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WEATHER EFFECTS ON THE DEMAND FOR COASTAL RECREATIONIAL FISHING: IMPLICATIONS FOR A CHANGING CLIMATE

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Abstract

This paper estimates the demand for coastal recreational fishing in the Atlantic and Gulf Coast regions of the United States and evaluates the potential welfare implications resulting from climate change. Specifically, we use short-run variability in temperature and precipitation to estimate the effect of weather on participation in shoreline fishing in coastal waters. We then simulate how climate change may impact those choices over time. Parameter estimates are combined with predictions from five global climate models under three emissions scenarios to estimate welfare changes associated with climate change over multiple time horizons. Overall, our results suggest the effects of climate change on shoreline recreational fishing are positive and significant in the long run (2080-2099) with simulation results predicting annual gains of up to \$6.83 per trip, or \$304 million in the aggregate. The results are decomposed seasonally and regionally to reveal substantial heterogeneity. Welfare gains associated with increasing temperatures in the non-summer months outweigh modest losses in the summer months. The Gulf Coast region has the potential to realize welfare losses, while the Mid-Atlantic and New England are likely to experience welfare gains in all seasons. Of the nearly 45 million annual trips predicted by the model, climate change may increase participation by 0.2 to 2.2 percent in the aggregate. Given the modest negative demand responses in the Gulf and Southeast regions, evidence of adaptation is identified from a model of night fishing. Results suggest that recreational anglers may shift their activities to night as daily high temperatures increase rather than change their participation decision.

JEL Codes: Q22, Q26, Q51, Q54, Q57
Keywords: climate change, recreational demand, adaptation, fishing, nested logit

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1 Introduction

Outdoor recreation is a popular use of leisure time for many residents of the United States. Recreation opportunities generate substantial economic activity, with annual spending in the U.S. reaching nearly $646 billion (OIA 2012). Specific to this research, marine recreational fishing produced $24.6 billion in spending and accounted for 72 million user days in 2012 (NMFS 2012)[2]. Outdoor recreation activities are highly dependent on natural resources and environmental conditions, making this sector of the economy sensitive to potential changes in climate that are predicted in both the near and long term. In this article we investigate how changes in weather may impact an angler's decision to participate in coastal shoreline recreational fishing. We then use these results to assess the potential welfare implications associated with climate change by estimating changes in participation and willingness to pay for recreational fishing under simulated climate scenarios.

Recently, incorporation of large data panels of weather variables into econometric models has emerged as an avenue for identifying the potential economic impacts of climate change. Exogenous fluctuations in observed weather are utilized as spatially and temporally explicit covariates to help explain effects on the outcome of interest. To date, this approach has been used to estimate the economic impacts of climate change in areas such as agricultural production (Deschênes and Greenstone 2007; Schlenker and Roberts 2009), labor productivity (Graff Zivin and Neidel 2014), and electricity demand (Auffhammer and Aroonruengsawat 2011).[3]

The short-run relationship between weather, as measured by daily maximum temperature

[2] The approximately 11 million saltwater anglers in the U.S. "spent $4.6 billion on fishing trips and $20 billion on durable fishing-related equipment. These expenditures contributed $58 billion in sales impacts to the U.S. economy, generated $30 billion in value added impacts, and supported over 381,000 jobs" (NMFS 2012, p. 8).
[3] See Dell, Jones, & Olken (2014) for an extensive review of research at the interface of economics and climate.

and precipitation, and outdoor recreation decisions can also be used to predict how climate change may impact those choices over time. This article advances an approach to model participation in shoreline recreational fishing as a function of weather conditions. A repeated discrete choice, random utility maximization (RUM) framework is implemented using a two-level nested logit model to sequentially estimate participation and site choice. The empirical application exploits data obtained from two separate and independent surveys administered by the National Oceanic and Atmospheric Administration's (NOAA) Marine Recreational Information Program (MRIP) – a point-of-access intercept survey and a random-digit-dial phone survey of coastal counties. Participation is modeled using the phone survey with data on both fishing and non-fishing households to avoid potential biases related to endogenous stratification and truncation present in the intercept data (see Alvarez et al. 2014). High resolution weather data enters into the participation model in order to estimate how these variables impact recreation decisions along the Atlantic and Gulf Coasts of the U.S.

With structural parameters on the weather variables estimated over a seven-year baseline (2004-2010), we then use temperature and precipitation projections from five global climate models (GCMs)[4] under three emission scenarios across three time horizons (2011-2030, 2040-2065, and 2080-2099) to simulate counterfactual climates. The simulations produce a number of notable results. First, the Atlantic and Gulf Coasts of the U.S. are likely to experience welfare gains in the aggregate associated with shoreline recreational fishing due to climate change. Welfare gains range from $1.62 per trip, or $72.4 million, in the short-run (2011-2030) to $6.83 per trip, or $304 million, in the long-run (2080-2099). Second, there is significant seasonal heterogeneity in the results. Welfare losses are predicted for nearly all emission scenarios in all

[4] GCMs are numerical models that represent physical processes in the atmosphere, ocean, and land surface simulate the response of the global climate system to increasing greenhouse gas concentrations.

time horizons in summer simulations (May – August). In the short-run, these losses are negligible but then increase to significant estimates of approximately -\$2.17 to -\$4.59 per trip (-\$60 to -\$127 million total) over the medium and long term. For non-summer models (January – April and September – December), the welfare impacts are positive and significant in all scenarios, indicating that rising temperatures are likely to expand the time available for recreational fishing in desirable, mild weather across the non-summer months. The simulations predict a welfare gain between \$3.49 per trip (\$58.6 million total) in the short-run and \$25.42 per trip (\$427 million total) in the long-run. In sum, the magnitude of the welfare gains in response to climate change in the non-summer months is projected to outweigh the welfare losses predicted for the summer months.

Third, the regional variation in the results is significant. Anglers in the Gulf Coast region face potential welfare losses in all seasons. Continuing on our current emissions trajectory (i.e. *business-as-usual*) is likely to result in welfare losses of nearly -\$15.83 per trip (\$300 million annually) in the long-run for the region. Reducing future greenhouse gas emissions to a *best-case* scenario has the potential to reduce those losses in the Gulf by \$8.29 per trip (\$157 million annually). Conversely, the Mid-Atlantic and New England experience welfare gains in all seasons. The gains are relatively modest in the summer months and increase dramatically in magnitude in the non-summer months. In non-summer months, average predicted welfare gains for the Mid-Atlantic and New England approach \$39.74 per trip (\$240 million) and \$43.11 per trip (\$303 million), respectively.

Fourth, the demand responses inferred by the changes in climate are positive and significant in the aggregate yet relatively modest (0.2 to 2.2 percent). This result suggests that coastal recreational fishermen may be adapting instead of changing their participation in response to a changing climate. Lastly, a potential adaptation is identified via *intraday* temporal substitution. A model of night fishing across all seasons suggests that coastal fisherman are likely already adapting, as increases in daily maximum temperature increase the probability of an angler choosing to recreate at night in both the Gulf and Southeast regions.

To put the long-run welfare results above into perspective with previous research, a recent meta-analysis of 13 studies of saltwater anglers found the average willingness to pay to catch an additional small game fish per day was $9.74 in 2010 dollars (Johnston and Moeltner 2014).[5] Using this welfare measure and the average catch rate for small-game saltwater anglers in the same meta-analysis (2.19 fish/trip), the aggregate long-run increase in welfare due to climate change on participation ($6.83 increase/trip) would require a decline in catch rates of approximately 32 percent (0.70 fish/trip) to offset the gains. In the summer, a 22 percent (0.47 fish/trip) increase in catch rates would need to occur to offset the estimated welfare losses (-$4.59/trip). Conversely, a 119 percent decrease in catch rates (2.61 fish/trip) would be needed to offset the gains in the non-summer months ($25.42/trip). As noted in the following section, there is substantial scientific uncertainty about how climate change will impact ecological factors such as catch rates, a limitation to our collective knowledge that represents an important challenge for future interdisciplinary research. However, the above calculations imply that these indirect effects would have to be substantial, and in some cases biologically infeasible, to offset the demand side effects of climate change on shoreline recreational fishing.

This article proceeds as follows. The previous literature on climate change and outdoor recreation is summarized briefly in Section 2. Section 3 describes the modeling approach and Section 4 details the data and the empirical implementation of the model. Section 5 discusses

[5] This number is appropriate for this context as small game fish are the most likely targets for shoreline recreational anglers that are the focus of this research.

results from the site choice and participation models and Section 6 details the climate simulations and the resulting welfare implications. Section 7 discusses the potential of individuals' adapting to higher temperatures by shifting to night fishing. Section 8 concludes and discusses some extensions of this research.

2 Outdoor Recreation and Climate Change

The potential impacts of climate change on outdoor recreation operate through multiple channels. First, the demand for a given activity may be directly affected by the direction and magnitude of changes in long-run weather conditions (i.e. climate). These effects are likely to vary seasonally, as deviations in climate from historical annual averages likely translate into different outcomes by season. For example, a 3°C increase in daily maximum temperature may reduce visits to a particular fishing site in the summer, yet increase visits in the spring and fall. Perhaps more difficult to quantify, changes in climate may also have indirect effects through impacts on the quality of the ecosystem services related to the recreation visit. For instance, Loomis and Crespi (1999) model climate-induced changes in the hydrology of streamflow to estimate the impact of climate on freshwater fishing.

Despite the substantial annual economic activity generated by outdoor recreation, the literature is sparse when looking at the potential effects of climate change on recreation compared to other sectors of the economy. As noted by Shaw and Loomis (2008), "much of the existing economic literature related to climate change neglects to mention the losses or gains in benefits from non-market goods such as recreation outings" (p. 260).[6] Mendelsohn and

[6] See Hamilton and Tol (2006) for a review of how the tourism and leisure literature assesses tourism impacts related to climate change.

Markowski (1999) and Loomis and Crespi (1999) offer initial national assessments of climate change on outdoor recreation in the U.S., with both studies predicting a similar net increase in annual welfare of approximately $2.8 billion. The impacts vary by activity type, with gains predicted for boating, fishing, and golfing and losses for snow skiing, camping, and wildlife viewing in both studies. Mendelsohn and Markowski (1999) account for direct effects of weather on recreation demand in a state-by-state, cross-sectional travel cost analysis. Loomis and Crespi (1999) also account for indirect effects related to climate-induced alterations in ecosystem services and use response functions to determine changes in the number of visits and the economic value associated with each visit.

Previous work on the climate impacts on recreational fishing have focused on freshwater locations. In a cross-sectional analysis, Pendleton and Mendelsohn (1998) model the indirect ecological effects on catch rate in freshwater sport fishing in the northeastern U.S. Their results suggest the annual welfare impacts of a changing climate range from a $4.6 million loss to $20.5 million gain and highlight two major areas of concern in this line of research. First is the potential issue of identification of climate effects with cross-sectional data. Weather in a particular year may not be representative of climate, which may create difficulty in differentiating the effect of climate from other correlated variables. Second, the tremendous uncertainty surrounding climate change and GCM output compel researchers to test multiple models and emissions scenarios when estimating projected impacts (see Burke et al. 2015). In this case, Pendleton and Mendelsohn (1998) use two GCMs that generate welfare predications with opposite signs, providing a mixed and ambiguous signal to policy makers.

Other freshwater fisheries research places emphasis on the indirect effects of climate change. Ahn et al. (2000) use a RUM framework and estimate the effect of loss of trout habitat in

North Carolina under different warming scenarios. Their results indicate a 2 to 20 percent loss in angler consumer surplus per trip with data limits preventing aggregation of estimates. More recently, Jones et al. (2013) conduct a national accounting of freshwater fishing in the U.S. and show a remarkable range of potential indirect annual losses driven by habitat loss from $81 million to $6.4 billion.

Our research contributes to and extends this literature in a number of dimensions. To our knowledge, it is the first study to investigate how individuals who participate in coastal (i.e. marine) fishing respond to climate change. By combining rich data on individual site choices, participation, and weather over time, it also extends the recent trend in economics of using high resolution panels of weather data to causally identify outcomes of interest to an outdoor recreation activity (Dell et al. 2014). The temporal and spatial size and scope of our data allow us to identify seasonal and regional heterogeneity in the effect of weather on participation which translate to welfare effects that vary significantly in sign and magnitude between seasons and across regions. Lastly, we use five GCMs over three emissions scenarios in the climate simulations to illustrate the potential climate uncertainties.[7]

This approach provides a rigorous assessment of the direct effects of climate change on outdoor recreation and a starting point to begin to answer much broader questions about the overall impacts of climate change. The primary limitation in this research is assuming no changes in indirect ecosystem effects as the climate changes. The implications of this assumption are unclear. Mendelsohn and Markowski (1999) and Loomis and Crespi (1999) find nearly

[7] We use ensemble forecasts for temperature and precipitation in the welfare simulations. It is important to note that these ensemble forecasts smooth over the variation across individual climate model runs. A more rigorous approach to assessing the economic impacts of climate change may be to assess welfare changes for each individual climate model run to generate a distribution of welfare impacts. This remains an area for potential collaborative efforts between economists and climate scientists.

identical welfare effects in their national accounts of climate impacts despite the former only estimating direct effects. Evidence from freshwater fishing studies (Ahn et al. 2000; Jones et al. 2013) suggests negative indirect welfare implications from climate-induced ecosystem changes. Intuitively, one may expect that effects in the marine environment may by less than the freshwater loss predictions due to the ability of fish stocks to migrate and of anglers to adapt to changing conditions. However, the magnitude of the potential indirect effects in a marine fishing environment is still an open empirical question.

Moreover, credible forecasting of future marine fish stocks is a substantial challenge. Scientific understanding of the impacts on marine fish stocks in response to climate change (i.e. mortality, shifts in species distribution, and responses to changing acidity) is evolving but yet to provide a clear path forward.[8] When projecting future stocks, policy matters as well. For example, policy reforms such as individual transferable quota (ITQ) systems or the establishment of marine reserves could significantly impact future marine fish stocks. Given the potential for increased knowledge in these areas, future work may incorporate dynamic bio-economic models of fish stocks and policy impacts into the assessment of the direct effects modeled here that could provide a more complete understanding of the effects of climate change on shoreline recreational fishing. [9]

[8] Initial work on fish stock response to climate change has been conducted in the East China Sea (Chueng et al. 2008), Canada (Chueng et al. 2009), the Baltic Sea (Nieminen et al. 2012) and Greenland/Iceland (Arnasen 2007).
[9] An additional missing element to this shoreline fishing analysis is the costs to adapt to climate change in terms of built infrastructure supporting the recreation activity (i.e., piers, jetties). As the impacts of climate change, such as sea level rise, increase, the usefulness of current infrastructure will be reduced or eliminated, necessitating the need to build new infrastructure.

3 Modeling Approach

Our approach utilizes the RUM discrete choice framework introduced by McFadden (1974) and first applied to recreation demand models by Hanemann (1978). The RUM model is the dominant method for recreation demand analysis due to its ability yield consistent welfare measures and allow for meaningful substitution among recreation sites.[10] To deal with participation, i.e., the possibility that different individuals take different quantities of trips, we employ a *repeated* discrete choice framework (Morey et al. 1993), whereby individuals repeatedly make discrete choice participation and site choice decisions across a series of choice occasions, with the sum of these choices representing their demand over a fixed time horizon.[11]

The key assumption with RUM models is that individuals choose the alternative that maximizes their utility. Not all factors that influence utility are observed by the analyst, so utility and choice can be interpreted as random from her perspective. Individual *i*'s conditional indirect utility from choosing site *j* on choice occasion *t* can be specified in general terms as:

$$V_{ijt} = U(m_{it} - c_{ij}, \mathbf{X}_j, \varepsilon_{ijt}) \qquad (1)$$

where m_{it} is income, c_{ij} is travel cost, $\mathbf{X}_j$ is a vector of site characteristics, and ε_{ijt} captures idiosyncratic, random factors. A rational, utility-maximizing individual selects the site that generates the highest utility, i.e., site *j* is chosen if $V_{ijt} > V_{ikt}, \forall k \neq j$. Assuming a probability density function for ε_{ijt}, the probability of selecting site *j* at time *t* is given as:

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[10] For examples, see Hausmann et al. (1995), Parsons and Hauber (1998), Parsons and Needleman (1992), Parsons and Kealy (1992), Hauber and Parsons (2000), Parsons et al. (2000), Whitehead and Haab (2000), Murdock (2006), and Carson et al. (2009).

[11] It is important to note that we do not observe a true panel of choices from each individual in the MRIP data set and the resulting repeated cross-section structure of the data precludes modeling unobserved preference heterogeneity and state dependence (i.e. Smith 2005).

$$\Pr_{it}(j) = \Pr[V_{ijt} > V_{ikt}] \;\; \forall \; k \neq j \, . \qquad (2)$$

As described in the next section, a distinctive characteristic of our data is that information about recreation participation and site choice are collected by independent samples. Therefore, when choosing an econometric model, we need a specification that allows for decomposition and separate estimation of these two dimensions of choice. We therefore employ a two-level nested logit model (Morey 1999) and estimate the site choice and participation decisions sequentially. The two-level nested logit model (see Figure 1 for a schematic of its implied structure) generalizes the traditional logit model by allowing for a common random factor to enter the site-specific errors, thus inducing a correlation among site utilities and more reasonable substitution patterns. Sequential estimation allows us to leverage and integrate all of the data into a consistent behavior model. Although there is some efficiency loss relative to full-information maximum likelihood estimation, the large size of our data suggests that this is relatively small price to pay. Assuming that utility is linear and additive in ε_{ijt} (i.e. $V_{ijt} = v_{ijt} + \varepsilon_{ijt}$), the probability of choosing site *j* on choice occasion *t* is:

$$P_{ijt} = P_{it}(j \mid trip) \times P_{it}(trip) = \frac{e^{\left(v_{ijt}/\lambda\right)}}{\sum_{j=1}^{J} e^{v_{ijt}/\lambda}} \frac{\left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}} = \frac{e^{\left(v_{ijt}/\lambda\right)} \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda-1}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}} \qquad (3)$$

where λ is the dissimilarity coefficient and bounded by theory between 0 and 1 (Herriges and Kling 1997). The probability of not taking a trip is then:

$$P_{i0t} = \frac{e^{v_{i0t}}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}} \qquad (4)$$

As described elsewhere (e.g., Ben-Akiva and Lerman 1985) and summarized below, all parameters of this model can be estimated by first estimating the site choice model and then conditionally estimating the participation model using standard logit estimation techniques.

3.1 *Empirical Specification*

In the empirical analysis, we assume the conditional indirect utility from visiting site *j* can be specified as follows:

$$V_{ijt} = \beta c_{ij} + \delta_j + \varepsilon_{ijt} \qquad (5)$$

where δ_j is an alternative specific constant (ASC) for site *j*. To account for time-varying site attributes, we allow the ASCs to vary by year and season, where seasons are either summer (May to August) or non-summer.[12] These ASCs capture all site specific characteristics that vary across years and seasons but are common across individuals (e.g., catch rates). We note that our model assumes a constant marginal utility of income (as is common in the literature) that does not vary by season.

To model participation, we specify the indirect utility function associated with not taking a trip (alternative 0) in the following way:

$$V_{i0t} = \boldsymbol{W}_i \alpha + \boldsymbol{D}_i \phi + \delta_0 + \varepsilon_{i0t} \qquad (6)$$

where $\boldsymbol{W}_i$ and $\boldsymbol{D}_i$ are vectors of individual/year/wave specific weather variables (e.g., temperature, precipitation) and demographics, respectively.[13] Although we leave the details for how these variables are constructed until the next section, we note here that weather is assumed

[12] Data limitations prevent us from using more refined seasonal categories (e.g., winter, spring, summer, and fall), as the intensity of sampling in the MRIP is reduced in the winter and shoulder seasons relative to the summer months.
[13] This participation model differs from previous efforts using the MRIP data (i.e. Whitehead et al. 2009) as it avoids issues with on-site sampling and the strong parametric assumptions (i.e. negative binomial model) needed to correct for this.

to influence recreation participation but not recreation site choice. Our rationale for this specification is driven by data limitations requiring that the empirical analysis focus on localized recreation where individuals travel not more than 300 miles. For these trips, climate variables over a two month period are not likely to vary substantively across sites within a 300 mile drive of one's home.

4 Data and Empirical Application

We obtain the data for this analysis from the NOAA National Marine Fisheries Service (NMFS) Marine Recreation Information Program (MRIP), formerly the Marine Recreational Fishery Statistics Survey (MRFSS). The data include a point-of-access Angler Intercept Survey (intercept data) and the Coastal Household Telephone Survey (phone data). Our analysis utilizes the intercept data to estimate site choice and the phone data to estimate participation.[14] The data are restricted to shoreline intercepts for individuals participating in localized recreation where the primary mode of transportation is driving, the angler's county of residence is included in the sampling frame for the phone survey and the vast majority of trips are likely to be contained within a single day. The data are compiled in two-month intervals, resulting in six waves per year.[15]

[14] Other researchers using MRIP data (e.g., Alvarez et al. 2014) have modeled participation using the self-reported 2-month and 12-month total trip information contained in the intercept survey. Because this information is collected on-site, it suffers from both truncation and endogenous stratification (Hindsley et al. 2011), and although several authors have developed methods to account for these data features, the methods require strong parametric distribution assumptions. Moreover, in our application, it is important to model the participation decisions for the full population (as opposed to just current anglers), as climate change may induce individuals who do not currently fish in coastal waters to do so.

[15] Waves: 1 = Jan/Feb, 2 =Mar/Apr, 3=May/Jun, 4 = Jul/Aug, 5 = Sep/Aug, & 6 = Nov/Dec.

4.1 *Intercept Survey Data*

The intercept survey collects trip data from interviewed individuals on their catch and fishing mode. The variables of particular interest for this work include the intercept location and a zip code of residence identifier for each survey respondent. There are 2,473 intercept sites along the Atlantic and Gulf Coast and nearly 14,000 origin zip codes that have been geocoded for inclusion in our analysis. The restriction of the analysis to localized recreation and shoreline fishing yield a sample size of 161,218 trips across 40 waves.

The survey is stratified by site, state, mode, year and wave. This survey design may lead to biased inferences in estimation of recreation demand if the sample selection process is stratified on an endogenous variable. There is also the potential for avidity bias if more avid fishermen are likely overrepresented in the data. Econometric approaches have been proposed to address these biases (see Hindsley et al. 2011). However, in 2012, the NMFS published design-based sampling weights and variance adjustments to the intercept data and applied these weights to the survey results dating back to 2004. These weights are constructed to generate unbiased estimates of angler effort and reflect the proper proportion of trips from coastal and non-coastal origins (Breidt et al. 2012; Lovell and Carter 2014). This research uses data from 2004-2010 in order to utilize these weights in site choice estimation to minimize the potential biases associated with using stratified survey data collected through on-site sampling.

The program *PC*Miler* calculates the round-trip distance traveled, travel time, and tolls from the centroid of each origin zip code to all sites in each choice set. We assume that any site within 300 miles (roughly a 6 hour drive one-way) of each origin zip is in the choice set. This assumption is based on the idea that 300 miles represents the furthest an individual would likely be able to travel on a single day for localized recreation, which is the focus of our analysis.[16]

We collect additional data to calculate travel costs on average fleet fuel economy (*fe*) from the U.S. Department of Transportation, gas prices by state (*gas*) from the U.S. Energy Information Administration, automobile per-mile operation costs (*cpm*) including tires, depreciation and maintenance from AAA, and zip code level household income from the U.S. Census Bureau. The opportunity cost of time (*oppc*) is then derived using the common assumption that it is 1/3 of the wage rate (Cesario 1976), where the wage rate is estimated as annual household income divided by 2080 hours. Costs that can be shared by all persons on a given trip (e.g. tolls, gas, and mileage) are divided by the average number of individuals in each party from the intercept data ($\bar{n}$).[17] Round trip travel costs (2010 dollars) for individual i to site j at time t are then calculated as follows:

$$c_{ijt} = 2 * \left(\begin{bmatrix} dist_{ij} * (cpm_t) + \\ (dist_{ij} \,/\, fe_t) * gas_t \\ + toll_{ij} \end{bmatrix} / \bar{n} + oppc_{it} * time_{ij} \right) \qquad (7)$$

Table 1 provides a concise summary of all variables used in each stage of the analysis.

4.2 *Phone Survey and Weather Data*

Using county stratified, random-digit-dialing (RDD) from households in coastal counties, the phone survey collects data on the frequency of fishing trips in the preceding two months. The data compiled from this survey include the state and county where the trip occurred and, importantly, the number of anglers who had taken trips and the number of trips taken by each

[16] Similar assumptions are typical in recreation demand analysis (e.g. Parson and Hauber 1998).
[17] The intercept data contains a variable for the number of people per fishing party. The average is 2.73.

angler in the previous two months. For the geographic areas in this study, the phone survey pulls from 328 counties with six-digit phone exchanges as the spatial unit of analysis (see Figure 2).

We utilize data on both fishing and non-fishing households from 12,075 unique phone exchanges from 2004-2010, resulting in 483,000 possible phone exchange/year/wave combinations. Of these combinations, 72,476 represent fishing households that characterize participation in the model. However, the non-fishing households contacted by the phone survey are only spatially identified at the county level. Since the survey is conducted using RDD within counties, the county level non-fishing data are disaggregated to the phone exchange level to facilitate analysis in the following manner. Each six-digit phone exchange is assigned a population weighted proportion of the count of non-anglers in the county where the exchange is located. For example, assume a county has three phone exchanges, each with a population of 10,000 people. If the survey contacted 300 non-anglers in the county, randomization implies we can assign 100 non-anglers to each phone exchange in that given two-month period. The full model includes 410,524 phone exchange/year/wave combinations characterizing non-participation in shoreline recreational fishing activities.

Demographic variables, temperature and precipitation are included in the second-level of model estimation as covariates affecting the participation decision. The demographic data are not collected in the phone survey, so we employ data from the U.S. Census Bureau's *American Community Survey* at the zip code level. Variables of interest include average household income (2010 dollars), race (percent white), and education (percent with Bachelor's degree or higher). A proprietary data set obtained from *Melissa Data* links phone exchanges to the zip code(s) located in each exchange.[18] Phone exchange level demographics are obtained by taking a population-weighted average of each zip code-level variable located in the exchange.

Temperature and precipitation data are generated from the Parameter-elevation Regressions on Independent Slopes Model (PRISM 2009). The PRISM model divides the contiguous U.S. into 2.5 x 2.5 mile grids and uses daily weather station data, while also accounting for factors such as elevation and wind direction, to interpolate approximate weather measures for each grid location. For each bi-monthly wave, daily maximum temperature (°C) and daily precipitation (in millimeters, mm) are averaged from the ten PRISM grid locations in the coastal area nearest to each origin zip code (covering ~ 25 mi^2) to represent weather conditions at the time of the participation decision. Table 2 provides summary statistics by region for weather variables used in the second-stage estimation.

4.3 *Empirical Implementation of the Model*

Estimation proceeds in three steps. The first step utilizes the intercept data to generate estimates of the normalized travel cost coefficients. To achieve this, a conditional logit site choice model with a full set of ASCs is estimated separately for every year of data. Regional heterogeneity in travel costs is accommodated by allowing the travel cost coefficient to vary across four regions of origin (i.e., New England, Mid-Atlantic, Southeast and Gulf).[19] Recall from equation (3) the site choice probabilities take the form:

[18] Dataset description available here: http://www.melissadata.com/reference-data/fonedata.htm

[19] The Gulf region is defined as all site choices and phone responses in Louisiana, Alabama, Mississippi, Florida, and Georgia while the Southeast includes Virginia, North Carolina, and South Carolina. The Mid-Atlantic includes New York, New Jersey, Delaware, and Maryland and New England is defined as Connecticut, Rhode Island, Massachusetts, New Hampshire, and Maine.

$$P_{it}(j \mid trip) = \frac{e^{\left(\beta c_{ij} + \delta_j\right)/\lambda}}{\sum_{k=1}^{J} e^{\left(\beta c_{ik} + \delta_k\right)/\lambda}} \tag{8}$$

Although the first step generates consistent estimates for travel cost, it does not generate consistent estimates for the ASCs because the MRIP only samples a fraction of shoreline fishing sites in every year/wave. For unsampled sites, the ASCs are not identified. We therefore employ the following procedures to recover ASC estimates for all sites in the second step. We first construct aggregate trip estimates by year/wave using the fishing pressure data in the site registry files that NOAA maintains and uses to determine which sites to sample (see Appendix A for details). Importantly, these trips are positive for sampled and unsampled sites in the MRIP intercept data. Using estimates of the share of trips originating from coastal/noncoastal counties in the intercept data, we adjust these aggregate estimates to reflect predicted trips originating from coastal counties. We then turn these estimates into shares of total trips and construct calibrated estimates of the ASCs using the contraction mapping proposed by Berry (1994). These calibrated ASCs are then used to construct the following inclusive value index:

$$IV_i = \ln\left(\sum_{k=1}^{J} e^{\left(\beta/\lambda c_{ik} + \delta_k\right)}\right) \tag{9}$$

where β/λ is estimated in step one and $\tilde{\delta}$ is estimated in step two. IV_i can loosely be interpreted as the expected utility of a trip (Hausman et al. 1995) and is used in the third and final step where we estimate participation. The participation model is a discrete choice logit model as a function of IV_i, demographics and weather variables. dddThe coefficient on IV_i is the dissimilarity coefficient (λ) and is allowed to vary across the four regions.

5 Results

First-stage estimation of the conditional site choice model yields results that conform to prior expectations for travel cost. As shown in Table 3, the coefficients are negative and robust across all years and regions. The precision of the estimates is evident from the large t-statistics. Individuals in the Gulf are more responsive to travel costs associated with a shoreline fishing trip than those in other regions. The parameter estimates on the ASCs are used to characterize unobserved site characteristics at the 2,473 potential sites in the data. As noted in the previous section and Appendix A, these estimates are calibrated using site registry data to account for the lack of sampling at all sites. The first-stage parameters for travel cost and the calibrated ASCs are then used to construct inclusive value terms (equation 9) to link the stages of the sequential nested logit estimation.

The second-stage model exploits seasonal differences in the participation decision by estimating separate models for summer months (May - August) and non-summer months (January - April & September - December). The precision of the travel cost estimates in the first-stage imply that the covariance matrix of the second-stage estimator should not contain significant noise induced by the first-stage estimates. Therefore, we do not correct the second-stage standard errors as is typically done with sequential estimators (Ben-Akiva and Lerman 1985), as doing so would involve considerable computational effort given the size of our data. Results from summer models are displayed in Table 4. For comparison, a simple all-season model (Model 1) using a common inclusive value, temperature, precipitation, and indicator variables for year and wave suggest a positive and significant effect of temperature on participation. Model 2 shows results using the same specification but restricting the observations to summer waves only. The effect of temperature is again significant but smaller in magnitude and precipitation is now significant and negative. However, the results from these models mask regional heterogeneity in the data that is uncovered in Model 3 using region-specific covariates. The impact of temperature is positive and significant in the Mid-Atlantic and New England and negative in the Gulf and Southeast (but only significant in the Gulf). These results are intuitive as the Gulf and Southeast are located in the humid subtropical climate zone and already experience hot, humid summers. Any further increases in temperature in these regions are likely to reduce participation in shoreline fishing activities. The Mid-Atlantic and New England are located in the milder humid continental climate zone and are likely to experience small increases in participation if temperatures increase. Only anglers in the Gulf region are significantly impacted by precipitation as the model predicts declines in participation for increases in precipitation.

In our preferred specification (Model 4), we include region-specific maximum temperature thresholds and temperature-precipitation interaction terms. The threshold variables are constructed by interacting maximum daily temperature with an indicator variable for when average daily maximum temperature is at least one standard deviation above the mean for a particular season in each region. The temperature-precipitation interaction terms are added to test whether the relationship between participation and temperature vary significantly for different values of precipitation (and vice versa). The results in Model 4 of the effect on participation from daily maximum temperature are of similar sign to the results in Model 3 but the magnitudes of the effects are larger. A significant negative threshold effect is observed in the Mid-Atlantic region, indicating that participation is likely to increase at a slower rate above the threshold.[20]

[20] Other specifications, including quadratics and number of days per wave exceeding a threshold, were explored and the effect of temperature on participation only appeared to be non-linear in the Mid-Atlantic in the summer model and the Gulf in the non-summer models.

The main effect of precipitation is positive and significant in the Mid-Atlantic and New England. These results are intuitively appealing, as precipitation is highly correlated with cloud cover and overcast days are anecdotally believed to increase fishing success. Yet, the interaction of two continuous variables (temperature and precipitation) included in the model has the potential to alter the net effect of precipitation conditional on daily maximum temperature. The parameter on the interaction term is negative and significant in the Mid-Atlantic, indicating the positive effect of precipitation on participation is attenuated by higher temperatures. For instance, at the mean for daily maximum temperature, the net effect of precipitation in the Mid-Atlantic is negative due to the interaction effect.[21]

Results of the non-summer models are displayed in Table 5. Results from Model 2 show that restricting the observations to non-summer waves increase the magnitude of the significant and positive impact of temperature. Model 3 again reveals regional heterogeneity in the parameter estimates with the effects of temperature positive and significant in New England, the Mid-Atlantic and the Southeast. The results are again intuitive, as warmer temperatures in non-summer months are likely to expand the available time for fishing activities and therefore increase participation. A negative and significant effect of temperature is found in the Gulf, suggesting that warmer temperatures in the shoulder seasons discourage participation more so than warmer winter temperatures stimulate participation in the humid subtropical region. The preferred model (Model 4) suggests significant and positive effects of temperature in the Mid-Atlantic and New England, albeit slightly smaller in magnitude than Model 3. The effect is strongest in New England where warmer weather in non-summer months has the greatest

[21] The net effect of precipitation on participation is calculated using the following: $\beta_{precip} precip + (\beta_{interaction} temp * precip)$. Using the summer Mid-Atlantic mean daily maximum temperature (27.3°C) and the estimated parameters on precipitation (4.88) and the interaction (-0.19), the net effect is (4.88**precip* + (-0.19(27.3)**precip*), or -0.309**precip*.

potential to increase participation. The threshold effects in the Gulf region suggest participation is likely to increase at a slower rate above the threshold. Precipitation is shown to have positive and significant effects in the Gulf on its own. Yet, the parameter on the interaction term is negative and significant as well, establishing that the relationship between participation and temperature is conditional on precipitation in that region during the non-summer months.

Lastly, the parameter estimates for the dissimilarity coefficients warrant discussion. While all estimates fall within the unit interval, a sufficient condition for consistency with the RUM model (Herriges and Kling 1997), the values are quite small. This suggests a very strong correlation in the unobserved portions of utility for alternatives in each nest. It also implies that site closures will result in small reductions in trips and thus large and possibly unrealistic trip values. For instance, the dissimilarity coefficient for the summer model in the Gulf implies a large value of a trip equal to nearly $370 dollars.[22] We suspect that this finding is driven by the imprecise nature of the trip origin information in the phone survey data. In particular, the phone data only includes the respondent's phone exchange or county of residence, not a more geographically precise origin such as a zip code. As a result, measurement error is introduced into inclusive values which in turn likely generates attenuation bias with the estimated dissimilarity coefficient.[23] As discussed in the next section, we develop a calibration procedure to address this issue with the policy scenarios. Here, however, it is important to note that the key parameters of interest from the participation model – daily maximum temperature and precipitation – are unlikely to be contaminated because weather is not as spatially sensitive to

[22] This estimate is constructed using the formula $-\frac{1}{\beta}$ for a value of trip, where β is estimated by taking the product of the mean value of the first-stage normalized travel cost estimate (-0.159) and the estimated dissimilarity coefficient (0.017) for the Gulf in the summer models. See Haab and McConnell (2002) for a derivation of this result.

[23] Moreover, the fact that the ASCs that feed into the inclusive values are calibrated with fishing pressure data in the site registry and not precisely estimated with choice data may introduce additional measurement error.

measurement error in the origin. Stated differently, temperature and weather variables are likely to be highly correlated across zip code and six-digit exchange origin specifications, so their parameter estimates are likely to be robust.

6 Counterfactual Climate Simulations

6.1 *Global Climate Models*

To investigate the range of potential impacts of climate change on coastal recreational fishing, counterfactual climate scenarios are generated using a variety of GCMs, emissions scenarios, and time horizons for the impacts to occur. A subset of GCMs used by the Intergovernmental Panel on Climate Change (IPCC) is selected based on data availability of ensemble forecasts in predicting *changes* for daily maximum temperature and precipitation under similar emissions scenarios and time horizons.[24] The five models examined here include the Bjerknes Centre for Climate Research's BCM2 model (Norway), the Commonwealth Scientific and Industrial Research Organization's MK3 model (Australia), the Center for Climate System Research's MIROC3_2_MED model (Japan), the Institute for Numerical Mathematics' CM3 model (Russia), and the NASA Goddard Institute for Space Studies' AOM model (U.S.).

In 2000, the IPCC issued a Special Report on Emissions Scenarios (SRES) that established multiple scenarios of future global development with a focus on greenhouse gas emissions.[25] Figure 3 displays the projected emissions associated with the three scenarios – A2, A1B, and B1 – and the three time horizons – short-run (2011-2030) medium-run (2040-2065)

[24] An ensemble contains a number of model simulations with small perturbations in the initial conditions. According to the IPCC, the mean of an ensemble should outperform individual ensemble members and provide a best estimate forecast. Data for the separate ensemble forecasts on the predicted changes in temperature and precipitation are available here: http://www.ipcc-data.org/cgi-bin/ddc_nav/dataset=ar4_gcm

[25] In the IPCC Fourth Assessment Report (2007), new emissions scenarios were found to change little in overall emission levels compared to the SRES. As of 2014 (outside the scope of the baseline in this analysis), SRES was replaced by Representative Concentration Pathways.

and long-run (2080-2099) – examined here. The A2 storyline characterizes the world as experiencing continued population growth, regional economic development, and lack of international unity. Atmospheric CO_2 concentrations are projected to reach 856 ppm by 2100 under this scenario.[26] The A1B storyline reflects a more integrated world with rapid economic growth, continued population growth, widespread technological innovation and adoption, and focus on a balanced energy portfolio. CO_2 concentrations will reach 717 ppm by 2100 under this scenario. Lastly, the B1 storyline describes a world focused on global solutions to environmental problems, development of clean and efficient technologies, and a transition to a service and information economy. Under the B1 scenario, atmospheric CO_2 are projected to reach 549 ppm by 2100. For the purposes of this exercise, consider A2 as a *business-as-usual* scenario, A1B as a scenario with *modest mitigation*, and B1 as a *best-case* scenario.

Weather variables in the data are averaged seasonally (i.e. summer and non-summer) over phone exchange and wave from 2004 – 2010 to establish the baseline climate. The predicted *changes* in daily maximum temperature and precipitation are estimated by the GCMs at a geo-coordinate representative of each region.[27] In general, all model/scenario combinations predict temperature increases for all regions while precipitation declines are predicted for the Gulf and Southeast and gains are expected in the Mid-Atlantic and New England. The changes driving the simulations are displayed in the six figures in Appendix B. Predictions from the GCMs are monthly and are aggregated to bi-monthly wave to match the baseline climate data. For each six-digit exchange and season, the predicted changes in temperature and precipitation are added to the baseline to arrive at the estimated climate conditions under each scenario. The change in

[26] For reference, 2014 levels of atmospheric CO_2 were estimated to be around 399 ppm.

[27] Note that BCM2 and AOM models did not have A2 scenario projections for maximum temperature and precipitation *changes* available so the averages are across 13 possible combinations: (3 models x 3 scenarios) + (2 models x 2 scenarios) = 13 model/scenario combinations.

WTP for shoreline recreational fishing in each future time horizon is estimated using the following equation (Haab and McConnell 2002):

$$WTP_i = -\frac{1}{\beta}\left(\ln\left(e^{-v_{i0}^{1}} + \left[\exp(IV_i)\right]^{\lambda}\right) - \ln\left(e^{-v_{i0}^{0}} + \left[\exp(IV_i)\right]^{\lambda}\right)\right) \text{ x Choice Occasions} \qquad (10)$$

where v_0^1 represents indirect utility in future time horizons and v_0^0 is indirect utility in the baseline period 2004-2010. In equation (3.10), the differences in indirect utility from the baseline to each climate scenario are driven by predicted variation in daily maximum temperature and precipitation.

6.2 *Parameter Estimates for the Simulations*

Two adjustments are made to the parameter estimates from the preferred participation model in order to improve the precision and credibility of the simulation results. First, as shown in Tables 4 and 5, the effect of precipitation was not significantly different from zero in three of the four regions in both seasonal models and the large standard errors introduced substantial noise to test runs of the simulations.[28] In order to improve the precision of the welfare estimates, the preferred participation model (i.e. Model 4) is estimated without the insignificant precipitation variables in each seasonal specification. These new parameter estimates are used in the simulations and are reported in Table 6.

Second, as discussed in the previous section, the dissimilarity coefficient is likely estimated with bias due to measurement error in travel costs. In order to correct for this in the simulations, the dissimilarity coefficient and constant term predicted by the participation model are calibrated to maintain consistent in-sample predictions under the assumption that the value of

[28] The test simulations predicted larger losses in the summer models but without statistical significance. Results of these simulations are available upon request.

a trip is \$30. This value is chosen as it best approximates the value of a marine fishing trip as shown by two recent meta-analyses of numerous valuation studies (Moeltner and Rosenberger 2014; Johnston and Moeltner 2014). Moeltner and Rosenberger (2014) report the average WTP/day for a saltwater fishing trip in the Northeast is \$39.39 (2010 dollars) from five relevant valuation studies. In Johnston and Moeltner (2014), the authors show that the mean Hicksian WTP/day from 14 different studies for saltwater fishing of big-game species is approximately \$33.06. They also report the average WTP/day for small-game saltwater fishing across 13 studies as \$21.33.[29] Since neither meta-analysis contains a directly equivalent value for this research (i.e. all shoreline fishing from New England to Louisiana), the average of the meta-analysis WTP/day means from the two studies (~\$30) is used here as the value of a trip.[30]

The calibrated model is then used to predict the marginal WTP (MWTP) for temperature and precipitation (Table 7). The marginal changes measured by these estimates are a 1°C increase in daily maximum temperature and a 1mm increase in daily precipitation. In the aggregate, MWTP is significant for temperature (\$1.07) and precipitation (\$5.75) in the non-summer model only. Again, the results also show significant regional variation. MWTP in the Gulf is negative and significant for temperature across both seasonal models. In the Mid-Atlantic and New England, MWTP for increased temperature is positive and significant in both models but larger in magnitude in the non-summer waves. MWTP for precipitation is negative and significant in the Gulf in the summer (-S13.83) and positive and significant in the Southeast in the non-summer (\$9.35).

[29] Note these WTP estimates are author calculations using data reported in tables in Johnston and Moeltner (2014). To get from the estimates in their tables, we multiply WTP per fish by mean base catch for each category and then convert from 2003 to 2010 dollars.
[30] Note that our welfare results are proportional to the value of a trip. This implies that if we employed a different value of a trip that was X% higher (lower), our welfare results reported below would also be X% higher (lower).

6.3 *Simulation Results*

Simulations are run for each separate ensemble forecast to generate a distribution of welfare outcomes. The WTP estimates are multiplied by the population in the coastal areas (as defined by MRIP phone survey) to arrive at the numbers presented. Population numbers are adjusted in future time horizons by U.S. Census Bureau predictions of population growth.[31] The following discusses the results in terms of the uncertainty of the climate model output *and* the precision of the welfare predicted by the participation model simulations.

To demonstrate potential climate uncertainty, the range of outcomes under the three emissions scenarios – *business-as-usual* (A2), *modest mitigation* (A1B), and *best-case* (B1) – are displayed in the aggregate and seasonally in Figure 4. The solid lines represent mean welfare change and the dotted lines show the range of estimates from the different model forecasts (i.e. maximum and minimum predictions). Mean welfare predictions in the aggregate (Panel A) suggest an increase reaching nearly $300 million annually in the long-run under all emissions scenarios. As demonstrated in the figure, the range of the sign of the welfare change is uncertain in the short and medium term but consistently positive in the long-run. The decomposition of the effects seasonally in Panels B and C suggest stable signs for the welfare changes across a majority of the ensemble forecasts. In Panel B, the welfare effects of climate change are consistently negative with the steepest decline predicting nearly $127 million in the long-run. Conversely, the welfare changes in the non-summer months are uniformly positive with increases ranging from $349 million to $427 million in the long-run. Both results are intuitive as higher predicted temperatures in the summer can lead to oppressively hot and uncomfortable

[31] http://www.census.gov/population/projections/files/summary/NP2014-T1.csv

conditions for outdoor activities while an analogous change in non-summer months can create more opportunities for outdoor recreation.

These results are also displayed in Table 8. Standard errors for the welfare estimates are generated with a parametric bootstrap (Krinsky and Robb 1986) and 50 draws from the asymptotic variance-covariance matrix.[32] T-statistics calculated from the bootstrapped standard errors are presented to show the precision of the welfare estimates. All emissions scenarios have the potential to significantly increase aggregate annual welfare in the long-run. Again, there is seasonal heterogeneity in these results as shown in Panels B and C of Table 8. In the medium-run, significant summer welfare losses are predicted under both *moderate mitigation* ($2.61/trip or -$99 million) and *best-case* (-$2.29/trip or -$63 million) emissions scenarios. Aggregate summer losses in the long-run exceed $120 million but are not statistically significant at the 95% confidence level. Conversely, nearly all welfare predictions in the non-summer models are positive and highly significant. Gains are predicted in all time horizons, ranging from $3.16/trip ($53 million) in the short run to $25.42/trip ($427 million) in the long-run. In sum, potential welfare gains in non-summer months are likely to exceed losses experienced in the non-summer months across the Atlantic and Gulf coasts.

The results are then decomposed seasonally by region to highlight the spatial variability masked by the aggregate results. The climate uncertainty is displayed in Figure 5 for summer months and in Figure 6 for non-summer months. In the summer scenarios, negative welfare changes are predicted in the Gulf with the range of the sign of the change stable across a majority of the emissions scenarios in the medium and long-run. Small welfare losses are also predicted for the Southeast region for the summer months. Conversely, welfare gains are predicted in both

[32] The complexity of the simulations and available computing resources limited the reasonable number of draws for the parametric bootstrap to 50. Running the simulations with 50 draws required > 24 hours of computing time.

the Mid-Atlantic and New England across all time horizons, with slight uncertainty demonstrated by the range of the impacts in the long-run in the Mid-Atlantic. In the non-summer scenarios, the change in welfare is unambiguously positive in the Mid-Atlantic and New England. Negative welfare is predicted in the Gulf under the *business-as-usual* scenario with the range of values tending toward negative impacts in the other two scenarios. Lastly, the climate model uncertainty precludes making a definitive claim either way in the Southeast region in the non-summer months.

The region-specific simulation results are also reported in Table 9 (Summer) and Table 10 (Non-Summer). In the summer months, negative and significant impacts are found in the Gulf and Southeast regions in the long-run. Substantial reductions in potential welfare losses from adopting greenhouse gas mitigation strategies are also found in the Gulf ($86 million annually). In the more temperate Mid-Atlantic and New England regions during the summer, mitigation efforts would result in declines in the potential welfare gains. In non-summer months, *best-case* mitigation would generate an annual decline in welfare compared to *business-as-usual* in the long-run in New England of nearly $166 million. The potential effects of mitigation in other regions are more moderate with the Gulf and Southeast seeing small improvements and the Mid-Atlantic experiencing a small decline. Overall, adopting efforts to mitigate greenhouse gas emissions in the near-term has the potential to prevent future welfare losses of nearly $157 million associated with recreational fishing in the Gulf region. Yet, the same reduction in emissions could also reduce the potential gains in New England in excess of $220 million.

The demand responses initiated by the changing climate are displayed in the aggregate (Table 11) and regionally (Table 12 Summer; Table 13 Non-Summer). In the aggregate, the simulations predict approximately 44.5 million trips originating from coastal counties in the

Atlantic and Gulf Coast regions. Maintaining a *business-as-usual* approach to greenhouse gas mitigation would result in a 0.7 to 2.2 percent increase in shoreline recreational trips, although there is substantial heterogeneity across summer and non-summer months. In particular, trips are predicted to decline significantly in the summer months under all mitigation scenarios, up to 4.6 percent in the long-run with *business-as-usual*. In the non-summer months, increasing temperatures provide more recreation opportunities and increase participation by up to 13.4 percent in the long-run with *business-as-usual*. In the regional summer table (Table 12), significant reductions in the long-run are predicted for the Gulf of nearly 2 million trips lost (17.6 percent) and the Southeast of 0.5 million trips lost (8.6 percent). Substantial percentage gains are predicted in both the Mid-Atlantic (62.7 percent) and New England (24.2 percent). In the regional non-summer table (Table 13), the result of note is the near doubling of participation in New England in the long-run under *business-as-usual* mitigation. More modest gains are predicted across all time horizons and emissions scenarios in the Mid-Atlantic and the Southeast. The Gulf region experiences declines across the board as climate change is likely to extend the hot and humid summer conditions into the shoulder seasons thereby reducing participation upwards of 7 percent in the long term.[33]

7 Adaptation in Recreation Choice

The results above suggest that long-run climate change will affect demand for shoreline fishing activities. Declines in the number of trips taken were predicted for the Gulf and Southeast

[33] The changes in participation rates may potentially have impacts on fish stocks that, in turn, may influence catch rates. For instance, an increase in participation may result in a small decline in catch rates, potentially offsetting some of the benefits from climate change identified here. Assessing this potential feedback loop is an area for future research and is not addressed in this paper.

regions in summer models in all future time horizons. However, these declines are relatively small given the magnitude of the simulated changes in climate, indicating that coastal recreational fishermen may adapt to a shifting climate. The focus on individuals participating in localized recreation in this research allows for the potential to identify a mechanism for an intensive margin adaptation – *intraday* substitution (i.e. shifting coastal fishing activities from day to night). Consider an individual taking a trip to a specific site on a particularly warm day (i.e. > 95°F). The ability to substitute to a different site within the individual's choice set with significantly more amenable weather conditions is unlikely. However, the individual has the ability to make an *intraday* temporal substitution of the timing of the activity to avoid the extreme daytime heat.

Since the change in the number of trips predicted for the Gulf and Southeast is relatively small and may suggest adaptation is already occurring, this analysis is restricted to those regions. Data from the phone survey are utilized to estimate the probability of an individual choosing to fish during nighttime hours. An observation is designated night fishing if the self-reported time that fishing activities were completed occurs between sunset and sunrise in that particular wave.[34] A simple logit model is estimated utilizing weather and demographic variables similar to the previous analysis and fixed effects for time (wave and year). Recognizing the ambiguity in the definition of a night trip, we conducted sensitivity analyses where we vary the definition of nighttime fishing to gauge the sensitivity of our results. Although not reported here, our main results are robust to these perturbations.

Results are presented in Table 14. They provide suggestive evidence that anglers may already be adapting to high temperatures in both the Gulf and Southeast. If maximum daily

[34] For example, in wave 1 (Jan/Feb), night fishing is defined as any observation in the 6 PM to 7 AM window. Night fishing in wave 4 (May/June) is defined using the interval 9 PM to 6 AM.

temperature increases by 1°C, the probability of night fishing increases 1.4 percent in the Gulf and 2.1 percent in the Southeast. This evidence could have substantial implications with a changing climate. For instance, a 3°C to 5°C increase in daily maximum temperature in the long-run as predicted by a majority of the GCMs for the Southeast implies a 6.3 to 10.5 percent increase in the probability of night fishing.

8 Conclusion

In this article, we extend the literature on quantifying the potential impacts of climate change to marine recreational fishing. Our results imply that temperature and precipitation significantly influence anglers' decisions to participate in coastal shoreline recreational fishing. Using a number of IPCC climate models and emissions scenarios, we then simulate counterfactual climate scenarios that suggest positive aggregate welfare impacts from climate change. This finding is broadly consistent with past research by Mendelsohn and Markowski (1999) and Loomis and Crespi (1999), although we also find impacts that vary substantially both seasonally and regionally. In general, our results imply relatively small welfare losses in the summer months and large welfare gains in non-summer months. Continuing on our current trajectory with limited greenhouse gas mitigation policies is predicted to result in welfare losses to shoreline recreational fishing in the Gulf region in all seasons. These losses could be reduced with more aggressive mitigation policies, although these same policies may *reduce* the potential welfare gains from climate change in New England and the Mid-Atlantic. Similar to our welfare estimates, predicted demand responses in the aggregate are relatively small but vary substantially both seasonally and regionally. Lastly, suggestive evidence of intraday temporal substitution to night fishing is identified as a potential adaptation to climate change.

Our results are subject to a number of important caveats. First, the MRIP data structure imposed several limitations on our analysis. The fact that participation and site choice information are collected with independent surveys, the phone survey samples only coastal counties, and the intercept and phone surveys collect information on the location of respondents' residences at different spatial scales significantly limited our statistical analysis. Although we believe our modeling decisions are defensible given these data constraints, they are certainly restrictive and should be considered when interpreting our results. Second, our use of *expected* temperature and precipitation changes from ensemble forecasts masks a great deal of uncertainty associated with these climate model predictions. A more complete analysis would combine the full distribution of climate model predictions with our estimated models to predict the full distribution of welfare impacts for coastal recreational fishing. Although we believe this would represent a significant advance over our chosen approach, it would also be computationally demanding, and so we leave it for future research.

Lastly, and perhaps most consequentially, the welfare impacts discussed here are limited in that they ignore indirect ecological changes associated with the climate scenarios. The implications of this assumption are uncertain (see Mendelsohn and Markowski 1999 and Loomis and Crespi 1999). It is plausible that climate effects on fish stocks and their resulting impacts on behavior through changes in catch rates may be significant. For instance, a reduction in catch rates would likely increase the losses predicted in the summer models and reduce the gains reported in the non-summer models. However, the magnitude and sign of the indirect effects remains an open empirical question. Progress in our understanding of dynamic responses of fish stocks to climate change will help advance this research agenda forward. As such, a full accounting of both direct and indirect effects of climate change remains an important avenue for future research.

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Table 1: Definition of Variables

	Description
Variables Enter Site Choice Model	
Site-Specific Travel Cost (TC)	From zip code of origin to specific site choice
Alternative Specific Constants (ASCs)	ASCs for each site choice captures all site characteristics that are the same across individuals, both observed and unobserved
Variable Entering Participation Model	
Weather	
Temperature	Maximum daily temperature *(°C)*
Precipitation	Daily precipitation *(mm)*
Demographics	
Income	Average annual real household income (2010 dollars)
Population Density	People per square mile
White	% of population that is white
Male	% of population that is male
Education	% of population completing bachelor's degree or higher
No Trip ASC	Alternative specific constant for no trip alternative

Source: Weather variables are obtained from PRISM (2009) and are authors' calculations representing the weather in the nearest coastal county to each phone survey respondent are averaged over each bi-monthly MRIP wave for analysis. Demographic variables are at the phone exchange level and represent a population weighted average of the U.S. Census American Community Survey zip code demographic data contained in each exchange.

Table 2: Summary Statistics for Temperature & Precipitation Variables

	Summer				**Non-Summer**			
Variables	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
Daily Maximum Temperature (°C)								
Gulf	31.7	1.13	27.8	34.3	24.6	3.98	13.2	32.8
Mid-Atlantic	27.3	2.66	20.0	33.0	15.2	5.52	2.4	27.0
New England	24.8	3.02	16.8	30.3	14.3	4.95	0.7	23.8
Southeast	29.9	2.07	23.7	34.2	19.8	5.15	5.4	29.3
Max Temperature Threshold								
Gulf	1.98	7.86	0	34.3	2.13	7.72	0	32.8
Mid-Atlantic	2.00	7.59	0	33.0	1.60	5.73	0	27.0
New England	0.97	5.18	0	30.3	0.80	3.91	0	23.8
Southeast	0.90	5.33	0	34.2	1.60	5.73	0	29.3
Precipitation (mm)								
Gulf	0.53	0.21	0.0	1.40	0.31	0.19	0.01	1.43
Mid-Atlantic	0.33	0.12	0.10	0.75	0.36	0.12	0.10	0.93
New England	0.35	0.17	0.11	1.18	0.41	0.15	0.12	0.86
Southeast	0.39	0.14	0.12	0.89	0.32	0.15	0.08	1.14

Note: Max temperature threshold is indicator variable for when average daily high temperature is at least 1 standard deviation above the mean in a given wave interacted with daily maximum temperature.

Table 3: Travel Cost Estimates from Conditional Site Choice Model

	Gulf Region		**Mid-Atlantic Region**		**New England**		**Southeast Region**	
Year	*Parameter*	*T-stat*	*Parameter*	*T-stat*	*Parameter*	*T-stat*	*Parameter*	*T-stat*
2004	-0.172	-30.87	-0.092	-15.81	-0.110	-5.73	-0.072	-19.99
2005	-0.161	-26.76	-0.079	-16.53	-0.085	-12.87	-0.070	-16.99
2006	-0.170	-32.20	-0.082	-15.85	-0.085	-14.06	-0.067	-19.03
2007	-0.157	-31.36	-0.087	-15.96	-0.094	-10.87	-0.081	-24.52
2008	-0.136	-29.39	-0.084	-16.55	-0.092	-11.20	-0.069	-19.51
2009	-0.160	-30.41	-0.069	-11.40	-0.086	-9.99	-0.070	-18.88
2010	-0.154	-24.54	-0.091	-19.45	-0.100	-12.40	-0.079	-23.22

Source: Authors' estimates from site choice model run in GAUSS.

Table 4: Participation Model Results: Summer Specifications

	Model 1 (All Seasons)		**Model 2**		**Model 3**		**Model 4 (Preferred)**	
Variables	*Parameter*	*Std. Err.*	*Parameter*	*Std. Err.*	*Parameter*	*Std. Err.*	*Parameter*	*Std. Err.*
Daily Max Temperature (°C)	0.066***	0.003	0.038***	0.009	-	-	-	-
Gulf	-	-	-	-	-0.093***	0.025	-0.098**	0.045
Mid-Atlantic	-	-	-	-	0.035***	0.012	0.109***	0.028
New England	-	-	-	-	0.039***	0.012	0.069***	0.026
Southeast	-	-	-	-	-0.023	0.017	-0.067	0.045
Precipitation (mm)	-0.051	0.046	-0.188***	0.068	-	-	-	-
Gulf	-	-	-	-	-0.457***	0.084	-0.694	2.357
Mid-Atlantic	-	-	-	-	-0.197	0.182	4.878***	1.845
New England	-	-	-	-	0.255	0.177	2.328*	1.363
Southeast	-	-	-	-	0.024	0.164	-3.433	3.283
Max Temperature Threshold								
Gulf	-	-	-	-	-	-	-0.0000	0.002
Mid-Atlantic	-	-	-	-	-	-	-0.0046***	0.002
New England	-	-	-	-	-	-	-0.0002	0.003
Southeast	-	-	-	-	-	-	-0.0014	0.002
*Temperature*Precipitation*								
Gulf	-	-	-	-	-	-	0.074	0.075
Mid-Atlantic	-	-	-	-	-	-	-0.190***	0.067
New England	-	-	-	-	-	-	-0.090	0.059
Southeast	-	-	-	-	-	-	0.114	0.109
Dissimilarity Coefficient	0.003***	0.0005	0.000	0.001	-	-	-	-
Gulf	-	-	-	-	0.017***	0.003	0.017***	0.003
Mid-Atlantic	-	-	-	-	0.030***	0.004	0.031***	0.004
New England	-	-	-	-	0.035***	0.004	0.035***	0.005
Southeast	-	-	-	-	0.010	0.005	0.008	0.006
Observations	488,694		205,116		205,116		205,116	
Model Fit (Log pseudo-likelihood)	-1.854e+10		-9.556e+09		-9.533e+09		-9.532e+09	

Note: Models are estimated conservatively with robust standard errors clustered by phone exchange. Demographics (income, race, sex, population density, and education) and year & wave fixed effects also included as regressors but not displayed. Max temperature threshold is indicator variable for when daily high temperature is at least 1 standard deviation above the mean in a given wave.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5: Participation Model Results: Non-Summer Specifications

	Model 1 (All Seasons)		**Model 2**		**Model 3**		**Model 4 (Preferred)**	
Variables	*Parameter*	*Std. Err.*	*Parameter*	*Std. Err.*	*Parameter*	*Std. Err.*	*Parameter*	*Std. Err.*
Daily Max Temperature (°C)	0.066***	0.003	0.081***	0.004	-	-	-	-
Gulf	-	-	-	-	-0.029***	0.011	-0.005	0.014
Mid-Atlantic	-	-	-	-	0.080***	0.008	0.047**	0.022
New England	-	-	-	-	0.131***	0.011	0.118***	0.035
Southeast	-	-	-	-	0.027***	0.009	0.013	0.015
Precipitation (mm)	-0.051	0.046	0.013	0.074	-	-	-	-
Gulf	-	-	-	-	-0.077	0.089	1.301**	0.515
Mid-Atlantic	-	-	-	-	0.520**	0.219	-0.004	1.110
New England	-	-	-	-	0.245	0.230	-0.029	1.381
Southeast	-	-	-	-	0.464***	0.167	0.285	0.728
Max Temperature Threshold								
Gulf	-	-	-	-	-	-	-0.005***	0.002
Mid-Atlantic	-	-	-	-	-	-	0.010	0.005
New England	-	-	-	-	-	-	-0.0003	0.009
Southeast	-	-	-	-	-	-	0.003	0.003
*Temperature*Precipitation*								
Gulf	-	-	-	-	-	-	-0.051**	0.020
Mid-Atlantic	-	-	-	-	-	-	0.021	0.054
New England	-	-	-	-	-	-	0.015	0.069
Southeast	-	-	-	-	-	-	0.005	0.033
Dissimilarity Coefficient	0.003***	0.0005	-0.004***	0.002	-	-	-	-
Gulf	-	-	-	-	0.003	0.002	0.004**	0.020
Mid-Atlantic	-	-	-	-	0.027***	0.006	0.028***	0.007
New England	-	-	-	-	0.056***	0.012	0.059***	0.012
Southeast	-	-	-	-	0.010	0.006	0.011	0.006
Observations	488,694		283,578		283,578		283,578	
Model Fit (Log pseudo-likelihood)	-1.854e+10		-8.969e+09		-8.926e+09		-8.924e+09	

Note: Models are estimated conservatively with robust standard errors clustered by phone exchange. Demographics (income, race, sex, population density, and education) and year & wave fixed effects also included as regressors but not displayed. Max temperature threshold is indicator variable for when daily high temperature is at least 1 standard deviation above the mean in a given wave.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 6: Parameters for Climate Simulations

	Estimate	*Std. Err.*	*95 % Confidence Interval*	
Summer Model				
Daily Max Temperature (°C)				
Gulf	-0.084***	0.037	-0.136	-0.031
Mid-Atlantic	0.110***	0.028	0.055	0.164
New England	0.032**	0.014	0.004	0.059
Southeast	-0.022	0.018	-0.057	0.013
Precipitation (mm)				
Mid-Atlantic	4.952***	1.845	1.336	8.568
Max Temperature Threshold				
Gulf	-0.0002	0.002	-0.003	0.003
Mid-Atlantic	-0.005**	0.002	-0.009	-0.001
New England	0.001	0.003	-0.004	0.007
Southeast	-0.015	0.002	-0.006	0.003
*Temperature*Precipitation*				
Gulf	-0.015***	0.003	-0.020	-0.009
Mid-Atlantic	-0.192***	0.067	-0.323	-0.061
New England	0.011	0.008	-0.004	0.026
Southeast	0.001	0.005	-0.010	0.012
Non-Summer Model				
Daily Max Temperature (°C)				
Gulf	-0.005	0.014	-0.032	0.022
Mid-Atlantic	0.047***	0.012	0.023	0.071
New England	0.118***	0.022	0.075	0.161
Southeast	0.009	0.011	-0.012	0.031
Precipitation (mm)				
Gulf	1.299**	0.515	0.289	2.301
Max Temperature Threshold				
Gulf	-0.005***	0.002	-0.009	-0.002
Mid-Atlantic	0.010*	0.005	-0.000	0.021
New England	-0.0003	0.009	-0.019	0.018
Southeast	0.003	0.003	-0.003	0.009
*Temperature*Precipitation*				
Gulf	-0.051**	0.020	-0.091	-0.011
Mid-Atlantic	0.021*	0.011	-0.001	0.043
New England	0.013	0.012	-0.009	0.036
Southeast	0.017**	0.007	0.003	0.032

Note: Models are estimated conservatively with robust standard errors clustered by phone exchange. Demographics (income, race, sex, population density, and education) and year & wave fixed effects also included as regressors but not displayed. Max temperature threshold is indicator variable for when daily high temperature is at least 1 standard deviation above the mean in a given wave.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 7: Marginal Willingness to Pay for Weather Variables

	MWTP	*Std. Err.*	*T-Stat*	*95 % Confidence Interval*	
Summer Model					
Daily Max Temperature (°C) [a]	-$0.59	0.53	-1.12	-$1.65	$0.42
Gulf	-$2.76	0.79	-3.49	-$4.19	-$1.25
Mid-Atlantic	$1.33	0.42	3.15	$0.64	$2.34
New England	$1.05	0.45	2.34	-$0.10	$1.71
Southeast	-$0.65	0.61	-1.07	-$1.98	$0.20
Precipitation (mm) [b]	-$4.66	2.84	-1.64	-$9.14	$0.92
Gulf	-$13.83	2.82	-4.90	-$19.13	-$7.63
Mid-Atlantic	-$4.74	6.28	-0.76	-$17.64	$8.71
New England	$8.03	5.30	1.51	-$5.38	$15.30
Southeast	$0.78	4.96	0.15	-$11.48	$8.80
Non-Summer Model					
Daily Max Temperature (°C)	$1.07	0.25	4.31	$0.53	$1.61
Gulf	-$0.68	0.32	-2.12	-$1.42	-$0.08
Mid-Atlantic	$1.69	0.35	4.83	$1.08	$2.40
New England	$3.71	0.57	6.54	$2.48	$4.88
Southeast	$0.44	0.32	1.39	-$0.15	$1.02
Precipitation (mm)	$5.75	3.11	1.85	$0.39	$12.67
Gulf	$0.47	2.21	0.21	-$3.47	$5.34
Mid-Atlantic	$8.37	5.65	1.48	-$1.47	$20.95
New England	$4.98	4.26	1.16	-$4.39	$12.94
Southeast	$9.35	4.12	2.27	-$0.41	$16.21

Note: [a] – Marginal change defined as 1°C increase in temperature. [b] – Marginal change defined as 1mm increase in daily average precipitation.

Table 8: Annual WTP under Different IPCC Emissions Scenarios

Time Horizon	**2011-2030**			**2040-2065**			**2080-2099**		
	WTP (millions)	*T-stat*	*WTP/trip*	*WTP (millions)*	*T-stat*	*WTP/trip*	*WTP (millions)*	*T-stat*	*WTP/trip*
Panel A: Aggregate									
A2: *Business-as-Usual*	$51.3	1.94	$1.15	$84.2	1.52	$1.89	$304	2.55	$6.83
A1B: *Moderate Mitigation*	$48.6	1.67	$1.09	$83.4	1.32	$1.88	$285	2.54	$6.41
B1: *Best-Case Scenario*	$72.4	3.27	$1.63	$61.4	1.37	$1.38	$260	2.87	$5.85
Panel B: Summer									
A2: *Business-as-Usual*	-$7.3	-0.24	-$0.26	-$72.4	-1.32	-$3.58	-$123	-1.18	-$4.44
A1B: *Moderate Mitigation*	-$4.5	-0.16	-$0.16	-$99.1	-2.18	-$2.61	-$127	-1.88	-$4.59
B1: *Best-Case Scenario*	$8.9	0.49	$0.32	-$63.4	-2.79	-$2.29	-$89.4	-1.39	-$3.23
Panel C: Non-Summer									
A2: *Business-as-Usual*	$58.6	4.60	$3.49	$156	7.51	$9.28	$427	7.74	$25.42
A1B: *Moderate Mitigation*	$53.1	2.82	$3.16	$182	8.24	$10.83	$412	6.42	$25.53
B1: *Best-Case Scenario*	$63.6	1.81	$3.79	$125	2.18	$7.44	$349	4.09	$20.78

Note: WTP is averaged across 5 climate models (BCM2, MK3, AOM, CM3, & MIROC3) for A1B and B1 and 3 climate models (MK3, CM3, & MIROC3) for A2.

Table 9: Annual WTP under Different IPCC Emissions Scenarios: Summer Models

Time Horizon	**2011-2030**			**2040-2065**			**2080-2099**		
	WTP (millions)	*T-stat*	*WTP/trip*	*WTP (millions)*	*T-stat*	*WTP/trip*	*WTP (millions)*	*T-stat*	*WTP/trip*
Panel A: Gulf									
A2: *Business-as-Usual*	-$3.53	-0.24	-$0.19	-$61.9	-1.75	-$3.27	-$182	-2.70	-$9.60
A1B: *Moderate Mitigation*	$1.09	0.05	$0.06	-$91.1	-3.58	-$4.81	-$143	-3.04	-$7.55
B1: *Best-Case Scenario*	$13.4	2.04	$0.71	-$58.2	-3.99	-$3.07	-$95.7	-4.48	-$5.05
Panel B: Southeast									
A2: *Business-as-Usual*	-$11.8	-1.30	-$1.25	-$25.6	-1.79	-$2.72	-$46.9	-1.97	-$4.98
A1B: *Moderate Mitigation*	-$10.7	-1.32	-$1.14	-$22.2	-1.78	-$2.36	-$35.7	-2.10	-$3.79
B1: *Best-Case Scenario*	-$10.2	-3.90	-$1.08	-$16.9	-0.77	-$1.79	-$23.6	-0.82	-$2.50
Panel C: Mid-Atlantic									
A2: *Business-as-Usual*	$9.52	1.48	$1.58	$15.1	2.96	$2.50	$113	3.02	$18.71
A1B: *Moderate Mitigation*	$6.89	1.39	$1.14	$4.57	0.38	$0.76	$46.6	2.39	$7.72
B1: *Best-Case Scenario*	$12.2	0.94	$2.02	$28.3	1.65	$4.69	$25.0	0.82	$4.14
Panel D: New England									
A2: *Business-as-Usual*	$26.5	4.08	$3.77	$45.0	1.70	$6.40	$120	2.74	$17.07
A1B: *Moderate Mitigation*	$23.1	2.33	$3.29	$46.0	4.25	$6.54	$94.8	4.13	$13.49
B1: *Best-Case Scenario*	$16.7	2.93	$2.38	$38.8	4.20	$5.52	$62.1	1.98	$8.84

Note: WTP is averaged across 5 climate models (BCM2, MK3, AOM, CM3, & MIROC3) for A1B and B1 and 3 climate models (MK3, CM3, & MIROC3) for A2.

Table 10: Annual WTP under Different IPCC Emissions Scenarios: Non-Summer Models

Time Horizon	**2011-2030**			**2040-2065**			**2080-2099**		
	WTP (millions)	*T-stat*	*WTP/trip*	*WTP (millions)*	*T-stat*	*WTP/trip*	*WTP (millions)*	*T-stat*	*WTP/trip*
Panel A: Gulf									
A2: *Business-as-Usual*	-$26.5	-4.99	-$1.40	-$71.8	-5.77	-$3.79	-$110	-7.66	-$5.80
A1B: *Moderate Mitigation*	-$25.4	-1.90	-$1.34	-$38.2	-2.85	-$2.02	-$102	-4.33	-$5.38
B1: *Best-Case Scenario*	-$13.9	-0.45	-$0.73	-$36.3	-0.91	-$1.92	-$38.7	-0.68	-$2.04
Panel B: Southeast									
A2: *Business-as-Usual*	$15.3	1.85	$1.62	$36.8	2.32	$3.91	$27.6	1.23	$2.93
A1B: *Moderate Mitigation*	$25.0	1.53	$2.65	$33.5	1.59	$3.55	$67.5	1.47	$7.16
B1: *Best-Case Scenario*	$2.91	0.33	$0.31	-$0.7	-0.05	-$0.07	$44.1	2.29	$4.68
Panel C: Mid-Atlantic									
A2: *Business-as-Usual*	$29.7	2.26	$4.92	$87.7	9.10	$14.52	$227	6.50	$37.59
A1B: *Moderate Mitigation*	$25.3	3.12	$4.19	$89.4	10.8	$14.80	$240	7.29	$39.74
B1: *Best-Case Scenario*	$36.4	5.99	$6.03	$77.3	4.99	$12.80	$197	6.08	$32.62
Panel D: New England									
A2: *Business-as-Usual*	$52.5	10.0	$7.47	$111	11.1	$15.79	$303	16.1	$43.11
A1B: *Moderate Mitigation*	$35.3	9.82	$5.02	$106	10.3	$15.08	$230	9.01	$32.72
B1: *Best-Case Scenario*	$39.0	4.05	$5.55	$85.4	5.88	$12.15	$137	4.28	$19.49

Note: WTP is averaged across 5 climate models (BCM2, MK3, AOM, CM3, & MIROC3) for A1B and B1 and 3 climate models (MK3, CM3, & MIROC3) for A2.

Table 11: Demand Responses (in millions of trips) for Counterfactual Climate Scenarios

Time Horizon	2011-2030			2040-2065			2080-2099		
	Trips [a]	*T-stat*	*Change* [b]	*Trips*	*T-stat*	*Change*	*Trips*	*T-stat*	*Change*
Panel A: Aggregate (Baseline: 44.5 million trips)									
A2: *Business-as-Usual*	44.8	10.2	0.7 %	44.6	9.16	0.2 %	45.4	7.26	2.2 %
A1B: *Moderate Mitigation*	44.8	9.59	0.7 %	44.4	8.83	-0.2 %	45.3	7.82	1.9 %
B1: *Best-Case Scenario*	45.1	10.2	1.4 %	44.5	9.47	-0.1 %	45.3	7.65	2.0 %
Panel B: Summer (Baseline: 27.7 million trips)									
A2: *Business-as-Usual*	27.6	12.6	-0.4 %	26.8	11.0	-3.2 %	26.4	8.44	-4.6 %
A1B: *Moderate Mitigation*	27.6	11.8	-0.2 %	26.5	10.5	-4.4 %	26.3	9.09	-4.8 %
B1: *Best-Case Scenario*	27.8	12.6	0.5 %	26.9	11.5	-2.8 %	26.7	9.01	-3.4 %
Panel C: Non-Summer (Baseline: 16.8 million trips)									
A2: *Business-as-Usual*	17.2	7.88	2.6 %	17.8	7.30	5.8 %	19.0	6.09	13.4 %
A1B: *Moderate Mitigation*	17.2	7.36	2.3 %	17.9	7.13	6.7 %	19.0	6.55	13.0 %
B1: *Best-Case Scenario*	17.3	7.84	2.8 %	17.6	7.49	4.6 %	18.6	6.28	11.0 %

Note: [a] – Number of trips taken under each scenario. [b] – Percentage gain or loss relative to baseline estimated in model for 2004-2010.

Table 12: Demand Responses (in millions of trips) for Counterfactual Climate Scenarios: Summer

Time Horizon	**2011-2030**			***2040-2065***			***2080-2099***		
	Trips [a]	*T-stat*	*Change* [b]	*Trips*	*T-stat*	*Change*	*Trips*	*T-stat*	*Change*
Panel A: Gulf (Baseline: 11.0 million trips)									
A2: *Business-as-Usual*	10.9	15.6	-1.3 %	10.2	11.0	-7.0 %	9.07	6.20	-17.6 %
A1B: *Moderate Mitigation*	11.0	11.5	-0.9 %	9.87	9.56	-10.2 %	9.47	7.58	-13.9 %
B1: *Best-Case Scenario*	11.2	17.5	1.4%	10.3	14.9	-6.6 %	9.98	9.57	-9.3 %
Panel B: Southeast (Baseline 5.73 million trips)									
A2: *Business-as-Usual*	5.56	15.7	-4.1 %	5.42	13.7	-5.5 %	5.24	12.1	-8.6 %
A1B: *Moderate Mitigation*	5.58	15.4	-2.5 %	5.46	13.4	-4.8 %	5.36	15.2	-6.5 %
B1: *Best-Case Scenario*	5.59	15.5	-1.5 %	5.53	14.2	-3.6 %	5.49	11.8	-4.3 %
Panel C: Mid-Atlantic (Baseline 1.95 million trips)									
A2: *Business-as-Usual*	2.10	2.27	7.3 %	2.31	2.13	18.4 %	3.18	2.23	62.7 %
A1B: *Moderate Mitigation*	2.06	2.32	5.3 %	2.14	2.14	9.9 %	2.46	1.99	25.9 %
B1: *Best-Case Scenario*	2.13	2.31	9.4 %	2.01	2.30	3.1 %	2.22	2.14	13.9 %
Panel D: New England (Baseline 5.28 million trips)									
A2: *Business-as-Usual*	5.67	11.7	7.5 %	5.76	13.1	9.2 %	6.55	6.06	24.2 %
A1B: *Moderate Mitigation*	5.62	10.8	6.5 %	5.84	10.5	10.7 %	6.29	7.28	19.2 %
B1: *Best-Case Scenario*	5.52	11.2	4.7 %	5.85	7.19	10.9 %	5.94	8.85	12.6 %

Note: [a] – Number of trips taken under each scenario. [b] – Percentage gain or loss relative to baseline estimated in model for 2004-2010.

Table 13: Demand Responses (in millions of trips) for Counterfactual Climate Scenarios: Non-Summer

Time Horizon	**2011-2030**			***2040-2065***			***2080-2099***		
	Trips [a]	*T-stat*	*Change* [b]	*Trips*	*T-stat*	*Change*	*Trips*	*T-stat*	*Change*
Panel A: Gulf (Baseline: 7.96 million trips)									
A2: *Business-as-Usual*	7.74	34.7	-2.5 %	7.51	19.8	-5.6 %	7.37	16.0	-7.4 %
A1B: *Moderate Mitigation*	7.76	18.8	-2.4 %	7.72	22.2	-3.0 %	7.41	14.5	-6.9 %
B1: *Best-Case Scenario*	7.85	39.7	-1.3 %	7.73	23.4	-2.9 %	7.75	24.0	-2.6 %
Panel B: Southeast (Baseline 3.35 million trips)									
A2: *Business-as-Usual*	3.80	5.12	3.1 %	3.91	4.10	6.1 %	3.83	2.23	3.9 %
A1B: *Moderate Mitigation*	3.87	4.20	4.9 %	3.89	4.15	5.6 %	4.04	1.93	9.6 %
B1: *Best-Case Scenario*	3.71	4.95	0.6 %	3.68	4.65	-0.1 %	3.92	2.24	6.3 %
Panel C: Mid-Atlantic (Baseline 4.35 million trips)									
A2: *Business-as-Usual*	4.27	5.53	4.7 %	4.63	5.71	13.5 %	5.28	4.85	29.4 %
A1B: *Moderate Mitigation*	4.26	5.92	4.2 %	4.64	5.89	13.6 %	5.36	4.47	31.2 %
B1: *Best-Case Scenario*	4.35	5.77	6.5 %	4.56	5.72	11.8 %	5.13	4.21	25.6 %
Panel D: New England (Baseline 1.74 million trips)									
A2: *Business-as-Usual*	2.14	4.53	21.9 %	2.44	4.63	39.3 %	3.35	3.68	91.0 %
A1B: *Moderate Mitigation*	2.01	5.06	14.8 %	2.40	4.57	27.3 %	2.82	3.92	61.2 %
B1: *Best-Case Scenario*	2.04	4.75	16.3 %	2.28	4.32	30.1%	2.48	3.90	41.4 %

Notes: [a] – Number of trips taken under each scenario. [b] – Percentage gain or loss relative to baseline estimated in model for 2004-2010.

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Table 14: Average Marginal Effects of Temperature & Precipitation on Night Fishing

	Observations	Daily Maximum Temperature (°C)		Precipitation (mm)	
Logit Model [1]		*Parameter*	*Std. Err.*[2]	*Parameter*	*Std. Err.*
Gulf	87,381	0.014***	0.004	0.070	0.047
Southeast	36,291	0.021***	0.007	0.083	0.065

Note: Logit model on night fishing is estimated with robust standard errors clustered by phone exchange. Standard errors are calculated by Delta-Method.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level

Figure 1: Schematic for Two-level Nested Logit Model

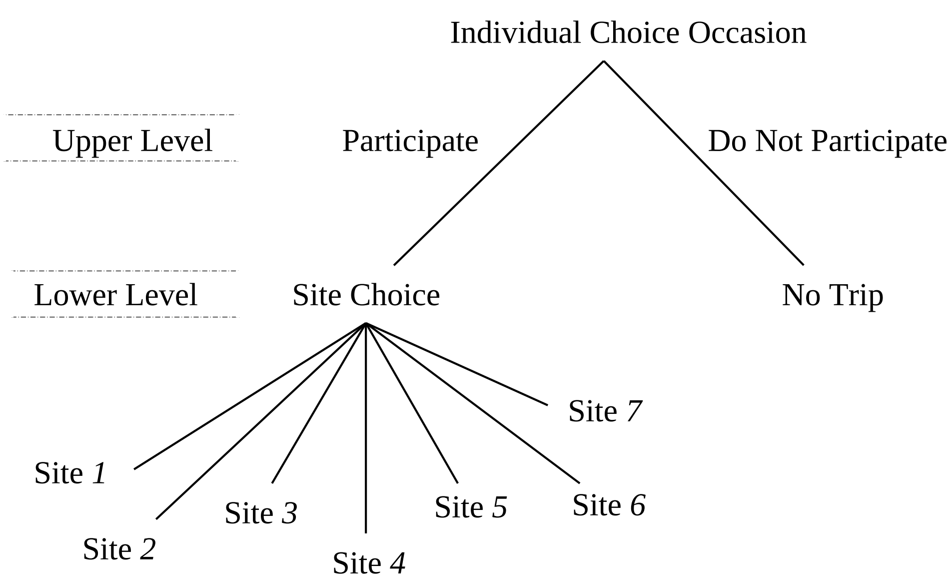
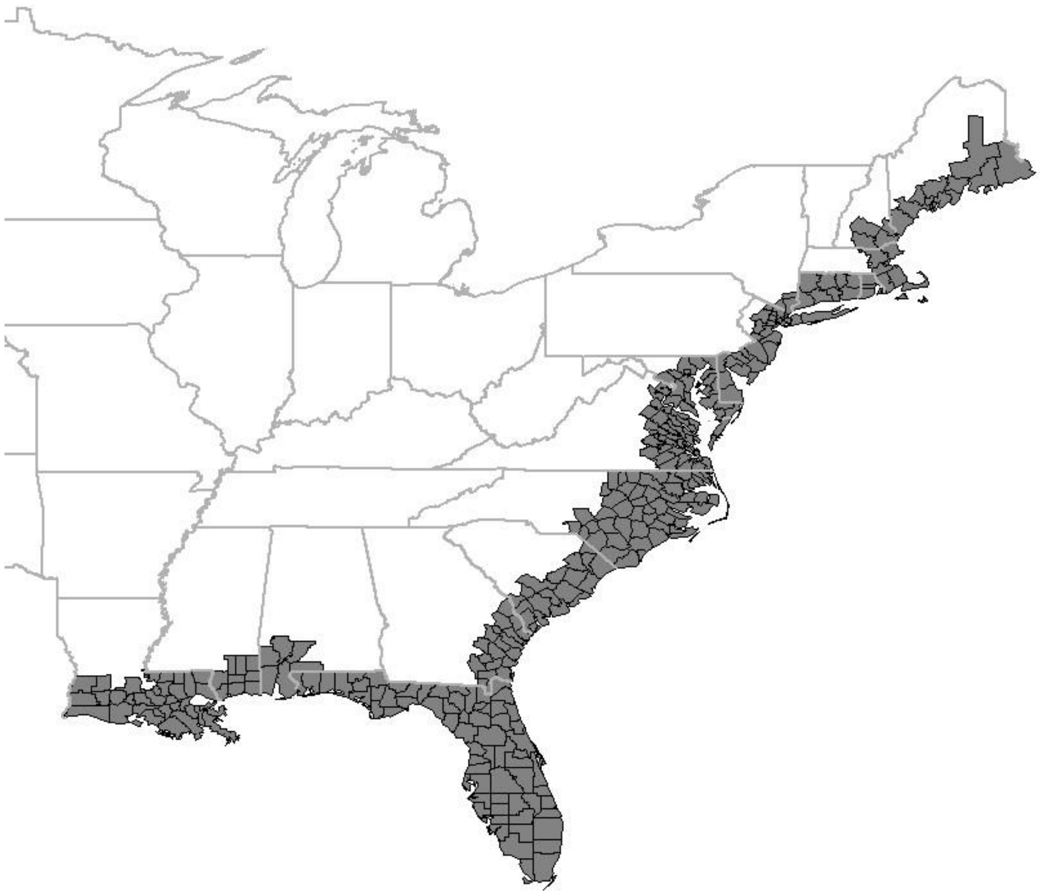


Figure 2: Coastal Counties in MRIP Phone Survey Data



Note: 328 coastal counties included in phone survey data shaded in dark grey.

Figure 3: Atmospheric CO_2 Concentrations under SRES Emissions Scenarios

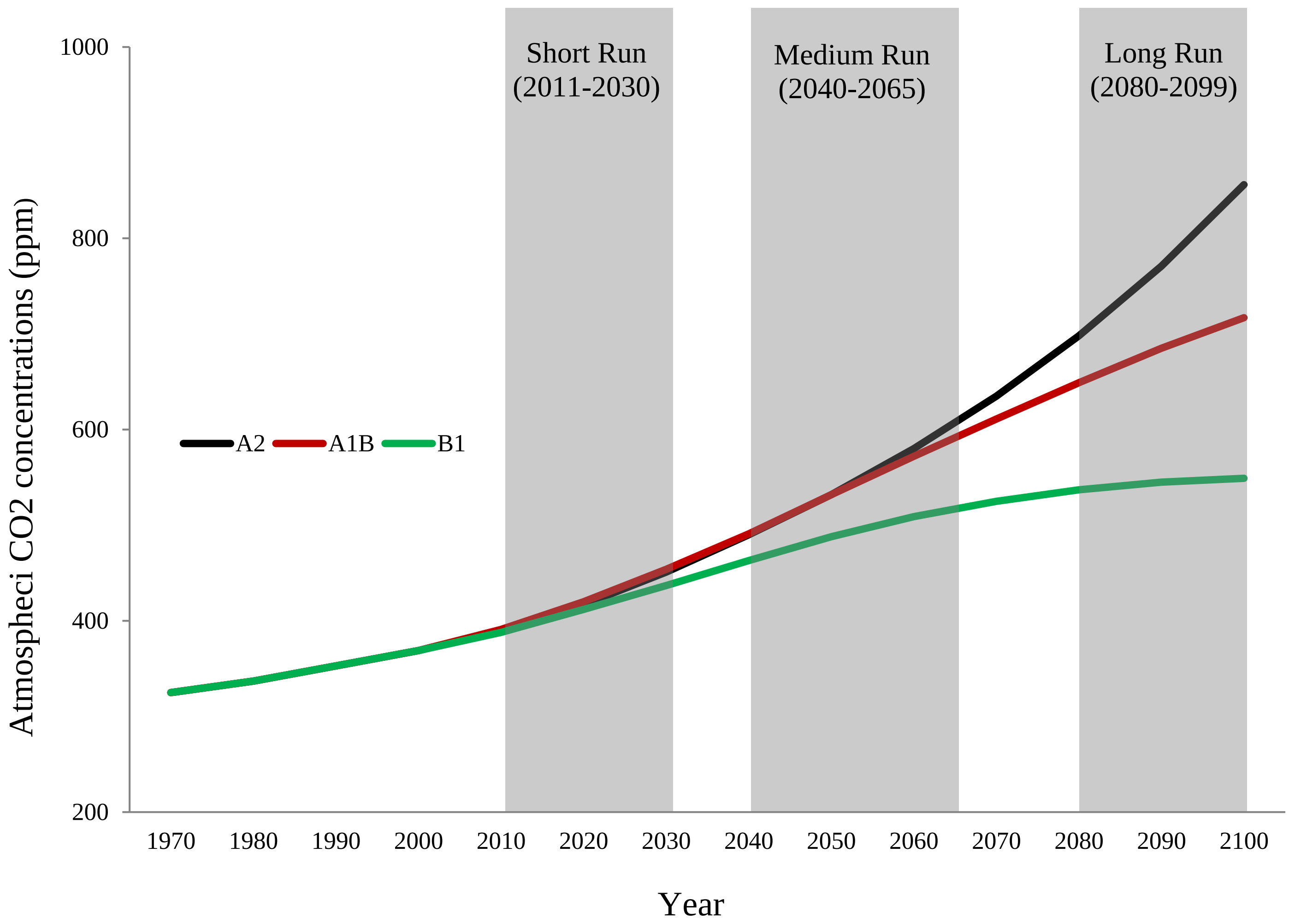
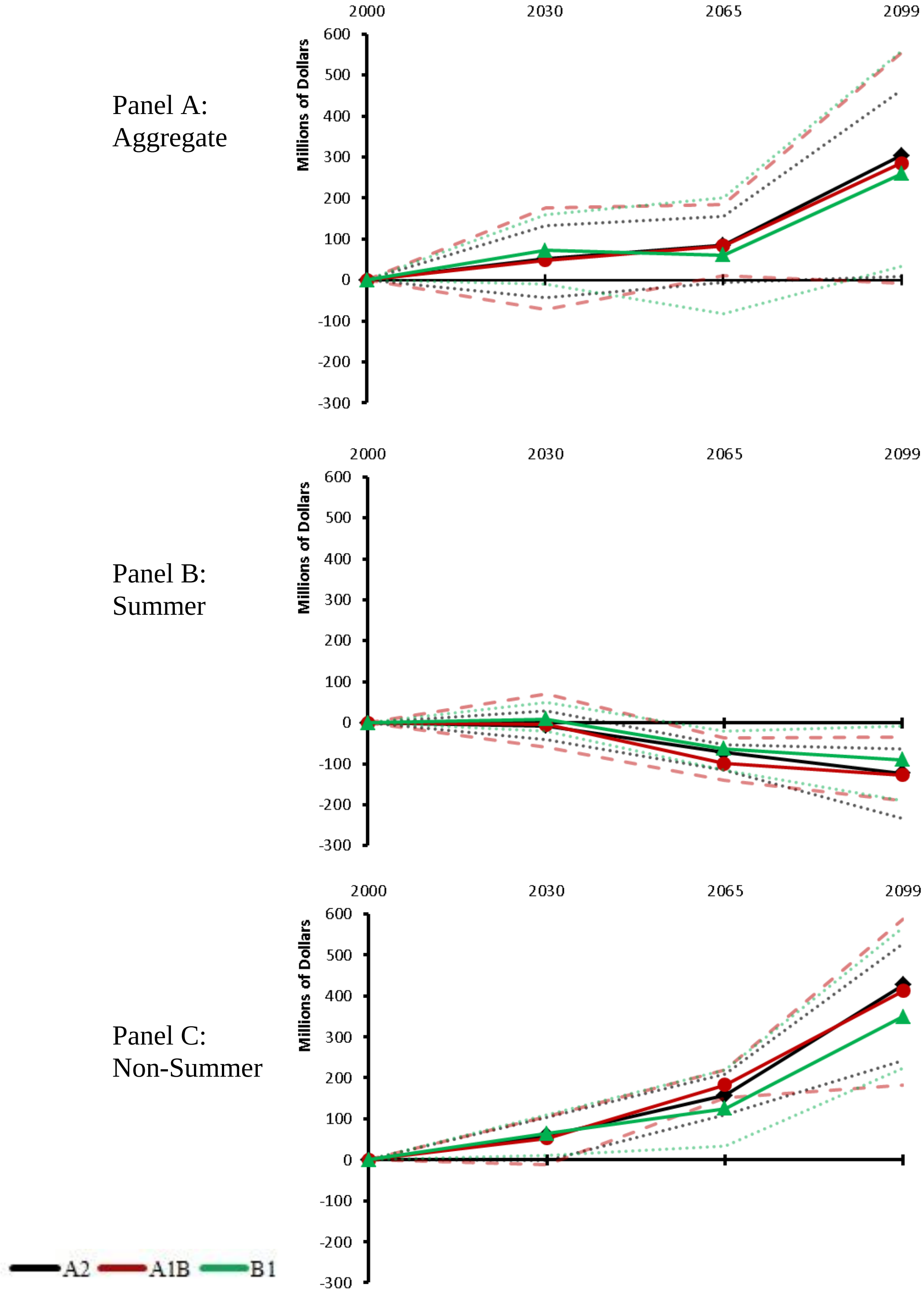
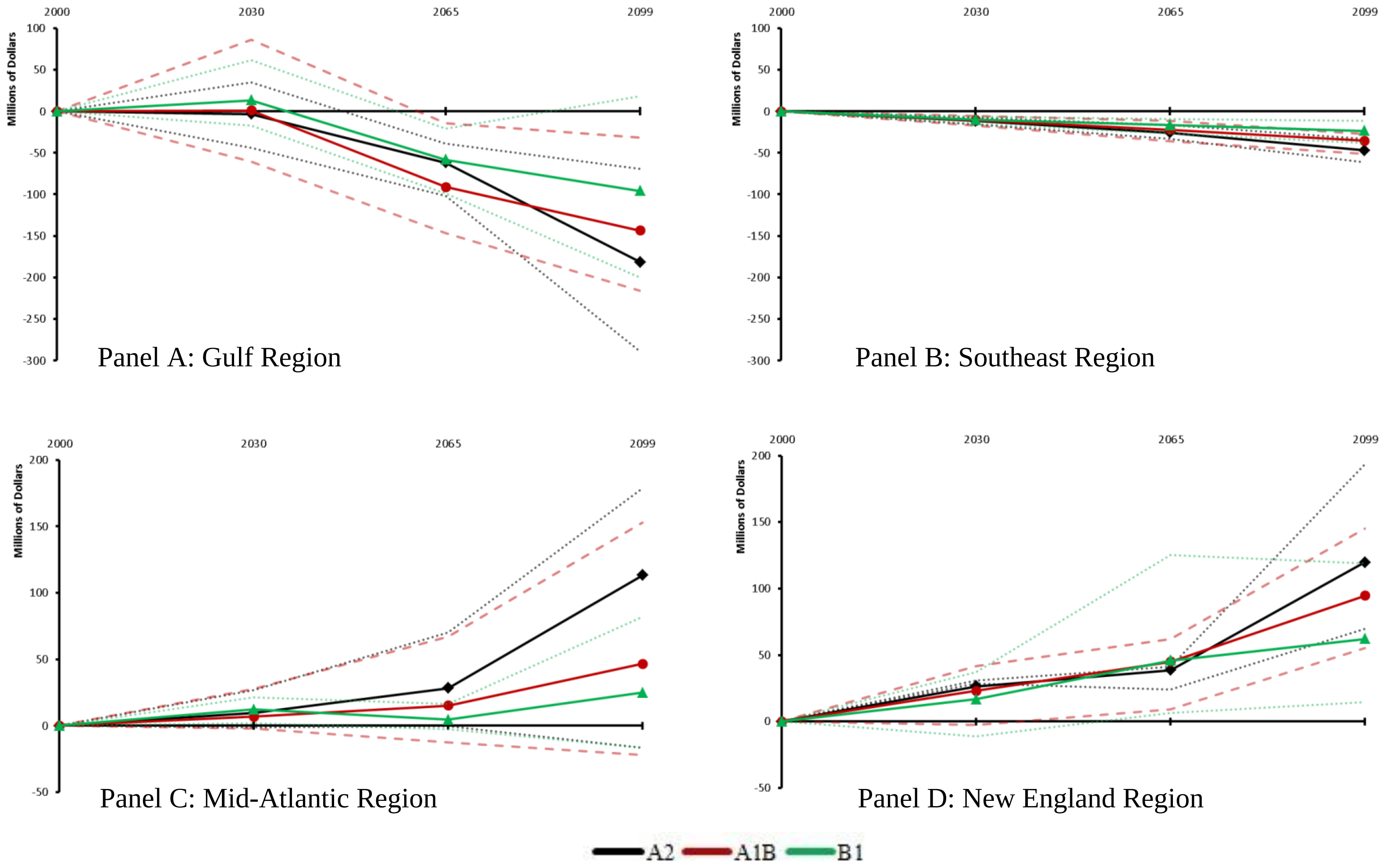


Figure 4: Predicted Welfare Change under Different Emissions Scenarios



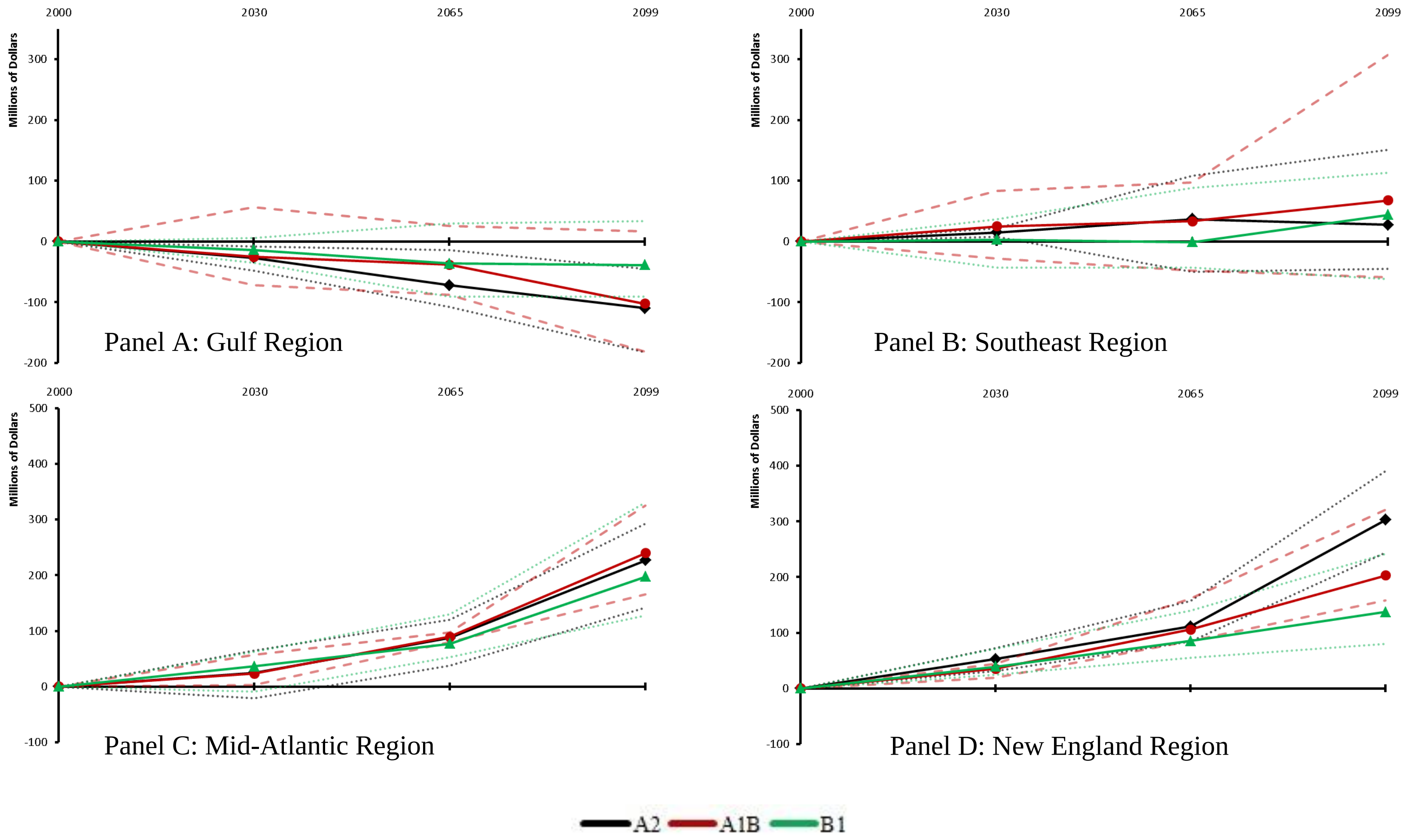
Note: Black lines represent emissions scenario SRES A2 (business as usual), red lines are SRES A1B, and green lines are SRES B1 (best-case scenario). Solid lines represent average welfare across different GCMs while dashed lines represent minimum and maximum welfare changes under each emissions scenario.

Figure 5: Predicted Regional Welfare Change under Different Emissions Scenarios: Summer



Note: Black lines represent emissions scenario SRES A2 (business as usual), red lines are SRES A1B, and green lines are SRES B1 (best-case scenario). Solid lines represent average welfare across different GCMs while dashed lines represent minimum and maximum welfare changes under each emissions scenario.

Figure 6: Predicted Regional Welfare Change under Different Emissions Scenarios: Non-Summer



Note: Black lines represent emissions scenario SRES A2 (business as usual), red lines are SRES A1B, and green lines are SRES B1 (best-case scenario). Solid lines represent average welfare across different GCMs while dashed lines represent minimum and maximum welfare changes under each emissions scenario.

APPENDIX (For Online Publication)

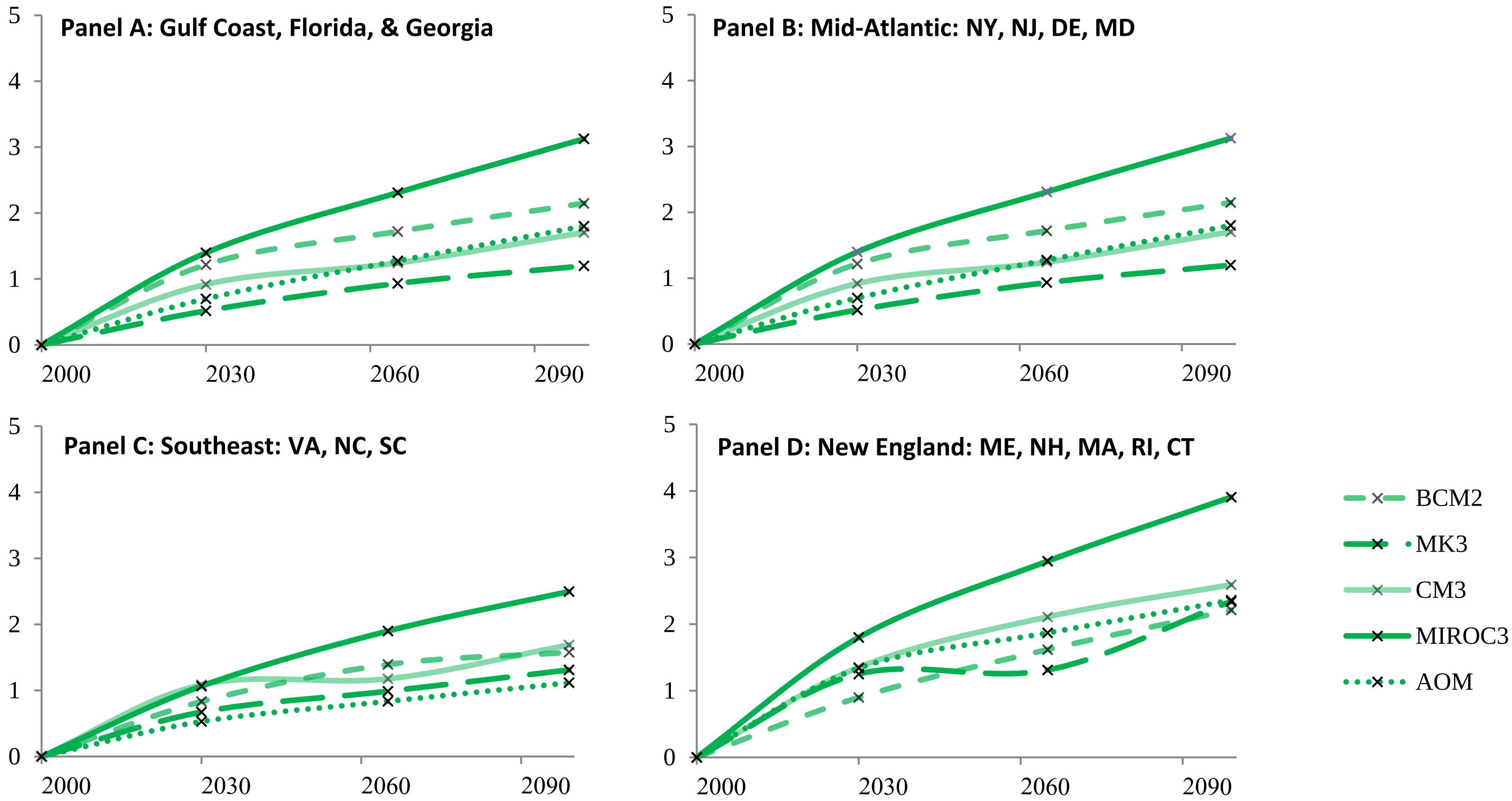
Appendix A: Site Registry Data

This appendix describes the steps used to transform the trip frequency information contained in the MRIP site registries into aggregate trip estimates for each of the 2,473 shoreline fishing sites along the East and Gulf coasts. Every two months, NOAA updates its master list of public access shoreline fishing sites, or site registry. Each site has weekday and weekend trip frequency or “fishing pressure” estimates associated with it, which are also updated bimonthly. These estimates represent NOAA’s best estimate of the number of trips occurring at a site in a normal 8-hour period, and this information informs whether and how intensely to sample at each site in each wave. Bimonthly updates are based on feedback from NOAA field staff as well as auxiliary sources (e.g., published newspaper reports about pier closures).

To construct estimates of aggregate trips for each MRIP site/wave/year combination, we employ the following steps. First, weekday and weekend trip estimates are constructed for each site and wave from the contemporaneous site registry. We assume that the average fishing day is 16 hours at manmade sites (e.g., piers) which are generally lighted and 12 hours for all other sites. These daily estimates are then aggregated to the bimonthly period. Finally, a regression-based adjustment is made to these estimates to account for the fact that not all trips at a site originate from coastal counties. Data from the MRIP intercept survey is used for this task. Specifically, intercepted respondents report their home zip code, which allows us to determine if they live in a costal or noncoastal county. For every sampled site, the share of trips originating from coastal counties can be constructed, and because sampling is by design simple random sampling at the site level, this constructed share is an unbiased estimate of the population share at that site. A weighted linear regression is then used to predict the share of coastal trips as a function of observable site characteristics. The weights employed in the regression analysis are inversely proportional to the intensity of sampling at the sites. These predicted shares are then combined with the bimonthly trip estimates to generate total trip predictions from coastal counties for all 2,473 MRIP sites.

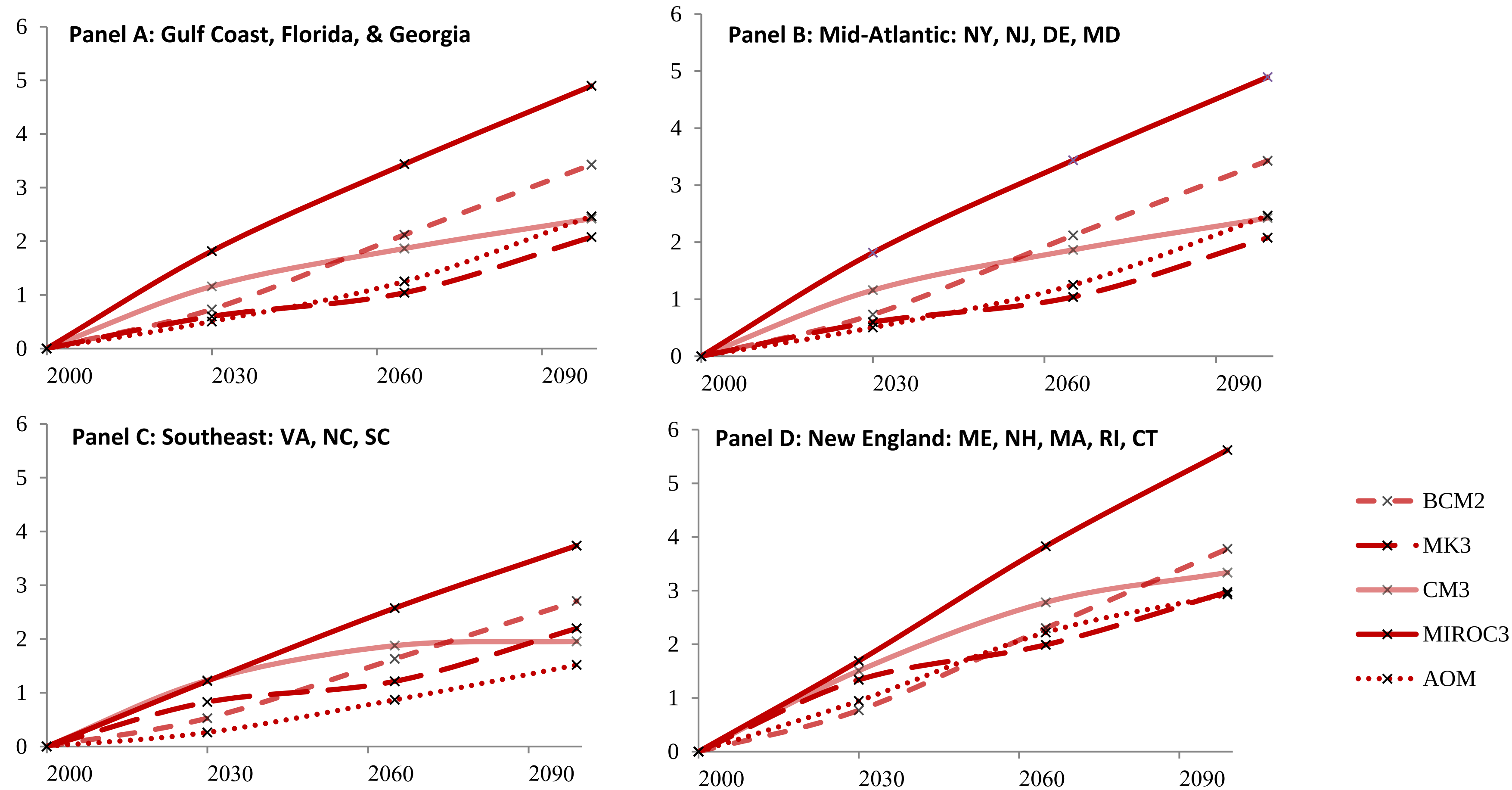
Appendix B: Climate Counterfactuals

Figure B.1: Change in Average Daily Maximum Temperature (°C) under Scenario SRES B1



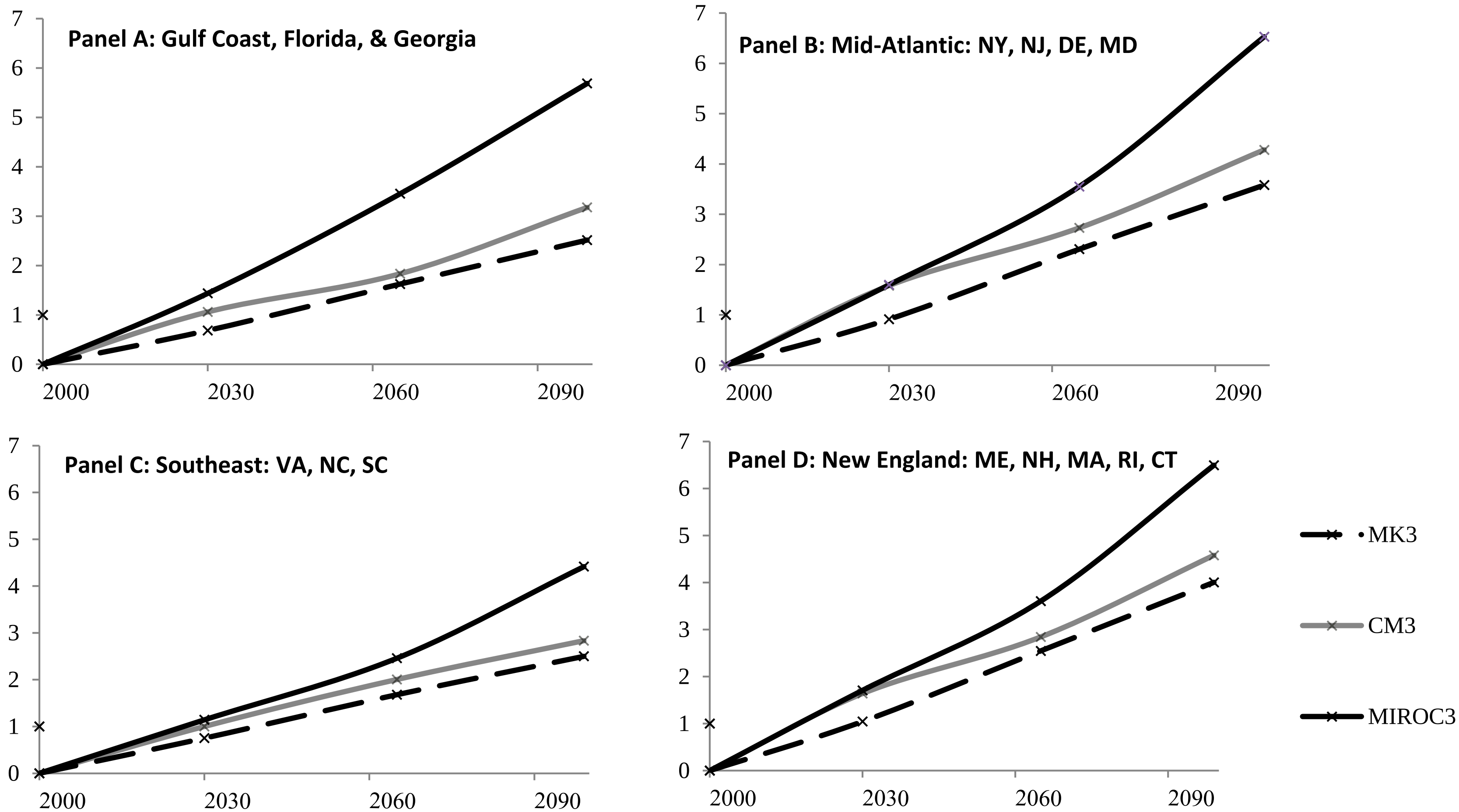
Note: The IPPC SNES B1 scenario operates on the key assumptions that a convergent world with low population growth but with rapid changes in economic structures toward a service and information economy, with reductions in materials intensity, and the introduction of clean and resource-efficient technologies.

Figure B.2: Change in Average Daily Maximum Temperature (°C) under Scenario SRES A1B



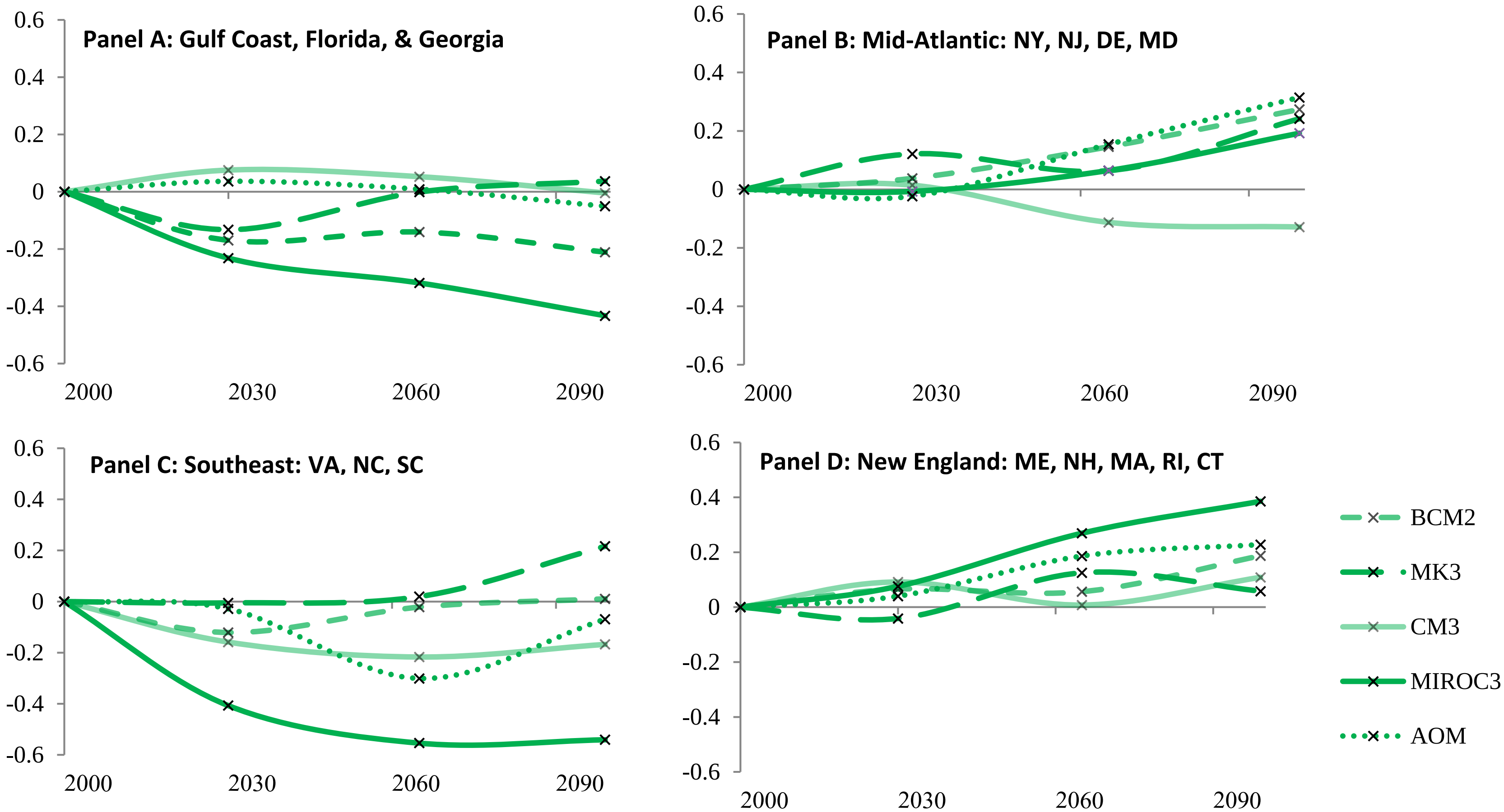
Note: The IPPC SNES A1B scenario operates on the key assumptions of a future world of very rapid economic growth, low population growth and rapid introduction of new and more efficient technology. Major underlying themes are economic and cultural convergence and capacity building, with a substantial reduction in regional differences in per capita income. In this world, people pursue personal wealth rather than environmental quality.

Figure B.3: Change in Average Daily Maximum Temperature (°C) under Scenario SRES A2



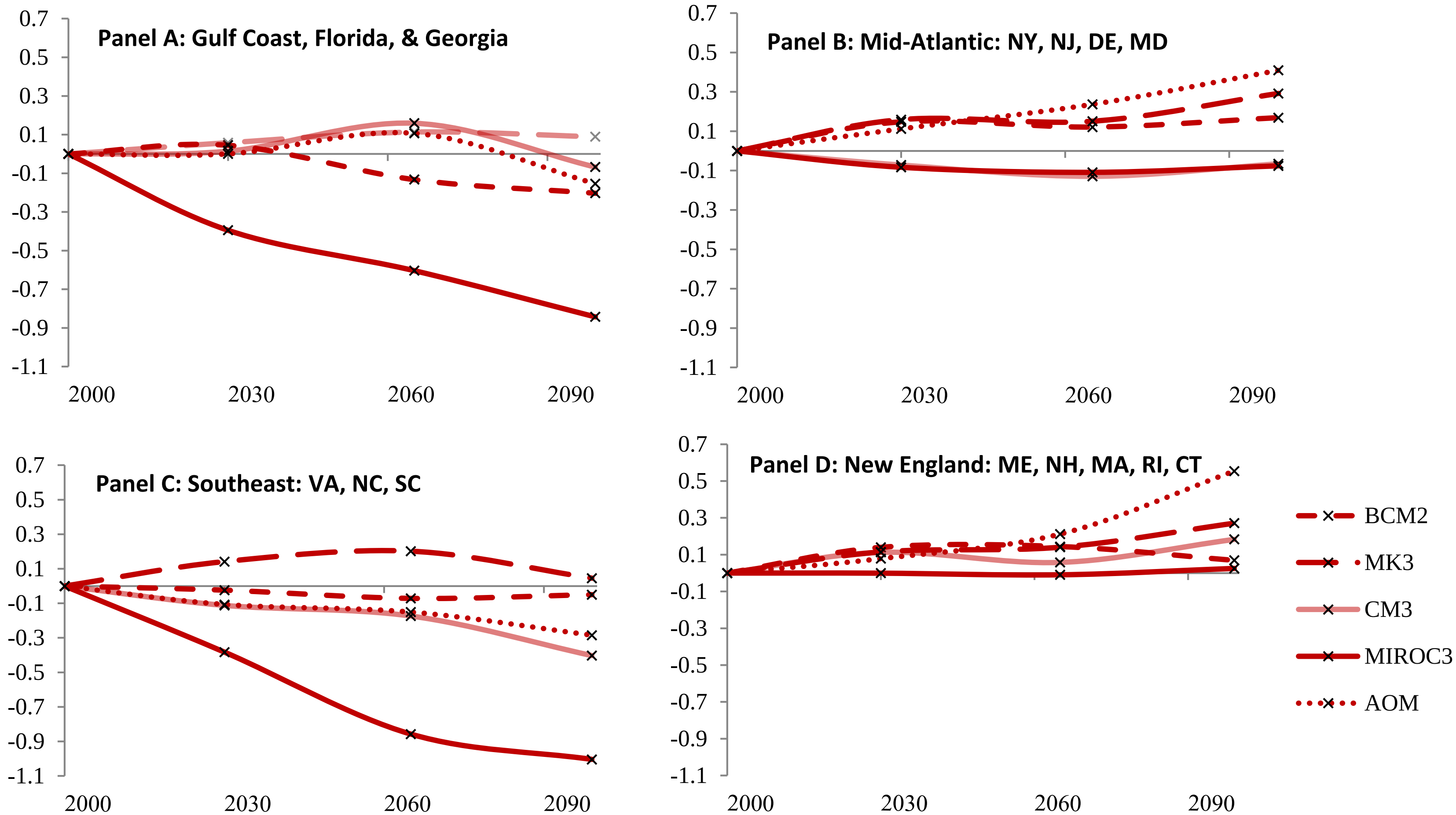
Note: The IPPC SNES A2 scenario operates on the key assumptions of a future world of strengthening regional cultural identities, with an emphasis on family values and local traditions, high population growth, and less concern for rapid economic development.

Figure B.4: Change in Average Daily Precipitation (mm) under Scenario SRES B1



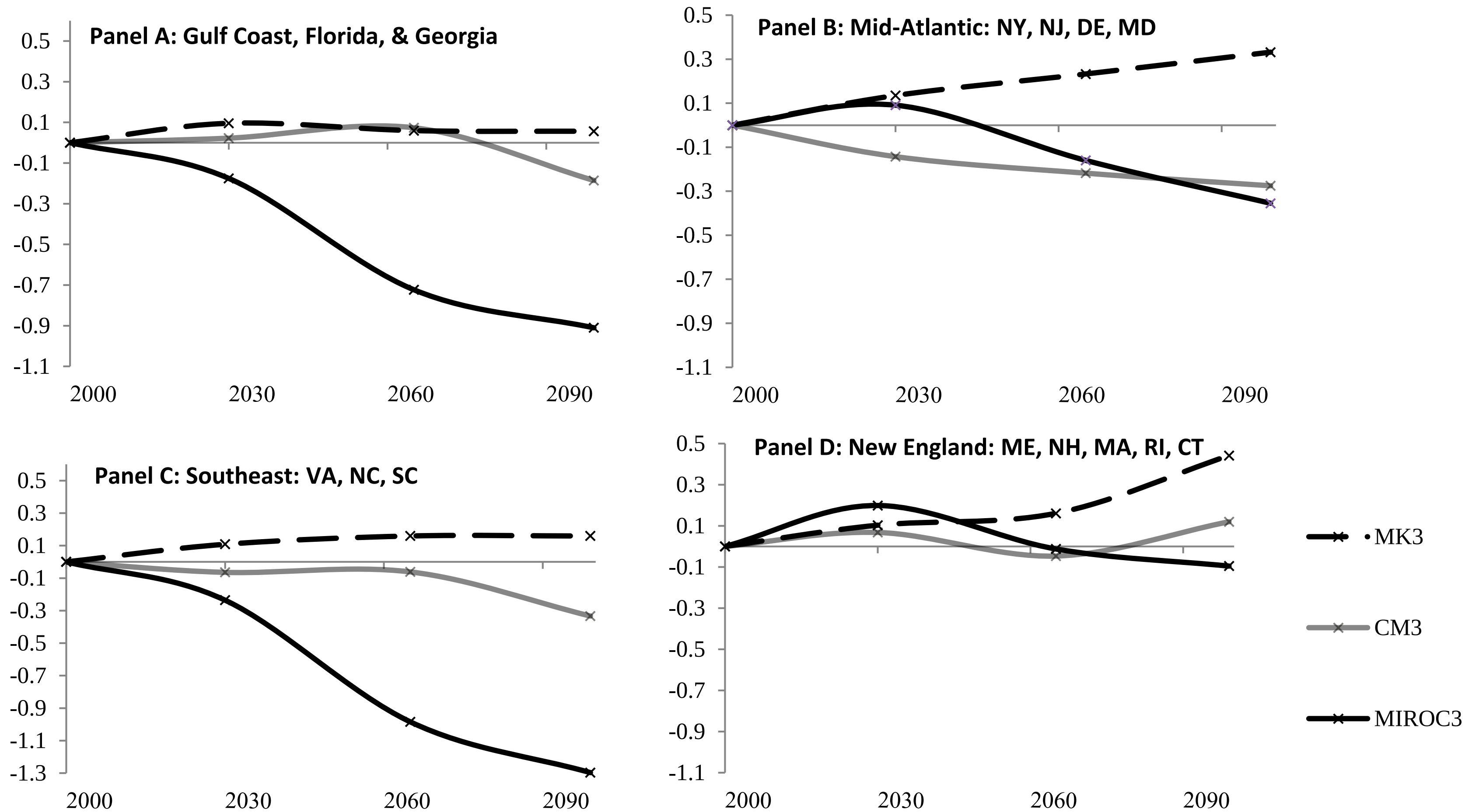
Note: The IPPC SNES B1 scenario operates on the key assumptions that a convergent world with low population growth but with rapid changes in economic structures toward a service and information economy, with reductions in materials intensity, and the introduction of clean and resource-efficient technologies.

Figure B.5: Change in Average Daily Precipitation (mm) under Scenario SRES A1B



Note: The IPPC SNES A1B scenario operates on the key assumptions of a future world of very rapid economic growth, low population growth and rapid introduction of new and more efficient technology. Major underlying themes are economic and cultural convergence and capacity building, with a substantial reduction in regional differences in per capita income. In this world, people pursue personal wealth rather than environmental quality.

Figure B.6: Change in Average Daily Precipitation (mm) under Scenario SRES A2



Note: The IPPC SNES A2 scenario operates on the key assumptions of a future world of strengthening regional cultural identities, with an emphasis on family values and local traditions, high population growth, and less concern for rapid economic development.