smith et al., 2019). However, individuals on average take more trips (10.21) during the regular season in the recall scenario than in the contingent behavior scenario (8.67). The insignificant estimate of the contingent behavior dummy variable as shown in Section 7.1 provides supporting evidence. Second, individuals take more trips because the hunting season in the stated preference scenario is around 25 days longer than the recall scenario.

6.1 Travel Costs

The first step of the empirical analysis is to calculate travel costs for trips to each location in each time period using relevant information from the survey. As discussed in Section 3, the time constraint is collapsed into the money constraint. The formula for travel cost calculation for individual i to travel from dwelling to an alternative site k at time m is given by (Zimmer et al., 2012):

$$TC_{ikm} = \left[DIST_{ikm} \times 2 \times \frac{\text{total cost}}{\text{kilometer}}\right] + \left[\left(\frac{INC_i}{2040} \times \frac{1}{3}\right) \times \left(\frac{DIST_{ikm} \times 2}{\text{average travel speed/hour}}\right)\right] \tag{7}$$

The first term is the monetary costs for each round trip and the second term is the value of time for the trip. Monetary costs are the round-way gas expenses for recreation trips. $DIST_{ikm}$ is the travel distance from individual i's residence (approximated by first three digits postal code) to the centroid of each alternative site k. INC_i is the annual household income reported by each individual in the survey. The self-reported annual income is converted to hourly wages by dividing the annual hours worked per individual (i.e. 2040 hours worked per year as in Lloyd-Smith et al. 2019[16]). Each individual is assumed to value their hourly time at one-third of his/her hourly wage when travelling (English et al., 2015). As more than half of the respondents used trucks to access the hunting sites, we use information on trucks to calculate total cost per kilometer and average travel speed per hour.[17]

6.2 Kuhn-Tucker Model

The first-order Kuhn-Tucker conditions (i.e. Equations 5 and 6) from the conceptual model directly derive the probabilities of observing choices for the likelihood function that is used for estimation in the empirical analysis (Phaneuf and Smith, 2005). Once the right-hand side of Equation (5)) has been obtained from travel costs calculation, we need to specify the utility function to operationalize the model. We use the translated generalized constant elasticity of substitution (tCES) utility function as in Bhat (2008). This utility function is additively separable across alternative sites and the time periods.[18] The functional form is

[16] The average working hours (weighted by gender and age) for full- and part- time employment were around 2080 in Alberta in 2017. Given the average age of sample is 50, a fraction of respondents might be retired. 2040 hours gives a lower bound estimate of hours worked. Estimates using 2080 hours are almost the same as estimates using 2040 hours. Detailed statistics is available in https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410004301&pickMembers%5B0%5D=1.10&pickMembers%5B1%5D=3.1&pickMembers%5B2%5D=5.2&pickMembers%5B3%5D=6.9

[17] These two pieces of information are available on the website of Alberta Motor Association. https://ama.ab.ca/2017/06/12/the-calculated-costs-of-driving-your-vehicle/

[18] The assumption on additive separation is admittedly strict and might not be consistent with actual hunting behavior, but the functional form we chose here is relatively more flexible than other specifications as discussed above.

as follows:

$$U(x_{km}, Q_{km}, z) = \sum_k \sum_m \frac{\gamma_{km}}{\alpha_{km}} \psi_{km} \left[\left(\frac{x_{km}}{\gamma_{km}} + 1 \right)^{\alpha_{km}} - 1 \right] + \frac{\psi_z}{\alpha_z} z^{\alpha_z} \tag{8}$$

where $\gamma_{km} \geq 0$ and $\alpha_{km} \leq 1$ for all k and m are required for this function to be consistent with the properties of a utility function (Bhat, 2008). γ_{km} allows for the corner solution (i.e. zero trips) and the rate of satiation (Bhat, 2008). α_{km} represents a satiation parameter by controlling the rate of diminishing marginal utility from additional trips (Lloyd-Smith et al., 2019). ψ_{km} is the baseline marginal utility when no trips are taken. This baseline marginal utility includes a random element that ensures ψ>0 through an exponential form. The model applies the most commonly-used form in the Kuhn-Tucker approach as follows: $\psi(Q_{km}, \varepsilon_{km}) = \exp(\beta Q_{km} + \varepsilon_{km})$ for recreation trips and $\psi_z = \exp(\varepsilon_z)$ for the numeraire good. In our application, variables included in the baseline marginal utility are site attribute variables (e.g. CWD prevalence levels, extended season dummy variable) and individual-specific variables (e.g. urban/rural dummy variable, years of hunting experience, landowner dummy variable), as listed in Table 3. The resulting utility form can be written as

$$U(x_{km}, Q_{km}, z) = \sum_k \sum_m \frac{\gamma_{km}}{\alpha_{km}} \exp(\beta Q_{km} + \varepsilon_{km}) \left[\left(\frac{x_{km}}{\gamma_{km}} + 1 \right)^{\alpha_{km}} - 1 \right] + \frac{\exp(\varepsilon_z)}{\alpha_z} z^{\alpha_z} \tag{9}$$

Since hunting seasons are divided into the regular and extended hunting seasons, $m = 2$ in the application. As 43 groups of sites were visited or would have been visited during the regular season, 38 groups of sites would have been visited during the extended season, the total number of choices is 81 in the final choice set.[19]

[Table 3]

Two restrictions are imposed to address the potential identification problems in estimation. First, as γ_{km} and α_{km} both capture satiation effects from the quantity of goods consumed, only one effect can be identified in one model (Bhat, 2008). As such, we restrict the satiation parameter to be constant across all goods including the numeraire good ($\alpha_{km} = \alpha_z = \alpha$) while allowing the translation parameter (γ_{km}) to vary across trips to each site in two hunting seasons.[20] Second, the satiation parameter (α) is restricted to be between 0 and 1 for convergence considerations (Lloyd-Smith et al., 2019).

As discussed in Section 2, the MDCEV specification is flexible in capturing substitution

[19] Sites that were visited less frequently are grouped by using K-means clustering based on geographic and biological attributes for convergence consideration. As we could only sample hunters who held licenses in the study area, some respondents took hunting trips outside of the study area. These sites are grouped into three aggregate sites according to Alberta Hunting Regulation (Alberta Environment and Parks, 2018)

[20] Bhat (2008) lists three functional forms that are the same conceptually. We chose the one that fits the data set best based on the values of log-likelihood and convergence results after estimating all three functional forms.

through utility parameters. According to Bhat (2008), the formula of marginal utility of trips taken to site k at time m for the analysis of spatial and temporal substitution in Section 7.2 is given by:

$$\frac{\partial U(x_{km}, Q_{km}, z)}{\partial x_{km}} = \exp(\beta Q_{km} + \varepsilon_{km})(\frac{x_{km}}{\gamma_{km}} + 1)^{\alpha - 1} \tag{10}$$

The Kuhn-Tucker conditions in Equation 5 and Equation 6 and the utility specification in Equation 9 produce the estimating equations, details shown in Appendix A:

$$V_{km} + \varepsilon_{km} = V_z + \varepsilon_z \text{ if } x^*_{km} > 0 \text{ and} \tag{11}$$

$$V_{km} + \varepsilon_{km} \leq V_z + \varepsilon_z \text{ if } x^*_{km} = 0 \text{ where} \tag{12}$$

$$V_{km} = \beta' Q_{km} + (\alpha - 1)\ln\left(\frac{x_{km}}{\gamma_{km}} + 1\right) - \ln(p_{km} + t_{km}w) \tag{13}$$

$$V_z = (\alpha - 1)\ln(z) \tag{14}$$

The error term for each individual is assumed to follow a type 1 extreme value distribution that is independent from other individuals and choice occasions.

7 Results

7.1 Estimation

Table 4 provides parameter estimates for the modified Kuhn-Tucker model. Baseline marginal utility parameters include site attributes variables, policy dummy variables and socio-demographic variables. CWD prevalence is the only specified site attribute variable. In order to control for unobserved site attributes, we include alternative-specific constants (ASCs) for each site (Murdock, 2006). For convergence consideration, only one ASC for each site is estimated, with the assumption that baseline marginal utility when no trips are taken for each site is the same during the regular and extended seasons. The dummy variable of extended season distinguishes the baseline marginal utility of trips during the extended season, while assuming that the baseline marginal utility of trips is the same across sites in the extended season. The dummy variables of October and December extended season are to capture the difference in baseline marginal utility caused by the time of the extended season in the proposed scenarios.[21]

[21] Although the overlapping definitions of the dummy variables of the extended season, October and December cause the potential issue of collinearity, they do not fall into a dummy variable trap for two reasons. First, as some respondents receive either October or December or October and December SP scenarios, we pooled the SP trip data in October and December into one extended season so that we have enough observations for estimation. As a result, we use the October and December dummy variables to distinguish which SP scenarios respondents received. Second, regardless of SP scenarios, since each individual's choice set has alternative sites in regular and extended seasons, we use the dummy variable of the extended season to distinguish the difference between the two seasons.

Models that account for observed heterogeneity by interacting Chronic Wasting Disease prevalence levels with socio-demographic variables (e.g. urban) do not largely change parameter estimates and estimated log-likelihood at convergence, results from the simplest model are presented and discussed here. Holding all other variables and travel costs constant, the negative and insignificant CWD coefficient indicates that CWD does not affect individuals' decisions – individuals are not likely to stop hunting in CWD-infected areas. This somewhat surprising result, although is different from the findings from Zimmer et al. (2012), is consistent with the qualitative responses in the survey: 74% of respondents in the survey stated Chronic Wasting Disease did not affect their site choice decisions although more than 90% of them were aware of it. In addition, as the respondents were randomly selected from the hunters who were still hunting in CWD-infected and surrounding areas, the sample does not capture the hunter population who either stopped hunting or did not hunt in these regions any longer due to CWD. From the perspective of disease management, the hunter population that is not captured by the sample is less likely to be interested in the extended season for CWD management and less responsive to the incentives.[22] Nevertheless, this finding is consistent with a study where Pattison-Williams et al. (2019) examine mule deer hunters' responses to the spread and prevalence of CWD at the aggregate level in Alberta. With hunting draw application data across 12 years in each Wildlife Management Unit in Alberta, they find hunters do not stop applying for mule deer special licenses in the infected areas at the province level.

Individuals are more likely to take trips when the hunting season is extended into December than October. However, extended seasons are less preferred than the regular season in November for hunting trips. This might be due to respondents' strong habit of hunting in November. Most socio-demographic variables do not significantly affect hunting trip decisions except for the landowner dummy variable and the children dummy variable. Individuals who own lands in CWD-infected areas are less likely to go hunting.[23] Individuals who have children are less likely to take hunting trips. The positive and insignificant coefficient for the contingent behavior dummy variable indicates that hypothetical scenarios are not likely to induce a behavioral difference from the real scenario. Estimates in Table 4 are similar to model estimates with RP and SP data separately in Appendix D.

[Table 4]

[22] English et al. (2018) provide approaches to address sample selection/non-response bias. However, we could not apply these approaches due to limited information.

[23] Although we expect hunters who own lands would hunt more due to the easy access to the land, they might not define the activity of hunting on their lands as hunting trips.

7.2 Spatial and Temporal Substitution

With coefficients of ASCs and translation parameters, the marginal utility of trips when trips are taken (i.e. positive numbers of trips) is calculated using Equation 10. Marginal utilities calculated by different combinations of these parameters provide information on hunters' preferences towards hunting sites and seasons. Figure 6 to 8 present the results of these combinations and show the corresponding spatial, temporal, spatial and temporal substitution patterns. Figure 6 shows that individuals receive higher (around 1.5 times) marginal utility of trips during the regular season than the extended season. Individuals satiate quickly as the number of trips increases and they satiate faster when they take trips during the regular season than the extended season. There might not be an obvious temporal substitution pattern from hunting in the regular season to the extended season among all sites. Similarly, preferences towards different groups of sites are compared. We spatially group sites into four site series according to Alberta Hunting Regulation as shown on the right pane of Figure 7 (Alberta Environment and Parks, 2018). The left pane of Figure 7 shows that trips to Wildlife Management Unit (WMU) 100 Series have the highest marginal utility, second are trips to Wildlife Management Unit (WMU) 200 Series. Individuals gain similar marginal utilities when hunting in the other two site groups. There might be spatial substitution from these two groups to WMU 100 Series and 200 Series. The right pane of Figure 7 shows that WMU 100 Series and 200 Series are located in the southeast of the province – the area that Chronic Wasting Disease has existed for a relatively long period and is mostly prevalent. However, individuals are still attracted to this area. This outcome is consistent with the negative but insignificant CWD estimate. Figure 8 presents hunters' preferences towards both hunting sites and seasons. Not surprisingly, individuals obtain the highest marginal utility when hunting in WMU 100 Series during the regular season, followed by hunting in the same area during the extended season and hunting in WMU 200 Series in the regular season. Marginal utilities of trips to Wildlife Management Unit 300 Series, Wildlife Management Unit 400 Series and Wildlife Management Unit 500 Series in both seasons remain relatively low. As a result, individuals might substitute from hunting in these areas during the regular season to hunting in WMU 100 Series and 200 Series in the regular and extended seasons. This substitution pattern indicated in Figure 8 is different from the ones with only spatial or temporal dimension in Figure 6 and 7.

Figure 9 presents a choropleth map of the marginal utility of trips in the extended season at 6 trips – the average number of trips would have been taken in the extended season as in Table 2. All sites with higher marginal utilities (in red and orange) are in the area with high Chronic Wasting Disease prevalence (with yellow boundaries). Individuals obtain relatively lower marginal utilities when hunting in areas without high CWD prevalence in the extended season. This means that the extended season attracts individuals to the area with high CWD prevalence and indicates the possibility of directing harvest to CWD infected areas with an extended season.

[Figure 6-9]

7.3 Welfare Impacts of the Extended Season

With the estimated utility parameters, we simulate Hicksian welfare estimates of hunting in extended seasons by following the method described by Lloyd-Smith (2018). Table 5 reports the welfare estimates (in Canadian dollars) per individual for hunting in the extended seasons. Individuals are willing to pay around 230 Canadian dollars to hunt in the extended seasons in all sites where the season expansion program is proposed. Individuals obtain the largest welfare benefit (around 151 Canadian dollars) from hunting in Wildlife Management Unit 100 Series in the extended season regardless of the high Chronic Wasting Disease prevalence in the area. Individuals obtain a smaller welfare benefit (around 76 Canadian dollars) from hunting in the WMU 200 Series in the extended season although this group includes a similar number of sites as WMU 100 Series. These findings correspond to the insignificant CWD coefficient and the highest marginal utility of hunting in the WMU 100 Series as discussed above. Individuals are only willing to pay around 1.6 Canadian dollars for hunting in the WMU 500 Series in the extended season because the season was proposed to extend only in one site in this group. Figure 10 presents the welfare estimates per individual for hunting in the extended seasons in each of the sites in WMU 100 Series and 200 Series. The welfare estimates are heterogeneous across sites. The site where individuals obtain the highest welfare benefit (around 25 Canadian dollars) is within the area with high disease prevalence.

[Table 5]

[Figure 10]

Table 5 and Figure 10 show that individuals are better off from hunting in the extended seasons but the welfare gains vary by hunting areas. From an economics standpoint, season expansion increases welfare benefits by increasing individuals' choice set from the time flexibility. From a policy/management standpoint, season expansion is less costly to increase harvests for wildlife management than other non-monetary incentives (e.g. extra hunting tags) and monetary incentives (e.g. rewards). [24] As the extended

[24] We simulated WTP for a monetary reward of CAD 50 with the same dataset in the same model. Although individuals are willing to pay higher for the monetary reward than the extended season, the net benefit (WTP less the monetary cost) is negative. Compared to monetary rewards that directly cost money from the wildlife management agency, the cost of non-monetary incentives is more from administration. Regarding the monitoring procedure, season expansion might cost less than extra hunting tags that require checks on hunting license and number of tags.

seasons could generate around 6 additional trips on average, which is more than half of the average number of trips (around 10) they actually took in 2017, extended seasons might generate sufficient harvest for CWD control. As such, extended seasons, by offering the time flexibility, could be an effective incentive to engage individuals in the disease management because it generates additional trips, increases welfare gains at a relatively low cost.

8 Conclusion

In this paper, we explore individuals' spatial and temporal responses to non-monetary incentives that allow for time flexibility in the context of recreational activities. We develop a modified Kuhn-Tucker model by combining spatial and temporal choices into one model and incorporating spatial and temporal substitution behavior. The empirical application of the proposed model is implemented using revealed and stated preference data from an online survey of recreational hunters in Alberta, with a focus on the impacts of a wildlife disease (Chronic Wasting Disease) and its management using season expansions on hunting activities and value. We find that individuals do not appear to avoid hunting in the disease infected areas. Individuals like the extended seasons to encourage harvesting animals. We find that individuals are likely to substitute from hunting in areas with lower disease risks in the regular season to hunting in the most infected areas in both the regular and extended seasons. We assess the welfare impacts of the extended seasons by accounting for spatial and temporal substitution behavior. We find that individuals gain welfare from an extended season for disease management, especially in areas with high disease prevalence. The welfare benefits are heterogeneous across hunting areas. Our findings suggest that extended seasons, by allowing for time flexibility for trip decisions, could be used as a cost-effective incentive for disease management.

This research provides insights for studies on recreation demand and economic decisions in general. For valuation studies on recreation demand, the proposed model can be applied to recreationists' decisions on trip locations and time periods as well as frequency in outdoor recreational activities (e.g. fishing, rock/ice climbing) that are often affected by environmental conditions and relevant policies. The flexible framework will also provide more realistic implications for policy makers on managing natural resources and associated recreational activities. This study shows the importance of incorporating human behavior into the management of natural resources. For other economic decisions with multiple dimensions, the proposed model can be easily extended or modified to fit the context such as livelihood choices within households (e.g. allocating household members to local farm activities and migratory off-farm activities in the dry season) and restaurant visits (e.g. time, location and frequency of eating out). By applying the model, these studies could explore the behavioral and welfare impacts of the incentives associated with temporal dimensions of choice.

Future research could address several limitations and extend the model from this study. Since the direct implication of the empirical application is for wildlife disease management, this study could be incorporated into epidemiological models (e.g. Potapov et al., 2016) and bioeconomic models as in Horan et al. (2011). In addition, although we find season expansion could be used as an incentive to change recreation behavior, we are not able to argue if it is actually cost-effective through a benefit-cost analysis or a benefit-cost ratio for the season expansion program due to the lack of information on program costs. As the data are collected from a stated preference survey, this study suffers from issues such as data collection challenges (e.g. response bias, recall bias) and the potential for hypothetical bias like other stated preference studies. The limited number of observations used to estimate a model with many parameters restrict the further extension of the model due to convergence considerations. A larger sample would be preferable when collecting data for the application of the model in the future.

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Table 1: A Summary of Recreation Demand Models

	Model examples	Choice	Assumptions on substitution pattern
Discrete Choice Models (DCM)	**Spatial choices:** Nested logit, RPL, etc. **Temporal choices:** repeated DCM, multinomial panel data model	Participation decision	Different error term structures Constant marginal utility of trips
Kuhn-Tucker Models (KT)	**Spatial choices:** LES utility specification, MDCEV **Temporal choices:** MDCEV	Participation and frequency decisions	Different utility parameters Diminishing marginal utility of trips

Table 2: Average Number of Trips Per Person under Different Scenarios

Scenarios	**Length**	**Average Trips / Person**
RP (Actual trips)	30 days	10.21
SP (All seasons)	55 days	14.68
SP: regular season	30 days	8.67
SP: extended season	25 days	6.00

Note: According to a two-sample t test of mean difference, the mean values of RP and SP trips are not significantly different, the mean values of trips in regular season (SP) and extended season (SP) are not significantly different. Appendix B provides trip distribution table and graphs.

Table 3: Descriptive Summary Statistics of Site Attributes and Socio-demographic Variables (Nobs=832)

Variable	Description	Mean	Min	Max
CWD	Chronic Wasting Disease infected rate (%) in four categories: 0, 2.5, 7.5, 12.5	2.65	0	12.5*
October	Dummy variable if the decision is made in the scenario where the hunting season is extended into October	0.27	0	1
December	Dummy variable if the decision is made in the scenario where the hunting season is extended into December	0.29	0	1
Extended season	Dummy variable if the trip is taken during the extended hunting seasons	0.47	0	1
College	Dummy variable if hold a college degree	0.31	0	1
Urban	Dummy variable if live in urban area (20,000 people or more)	0.52	0	1
Children	Dummy variable if children under 12 in household	0.24	0	1
Yrshunt	Years of hunting experience	25.64	2	65
Landowner	Dummy variable if own land in CWD-infected areas	0.12	0	1
Income	Annual household income	98714	10000	150000

*CWD testing results come several months after the hunting season and are based on heads submitted by hunters. In other words, hunters only had CWD information from 2016 hunting season when they made trip decisions for 2017 hunting season. Therefore we use CWD information from 2016 hunting season to address potential endogeneity issue. As CWD occurs primarily to mule deer and we sampled mule deer hunters, we chose to calculate the CWD infected rate only for mule deer. The numbers represent the average infected rate in four categories: none (0%), low (1-5%), medium (6-10%), high (10% and above) (Zimmer et al., 2012).

Table 4: Parameter Estimates for Kuhn-Tucker Model

	Estimate[a]	z-stat
Baseline marginal utility parameters (β_{km})		
CWD	-0.427	-1.29
Extended season	-0.495***	-13.708
October	0.063	0.654
December	0.233**	2.252
College	-0.039	-0.64
Urban	0.013	0.266
Children	-0.159***	-2.343
Yrshunt[b]	-0.017	-0.933
Landowner	-0.178***	-2.813
Contingent behavior	0.063	0.493
ASC (mean)[c]		
ASC_WMU 100 Series&732	-3.239***	-2.362
ASC_WMU 200 Series&728&730	-4.814***	-5.48
ASC_WMU 300 Series & 400 Series	-4.436***	-12.929
ASC_WMU 500 Series	-4.943***	-14.225
Mean Translation Parameters (γ_{km})[d]		
Regular season		
WMU 100 Series&732	4.794***	12.668
WMU 200 Series&728&730	8.072***	10.6
WMU 300 Series & 400 Series	5.157***	5.922
WMU 500 Series	6.244***	4.848
Extended season		
WMU 100 Series&732	4.331***	6.954
WMU 200 Series&728&730	5.561***	7.47
WMU 500 Series	5.404***	2.458
Satiation Parameter (α)	0.219***	5.09
Scale Parameter	0.553***	42.56
N		832
Log-likelihood (mean)		-11789.17

[a]***and ** denote statistical significance at the 1% and 5% level respectively.
[b]Years of hunt (Yrshunt) index is scaled as the year of hunting experience divided by 10.
[c]One alternative specific constants (ASC) is estimated for each hunting site regardless of hunting seasons. The table presents the average baseline marginal utility estimates for each site group. The grouping follows the hunting season categories in Alberta Guide to Hunting Regulations (Alberta Environment and Parks, 2018). Appendix C presents a bar plot of significant baseline marginal utility (i.e. exponential of ASC parameters) for each site.
[d]Translation parameters (81 in total) are estimated for each hunting site during regular and proposed extended hunting seasons. The table presents the average translation parameters for each site group. The extended season was proposed in all WMU 100 Series, 200 Series sites and one site in 500 Series.

Table 5: Welfare Estimates for Hunting in the Extended Season

Series	**Mean (CAD/person)**	**Standard Error**
All hunting sites	229.62	13.23
WMU100s (18 sites)	151.78	10.67
WMU200s (19 sites)	76.28	4.83
WMU500s (1 site)	1.56	0.26

Note: Welfare estimates for each site group are calculated by taking difference of welfare loss (negative willingness-to-pay) of closing extended seasons. For example, the welfare estimate for WMU 100s is the difference between welfare loss of closing the extended season in all sites and welfare loss of closing the extended season sites other than WMU 100s.

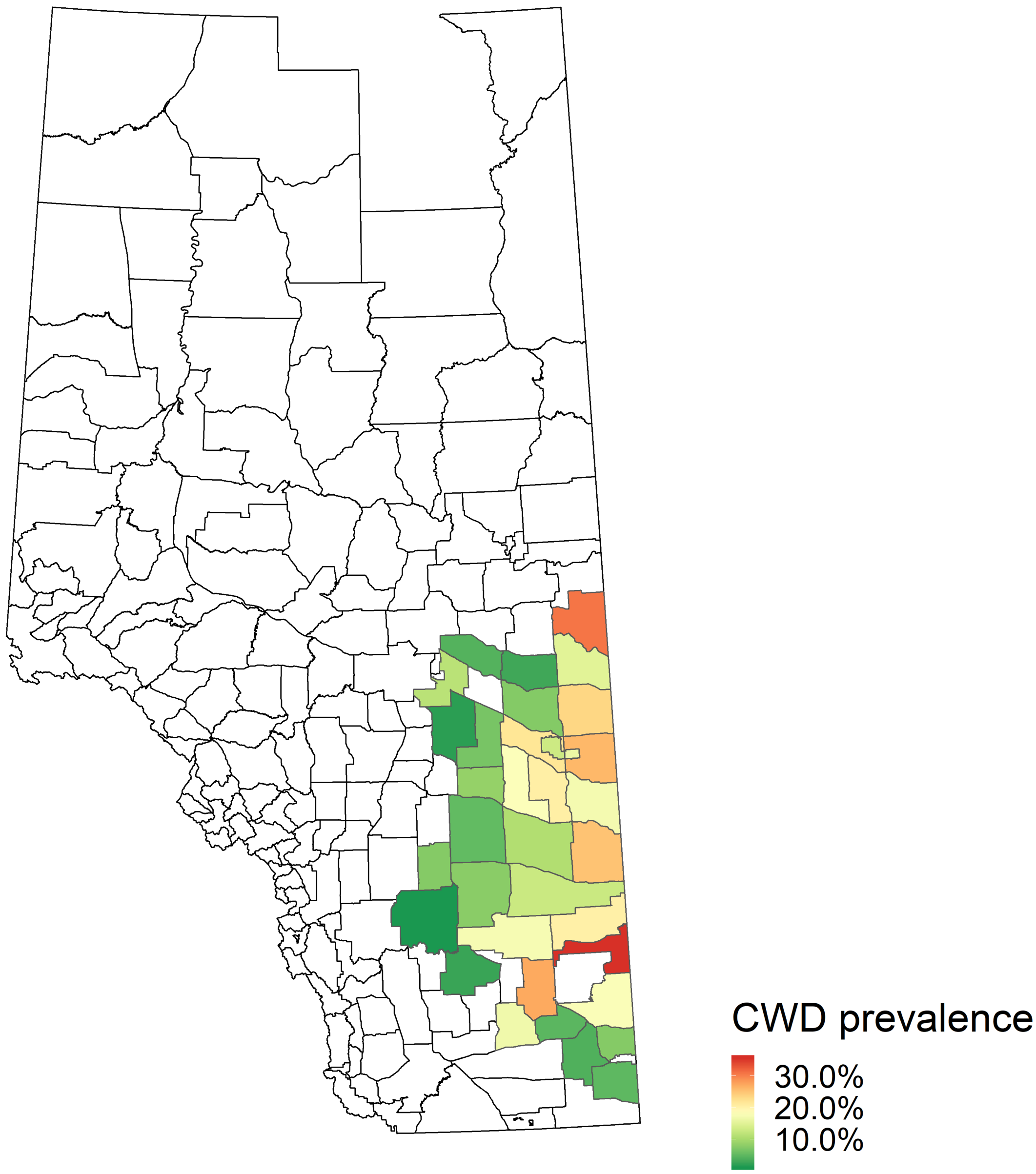

Figure 1: CWD prevalence map in Alberta (2018)

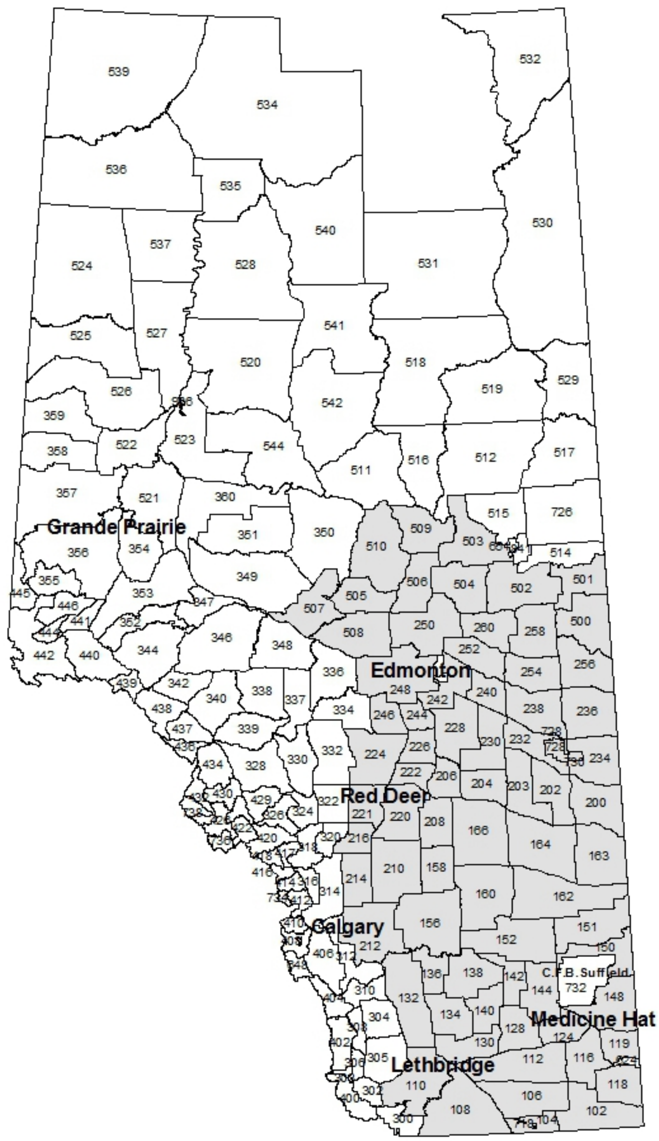

Figure 2: Study Area

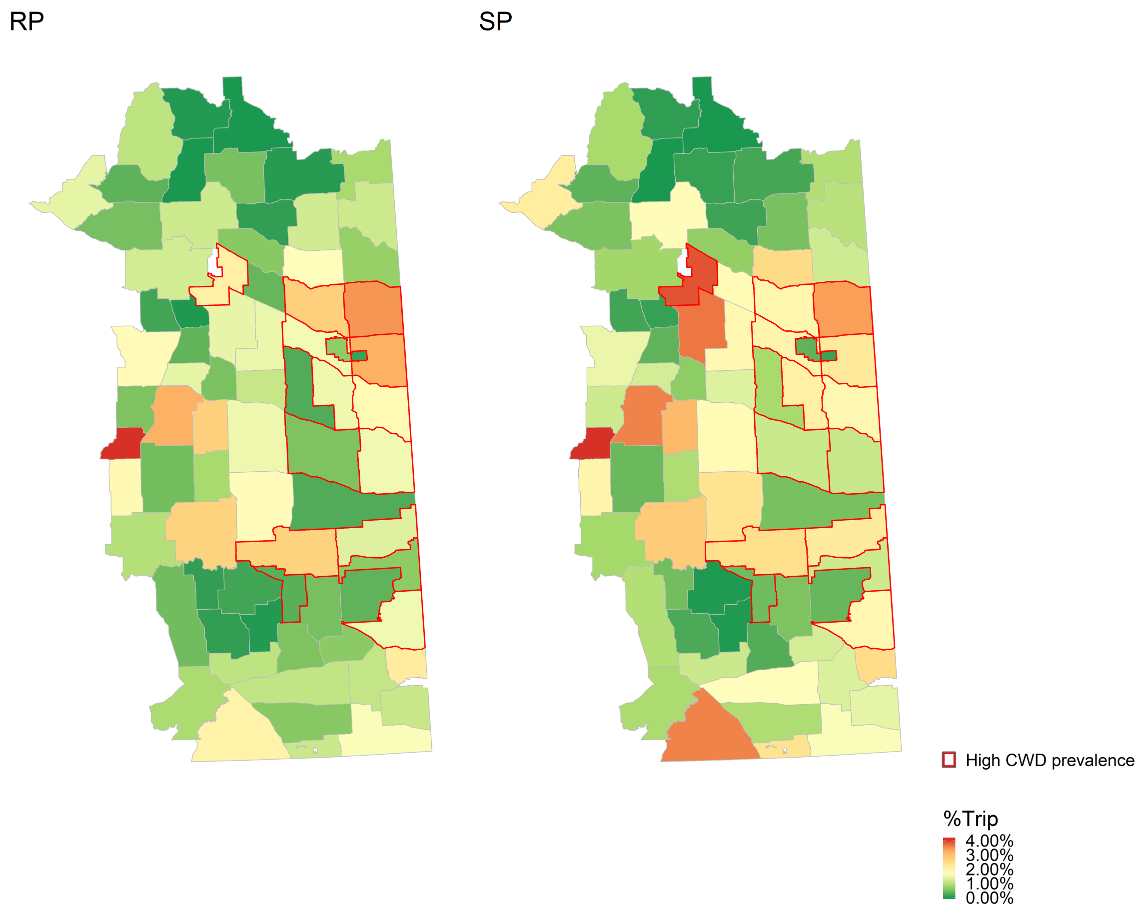

Figure 3: Trips (%) Under RP and SP (Both Seasons) Scenarios, Aggregated by Hunting Sites

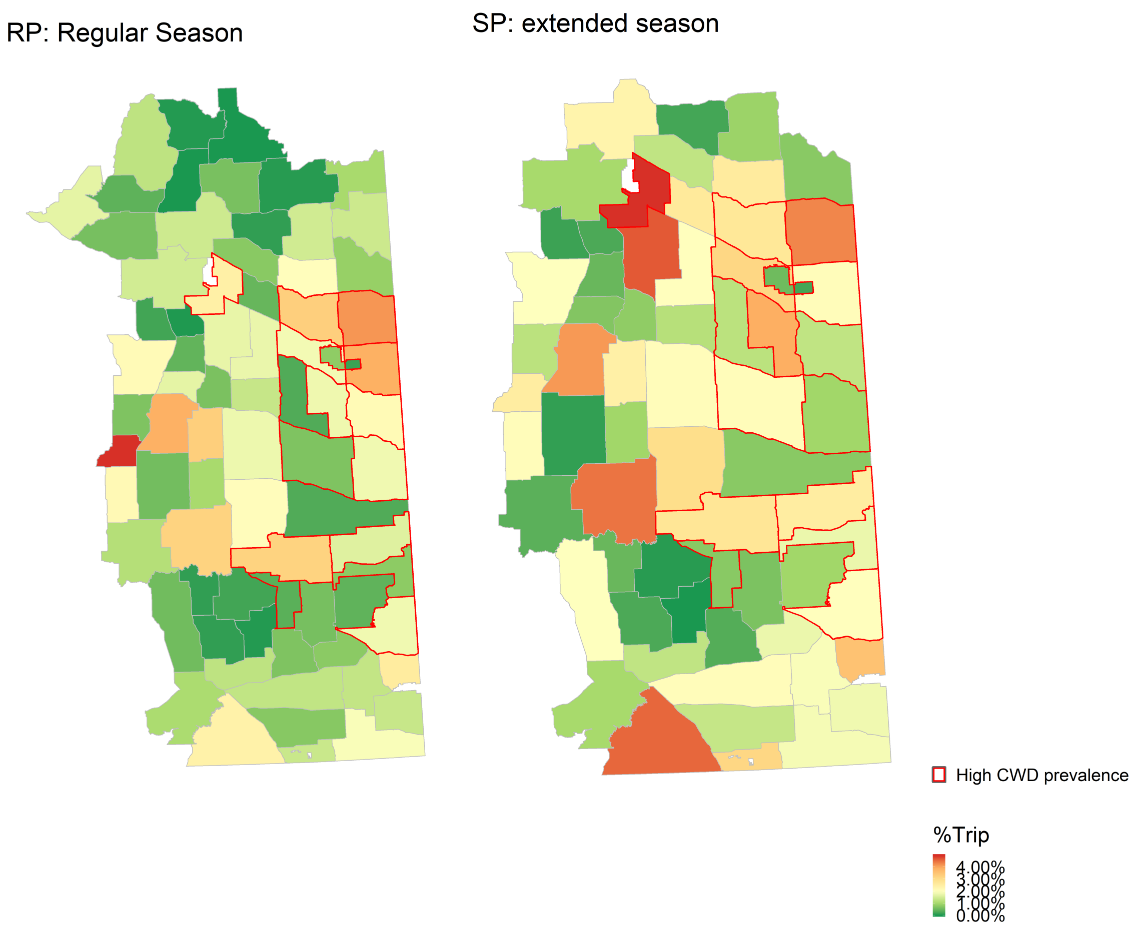

Figure 4: Trips (%) in Regular Season and SP Trips (%) in the Extended Season, Aggregated by Hunting Sites

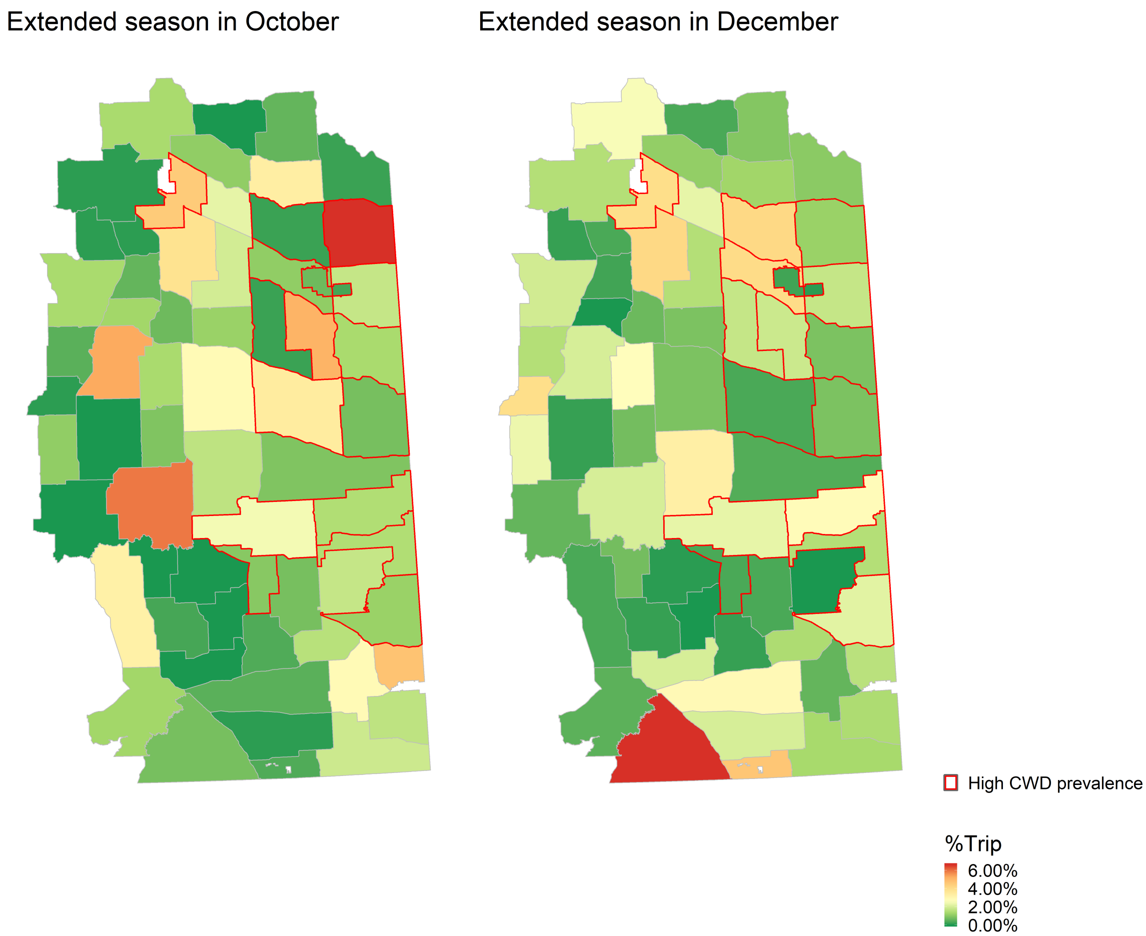

Figure 5: SP Trips(%) to WMU in the Extended Season (October vs. December), Hunting Sites

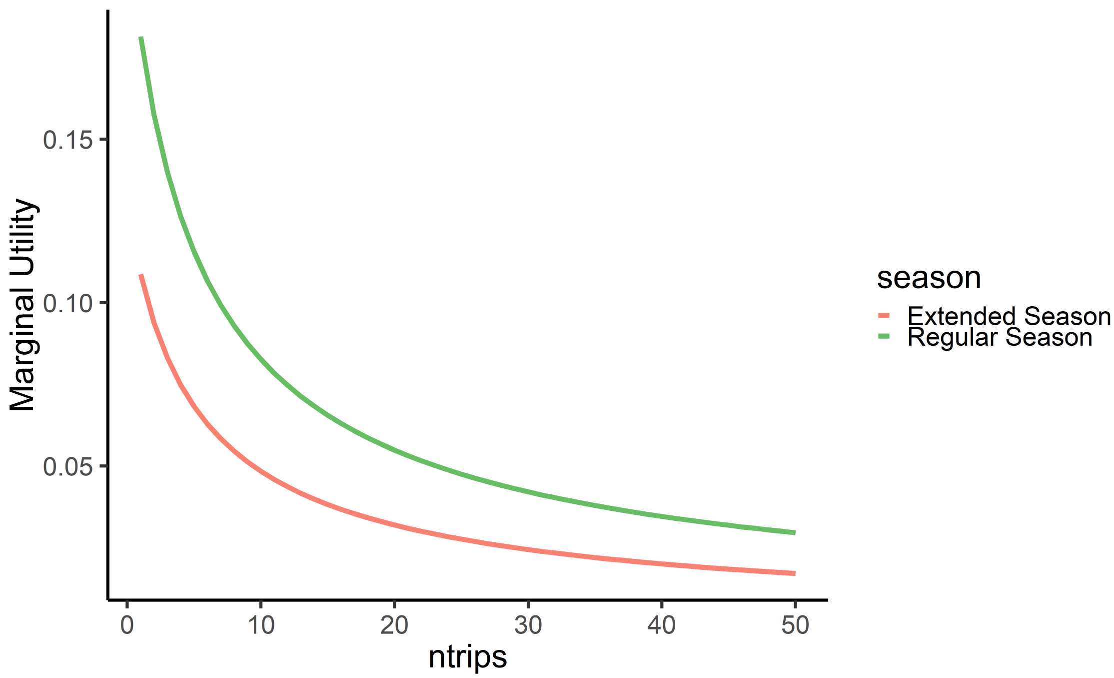

Figure 6: Marginal Utility of Trips (Temporal Substitution)

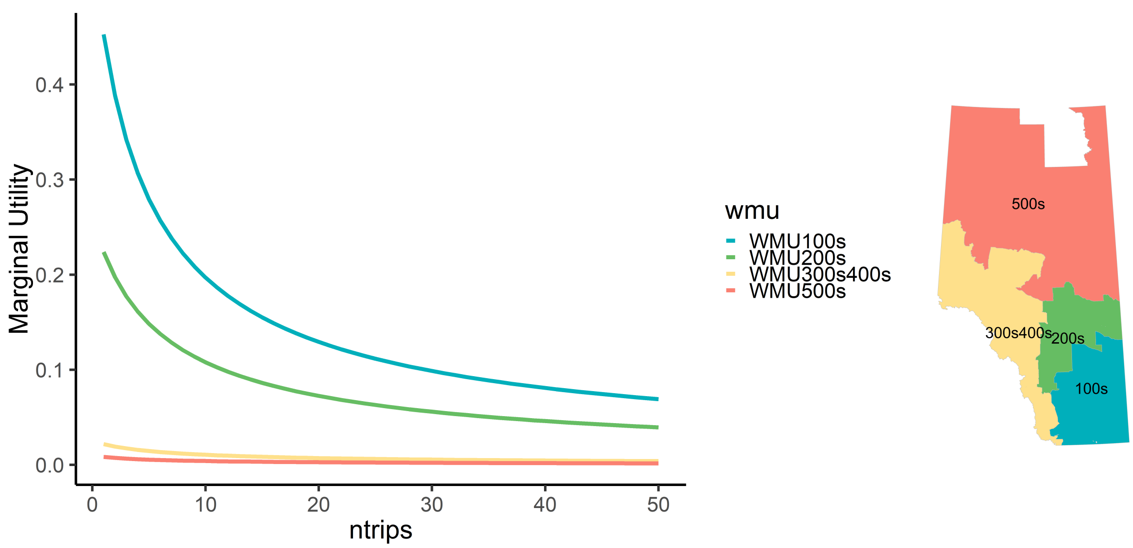

Figure 7: Marginal Utility of Trips (Spatial Substitution)

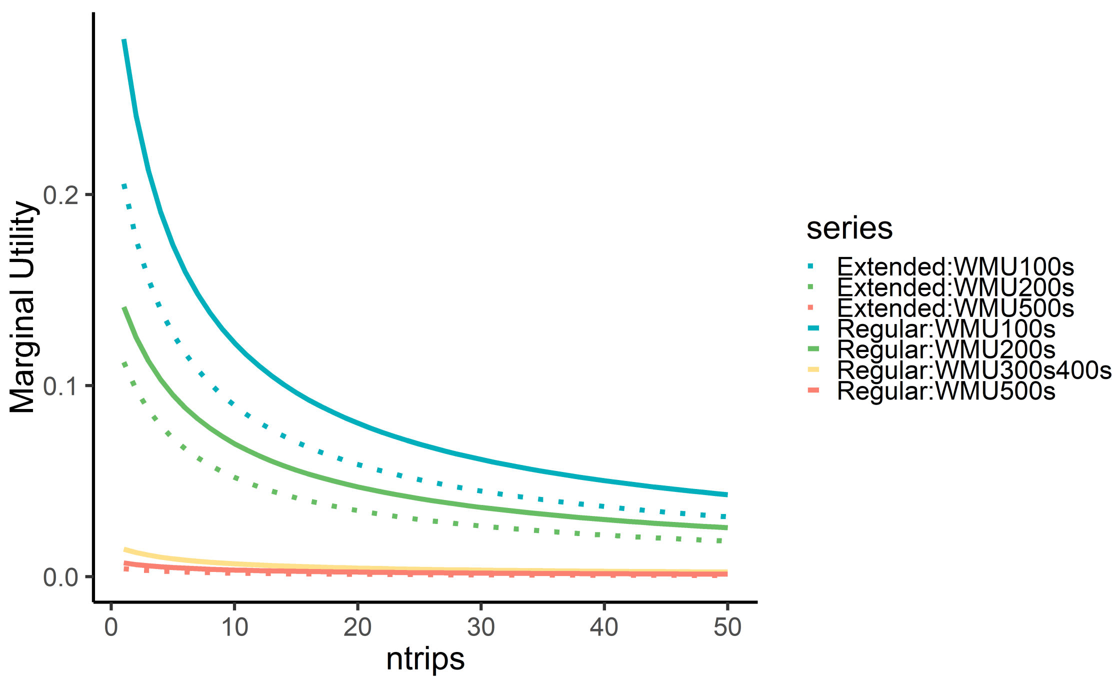

Figure 8: Marginal Utility of Trips (Spatial and Temporal Substitution)

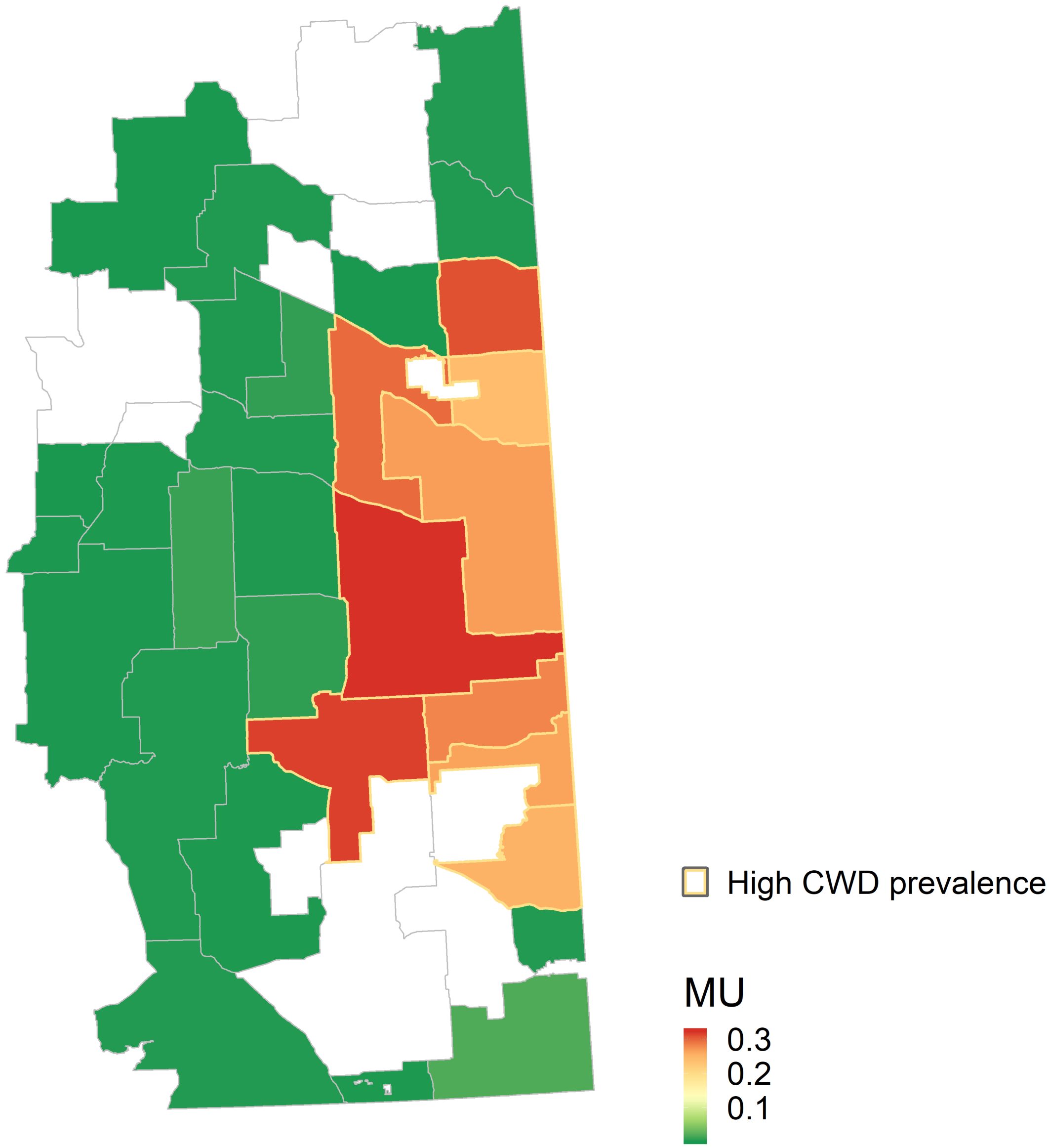

Figure 9: Marginal Utility of Trips in Extended Season at Average Number of Trips

Note: Marginal utility of trips in extended season at 6 trips. Hunting sites after grouping with high CWD prevalence rate are marked with the yellow boundary. Sites that are visited but with insignificant ASC or translation parameters are in white.

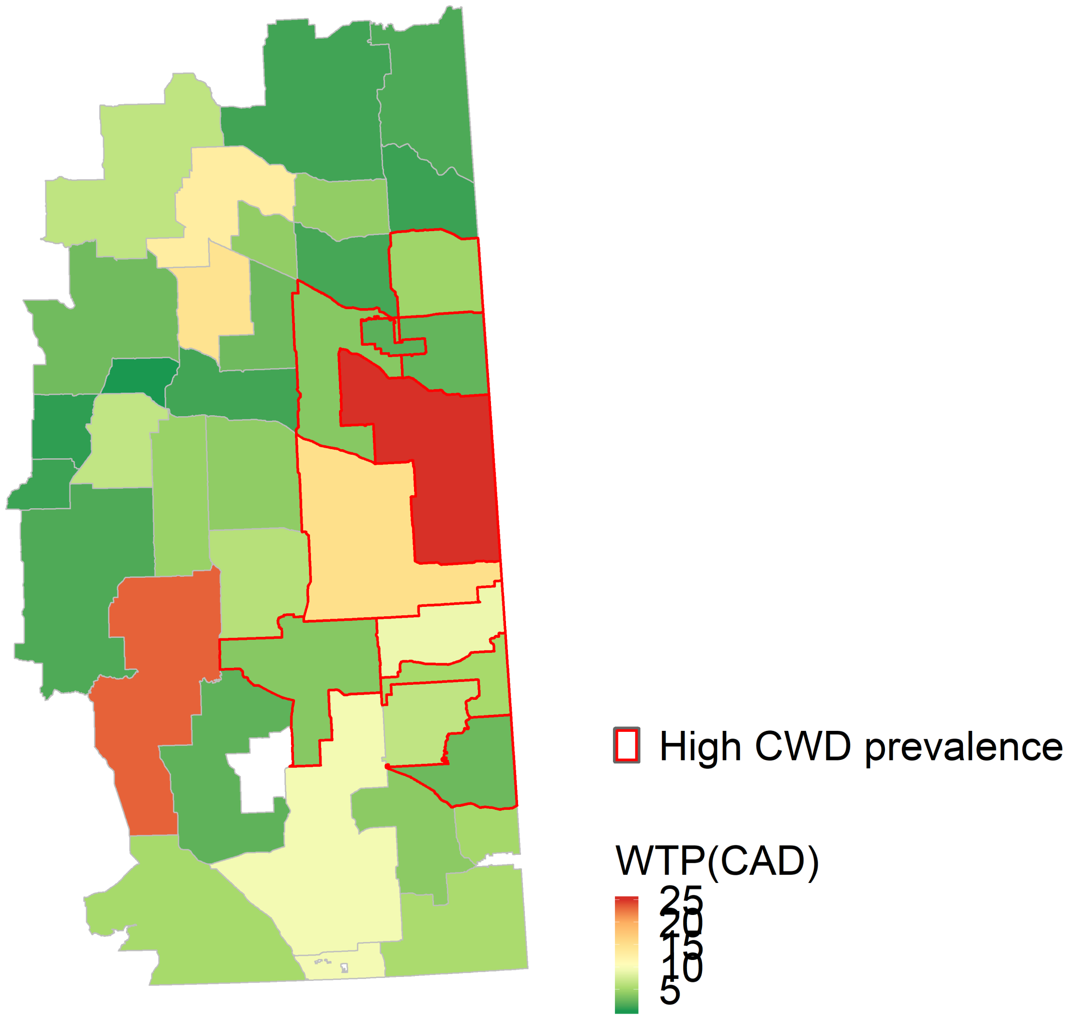

Figure 10: WTP/Person for Hunting in the Extended Season

Spatial and Temporal Responses to Incentives

Appendix

Lusi Xie   Wiktor Adamowicz   Patrick Lloyd-Smith

Appendix A

Lagrangian function and first-order conditions for conceptual model

The Lagrangian for the optimization problem defined in equations 1 to 4 is given by

$$L = \sum_k \sum_m U(x_{km}, Q_{km}, z) + \lambda[\overline{y} + w\overline{T} - \sum_k \sum_m (p_{km} + t_{km}w)x_{km} - z]$$

We assume that the numeraire good have positive demand so that the constraint is always binding and the Lagrangian multiplier is positive (i.e. positive marginal utility of money). The resulting first-order conditions are

$$\frac{\partial L}{\partial x_{km}} = \frac{\partial U}{\partial x_{km}} - \lambda(p_{km} + t_{km}w) \leq 0, x_{km} \geq 0, x_{km}\frac{\partial L}{\partial x_{km}} = 0, \text{, k = 1,...K, m =1,...M}$$

$$\frac{\partial L}{\partial z} = \frac{\partial U}{\partial z} - \lambda = 0$$

$$\frac{\partial L}{\partial \lambda} = \overline{y} + w\overline{T} - \sum_k \sum_m (p_{km} + t_{km}w)x_{km} - z = 0$$

From the second first-order condition we get $\lambda = \frac{\partial U}{\partial z}$. Dividing the first first-order condition by λ, we have

$$\frac{\partial U/\partial x_{km}}{\partial U/\partial z} \leq p_{km} + t_{km}w, \text{, k = 1,...K, m =1,...M}$$

$$x_{km}[\frac{\partial U/\partial x_{km}}{\partial U/\partial z} - p_{km} - t_{km}w] = 0, \text{, k = 1,...K, m =1,...M}$$

Derivation of the estimation equations in Section 6.2

From equation 10, we have the partial derivative of the utility function in equation 9 with respect to a recreation trip is

$$U_{x_{km}} = \exp(\beta Q_{km} + \varepsilon_{km})(\frac{x_{km}}{\gamma_{km}} + 1)^{\alpha-1}$$

The partial derivative of the utility with respect to the numeraire good is equal to

$$U_z = \exp(\varepsilon_z) z^{\alpha-1}$$

Substituting these two equations into equation 5, we have

$$\frac{\exp(\beta Q_{km} + \varepsilon_{km})(\frac{x_{km}}{\gamma_{km}} + 1)^{\alpha-1}}{\exp(\varepsilon_z) z^{\alpha-1}} \leq p_{km} + t_{km} w, \text{, k = 1,...K, m =1,...M}$$

Taking logarithms of both sides yield the estimating equations 11 to 14:

$$V_{km} + \varepsilon_{km} = V_z + \varepsilon_z \text{ if } x^*_{km} > 0 \text{ and}$$

$$V_{km} + \varepsilon_{km} \leq V_z + \varepsilon_z \text{ if } x^*_{km} = 0 \text{ where}$$

$$V_{km} = \beta' Q_{km} + (\alpha - 1) \ln\left(\frac{x_{km}}{\gamma_{km}} + 1\right) - \ln(p_{km} + t_{km} w)$$

$$V_z = (\alpha - 1) \ln(z)$$

Appendix B Trip Frequency

Table B1: Trip Frequency Distribution Table

Trip	Frequency	Percent	Trip	Frequency	Percent
1	480	26.39%	22	1	0.05%
2	341	18.75%	23	3	0.16%
3	209	11.49%	24	3	0.16%
4	152	8.36%	25	11	0.60%
5	98	5.39%	27	2	0.11%
6	90	4.95%	28	1	0.05%
7	57	3.13%	30	11	0.60%
8	73	4.01%	31	2	0.11%
9	13	0.71%	32	1	0.05%
10	83	4.56%	34	1	0.05%
11	10	0.55%	35	3	0.16%
12	28	1.54%	40	5	0.27%
13	5	0.27%	42	2	0.11%
14	14	0.77%	43	1	0.05%
15	48	2.64%	44	1	0.05%
16	5	0.27%	45	1	0.05%
17	2	0.11%	48	3	0.16%
18	4	0.22%	50	20	1.10%
20	34	1.87%	60	1	0.05%

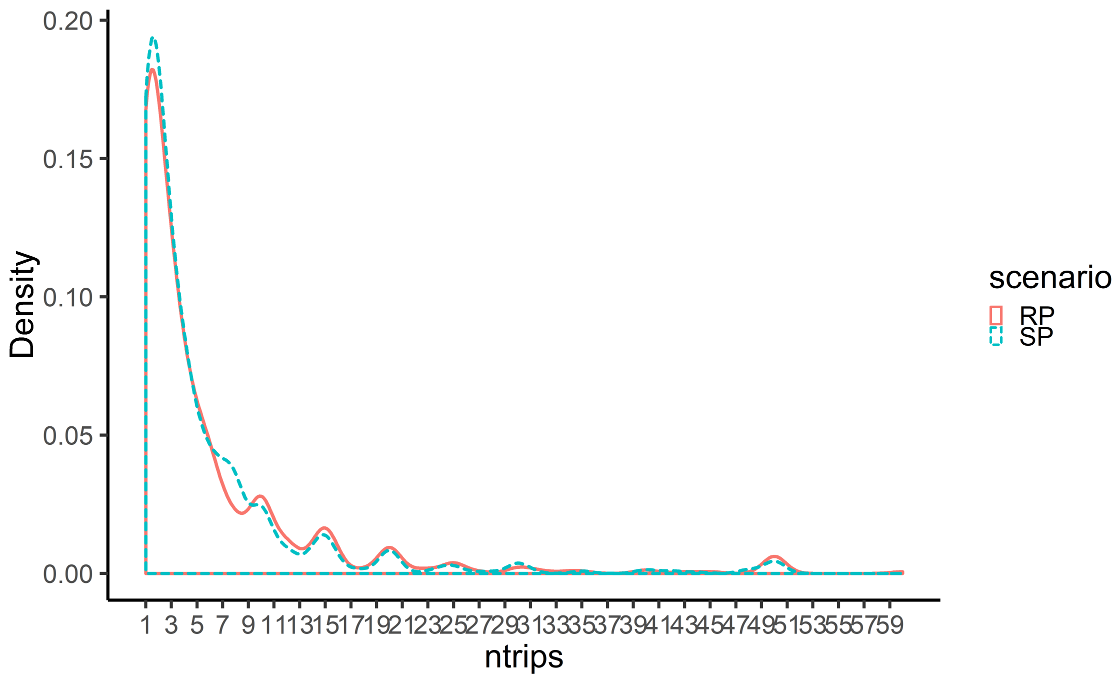

Figure B1: Trip Frequency Density (RP vs. SP)

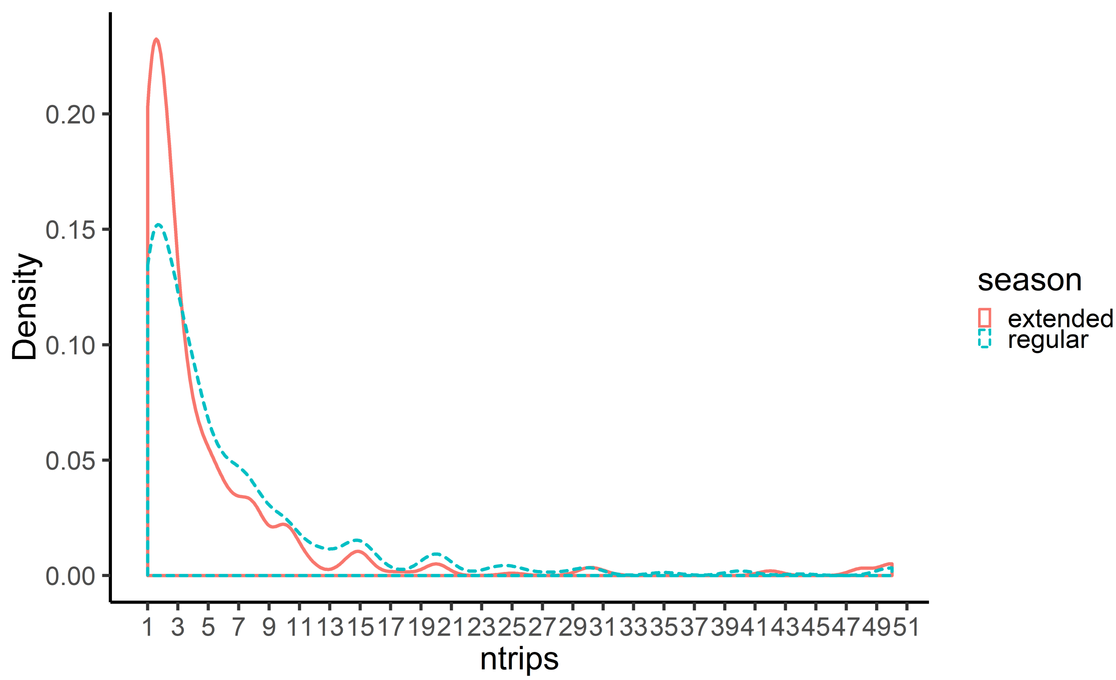

Figure B2: SP Trip Frequency Density (Regular vs. Extended Season)

Appendix C

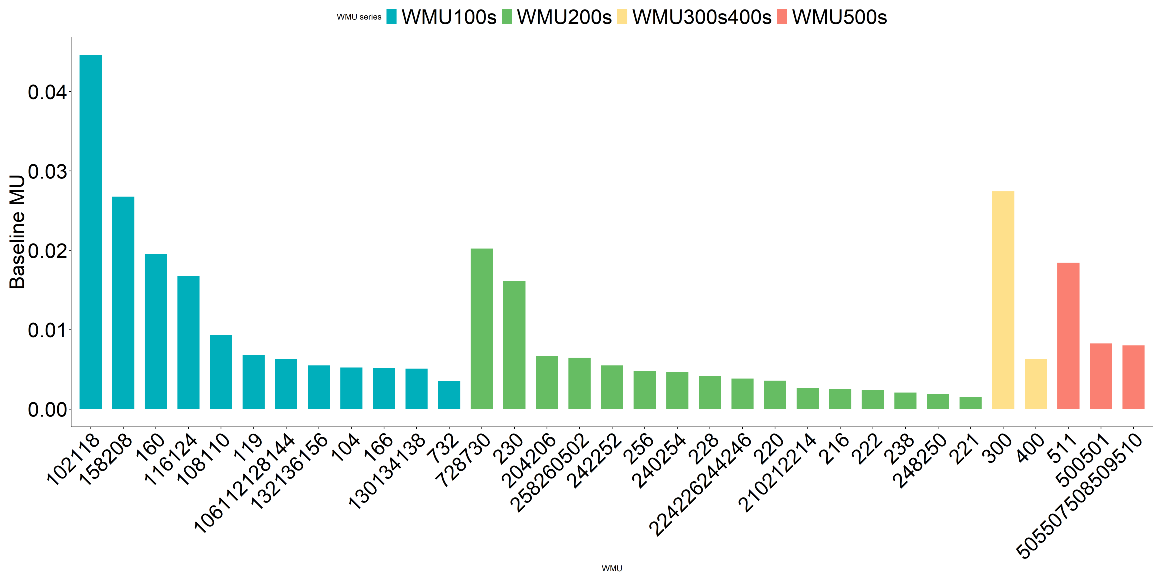

Figure C1: Baseline Marginal Utility

Appendix D Robustness Checks

Table D1: Parameter Estimates for Kuhn-Tucker Model (RP and SP Data Respectively)

	RP data		SP data	
	Estimate	z-stat	Estimate	z-stat
Baseline marginal utility parameters (β_{km})				
CWD	-0.422	-1.34	-0.441	-1.41
Extended season			-0.061*	-1.75
October			0.062	0.57
December			0.234**	2.09
College	-0.025	-0.32	-0.025	-0.34
Urban	0.059	0.78	-0.033	-0.48
Children	-0.137	-1.48	-0.199***	-2.34
Yrshunt	-0.013	-0.48	-0.019	-0.76
Landowner	-0.158	-1.37	-0.217**	-2.03
ASC (mean)				
ASC_WMU 100 Series&732	-2.900**	-2.014	-3.170***	-2.508
ASC_WMU 200 Series&728&730	-4.350***	-4.522	-4.662***	-5.491
ASC_WMU 300 Series & 400 Series	-3.787***	-7.638	-4.350***	-10.427
ASC_WMU 500 Series	-4.339***	-8.541	-4.875***	-10.807
Mean Translation Parameters (γ_{km})				
Regular season				
WMU 100 Series&732	5.281***	7.365	5.190***	7.619
WMU 200 Series&728&730	6.894***	7.759	7.477***	7.893
WMU 300 Series & 400 Series	4.592***	3.416	6.614***	3.363
WMU 500 Series	3.468***	4.933	6.004***	4.263
Extended season				
WMU 100 Series&732			4.226***	7.502
WMU 200 Series&728&730			5.363***	7.276
WMU 500 Series			4.614**	2.126
Satiation Parameter (α)	0.254***	4.53	0.244***	4.99
Scale Parameter	0.555***	27.76	0.536***	33.5
N	416		416	
N of "goods" in choice set	43		81	
Log-likelihood (mean)	-4585.83		-6868.54	

Note: There is only one season (i.e. regular season) in the recall scenario, therefore estimation with RP data do not have variables of extended season, October and December – this is different from the estimation with SP data where two seasons (i.e. regular and extended seasons) are proposed in the contingent behavior scenario.

Appendix E Survey – Contingent Behavior Scenario Example

Potential Hunting Policy Scenario

Expanding the hunting seasons for one week into October:

- Prairie WMUs 100 Series (except 162, 163, 164, 166), marked in dark green on the map:

  Wednesday to Saturday in **the last week of October** and November (**Oct.25** – Nov.30)

- Parkland WMUs 200 Series; WMU 162, 163, 164, 166; WMU 500, marked in light green on the map:

  Oct.23 – Nov.30

Figure E1: Contingent Behavior Scenario: Proposed Extended Season in October

EXTENDED HUNTING SEASON TRIPS (OCTOBER)

Please complete the following table for each WMU you would have gone BIG GAME hunting in during ***the extended hunting season (i.e. October) in 2017*** under the scenario above.

	Number of trips you would have taken in *October* of 2017 under the scenario above	Average number of days you would have spent in *October* of 2017 under the scenario above	Number of deer you would have harvested in *October* of 2017 under the scenario above
WMU			
WMU			
WMU			
WMU			
WMU			

REGULAR HUNTING SEASON TRIPS (NOVEMBER)

Please complete the following table for each WMU you would have gone BIG GAME hunting in during the ***regular hunting season (i.e. November) in 2017*** under the scenario above.

	Number of trips you would have taken in 2017 under the scenario above	Average number of days per trip you would have spent in 2017 under the scenario above	Number of deer you would have harvested in 2017 under the scenario above
WMU			
WMU			
WMU			
WMU			
WMU			

Figure E2: Contingent Behavior Scenario: Responses Entry Table