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Analysis

Benefit transfer with limited data: An application to recreational fishing losses from surface mining

Marisa Mazzotta [a,*], Lisa Wainger [b], Samantha Sifleet [c,1], J.Todd Petty [d], Brenda Rashleigh [a]

[a] U.S. EPA Office of Research and Development, Atlantic Ecology Division, 27 Tarzwell Drive, Narragansett, RI 02882, United States
[b] University of Maryland Center for Environmental Science, Chesapeake Biological Lab, P.O. Box 38, Solomons, MD 20688, United States
[c] RTI International, 3040 Cornwallis Road, Research Triangle Park, NC 27709, United States
[d] Division of Forestry and Natural Resources, West Virginia University, Morgantown, WV 26506, United States

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ABSTRACT

The challenges of applying benefit transfer models to policy sites are often underestimated. Analysts commonly need to estimate site-specific effects for areas that lack data on the number of people who use the resource, intensity of use, and other relevant variables. Here, we address issues of applying transfer functions to sites that have sparse or missing data. We present options for estimating data to apply meta-regression models (MRMs) in ways that are scale-appropriate and sensitive to local conditions. Using a case study of the potential lost welfare to freshwater anglers as a result of mountain top coal mining within West Virginia, we integrate: 1) an empirical ecological model of fish community changes; 2) an MRM that relates changes in catch rates to changes in anglers' utility; and 3) a spatial participation analysis that maps trip distribution using multiple survey datasets. We evaluate two scenarios: partial (20%) and full use of existing mine permits. Our conservative estimates of annual welfare loss are $120,500 for the partial scenario and $627,800 for the full scenario, due to changes in recreational fishing catches. These results are sensitive to catch rate assumptions and socio-demographic characteristics that varied widely depending on the spatial scale of measurement.

1. Introduction

Benefit transfer (BT) is often considered to be a straightforward valuation method that is relatively easy and inexpensive to apply, as compared to conducting primary studies (Iovanna and Griffiths, 2006; Ready and Navrud, 2005; Richardson et al., 2015; Wilson and Hoehn, 2006). The current state of the art in benefit transfer is the use of meta-analysis approaches to develop a transfer function, and meta-regression models (MRMs) are increasingly being estimated with the intention of providing the best possible transfer functions (Bergstrom and Taylor, 2006; Johnston and Rosenberger, 2010; Richardson et al., 2015; Shrestha et al., 2007; U.S. EPA, 2010). While issues remain with MRM techniques, generally accepted standards for conducting and testing MRMs have been developed to promote the rigor and consistency of applications (Bergstrom and Taylor, 2006; Boyle et al., 2010; Boyle et al., 2013; Nelson and Kennedy, 2009; Rosenberger and Loomis, 2001; Stanley et al., 2013).

Given a well-conducted and robust MRM with policy-relevant parameters, additional complications arise from the sparse to nonexistent data available to fit the model to a novel location. In order to apply an MRM to a policy scenario, various types of site-specific information are needed, and it is typically assumed that such information is readily available. In the ideal world, all the necessary policy-relevant data would be available to allow practitioners to follow the most rigorous standards when conducting a benefit transfer. However, managers commonly need to estimate site-specific effects for areas that lack data on the number of people who use the resource, total participation, and other relevant variables needed to transfer benefits.

In the literature, most studies that address issues related to applying meta-analysis focus on out of sample transferability and other methodological and model robustness issues. Here, we focus on issues related to data needs and approaches to dealing with sparse or missing data for policy sites; these issues have been less widely discussed in the literature, though there are various examples of policy evaluations using MRM for benefit transfer (Iovanna and Griffiths, 2006; Johnston et al., 2005; Mazzotta et al., 2014; Van Houtven et al., 2007). In this paper, we describe the integration of ecological and economic models and present approaches to addressing data limitations. In particular, we present an approach to modeling recreation participation by location through spatial modeling of existing national databases. We illustrate model estimation challenges and approaches to dealing with those challenges by presenting a specific policy application — evaluating potential lost fisheries ecosystem service (ES) values caused by surface coal mining in the Appalachian region of the U.S., focusing on recreational fishing

* Corresponding author.
E-mail address: mazzotta.marisa@epa.gov (M. Mazzotta).
[1] Formerly ORISE fellow at U.S. EPA Office of Research and Development.

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values. Section 2 describes the policy context and case study; Section 3 describes our methods; Section 4 presents results of the models and the policy application; and Section 5 contains a discussion and conclusions.

2. Policy Context and Case Study Description

Mountaintop coal mining is a surface mining practice involving the removal of mountaintops to expose coal seams, and disposing the associated mining overburden in adjacent valleys, termed "valley fills." Valley fills occur in steep terrain where disposal alternatives are limited. Mountaintop coal mining operations are concentrated in eastern Kentucky, southern West Virginia, southwestern Virginia, southeastern Ohio, and scattered areas in Tennessee (U.S. EPA, 2011) (Fig. 1). Bernhardt and Palmer (2011) note that, to date, about 1.1 million hectares of forest in this region have been converted to surface mines and more than 2000 km of stream channel have been buried beneath mining overburden as a result of these activities.

Several environmental issues are associated with mountaintop mining and valley fills, including forest fragmentation, altered hydrology, degraded water quality, and possible negative impacts on macroinvertebrates, fish, and drinking water (Freund and Petty, 2007; Merriam et al., 2013; Palmer et al., 2010; Petty et al., 2010; U.S. EPA, 2011). As a result, regional policy-makers and environmental managers are interested in quantifying the effects of mining on ecosystem services to support environmental decision making associated with managing mountaintop removal-valley fill (MTR-VF) mining (e.g., permit decisions or remediation requirements) and long-term strategic planning by communities. Because mountaintop mining impacts vary spatially, depending on affected systems and populations, managers can benefit from spatially-explicit analysis of potential economic impacts from scenarios of mining intensity to inform their decisions.

Our study area includes a portion of West Virginia that encompasses most of the area in the state where MTR-VF mining occurs (Fig. 1). The study area includes the watersheds of the Elk, Gauley, Upper Kanawha, Coal, Upper Guyandotte, and Lower Guyandotte Rivers, Tug Fork, and Twelvepole Creek, which drain a total of 20,795 km^2. The area is about 80% forested, and the primary developed land uses are coal mining and residential. MTR-VF mining currently accounts for around 3% and residential development accounts for around 6% of the total land area in the study area. We limited our analysis to effects on wadeable streams and large rivers (8.0 km^2 to 4354 km^2 drainage area) within the mining region, and did not include headwater streams or great rivers.

Recreational fishing is highly relevant to policy discussions, because it is potentially adversely affected by MTR-VF mining and it is a popular activity for Appalachian residents and visitors. In addition, fishing provides a supplemental food source for some food insecure populations in the region (Gorimani and Holben, 1999). However, creel survey data are not collected locally, so little site-specific data exist on the number of anglers, days spent fishing, catch rates, and other angler characteristics (e.g., income, age, avidity) that are relevant to assessing value of recreational fishing changes. The best available data on participation and angler characteristics are from the U.S. Fish and Wildlife Service's (USFWS) National Survey of Fishing, Hunting, and Wildlife-Associated Recreation (FHWAR) (U.S. Fish and Wildlife Service (USFWS), 2011a), which, given sampling density, cannot be robustly disaggregated to spatial scales finer than the state (U.S. Fish and Wildlife Service (USFWS), 2011b).

To examine the influence of surface coal mining on the economic values associated with recreational fishing, we developed integrated ecological and economic models and applied them to the case study area. We first developed and refined ecological models to relate mining

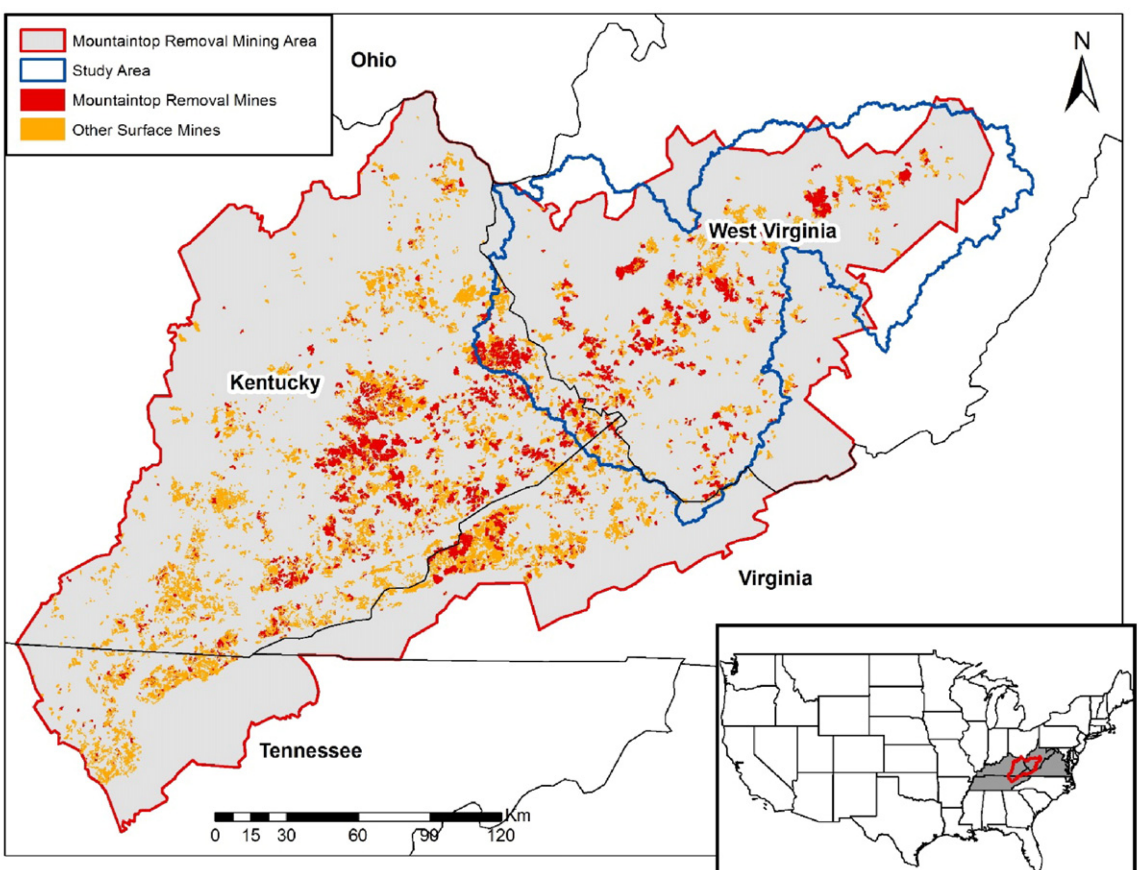

Fig. 1. Study area and the encompassing Appalachian mountaintop removal and surface coal mining region (mines were mapped by Skytruth (2009)).

activities to changes in the abundance of recreational fish (Petty et al., 2014). We then combined an MRM and participation modeling analysis to estimate the potential loss of recreational fishing benefits from mining. The integrated models provide a means to examine the changes in freshwater recreational fishing opportunities within the context of other stressors in the case study watersheds, such as existing land uses and water quality stressors. In our study area, bass and other warm water species are the most abundant species; therefore we focused our recreational fishing analysis on these species groups. However, the MRM we developed can be used to examine welfare changes for a range of freshwater species.

To evaluate the potential magnitude of change in recreational fishing values, we evaluated two hypothetical mining scenarios: 20% of current leases mined (randomly distributed) and 100% of current leases mined. As shown in Fig. 1, MTR-VF mining covers the majority of the study area but is concentrated in some regions. As the actual projected mining is unknown, these two scenarios bracket the potential magnitude of mining effects in the region.

3. Methods

We integrated three models to relate surface mining impacts to changes in social welfare (Fig. 2). The first was an empirical ecological model that evaluated surface mining impacts on fish communities as a function of changes in land cover characteristics, including amount of mining, within the watersheds. The second model was the MRM, an empirical model that related changes in catch rates to changes in anglers' utility. The third model was a spatial participation analysis, which used GIS tools, national databases, and empirically-based dispersal functions to estimate angler usage by location. The third model was used to apply the MRM to the case study area.

The ecological model used to project changes in fisheries due to mining used boosted regression trees to evaluate a wide variety of stream monitoring data that included water quality and fish community variables (Petty et al., 2014). Boosted regression trees are a particular type of classification and regression tree that is useful when relationships between independent and dependent variables are non-linear (Elith et al., 2008). Once the trees were built, the scenario effects were estimated from the empirical model by converting forest cover to mined land in appropriate proportions and generating new predictions of fish assemblages and abundance using the fitted decision trees. The land use changes were the main drivers of stream condition because they reflected a host of processes that occurred to influence fish habitat and abundance including the quality, magnitude and timing of water moving into streams (Petty et al., 2014).

To integrate the ecological and economic (MRM) models, we evaluated how changes in fish abundance were likely to translate into changes in catch rates. In addition, we used the spatial participation model to model the spatially variable degree of impact to the population of affected anglers by considering population distribution, angling participation rates, and travel behavior. This spatial participation model was then used to estimate the sum of utility losses across all affected anglers, using the MRM. In this paper, we describe the MRM and the spatial participation model; details of the ecological model are described elsewhere (Petty et al. 2014).

3.1. Meta-regression Model

Our MRM built on past work that developed an MRM to estimate changes in saltwater and freshwater recreational fishing values (Johnston et al., 2006; U.S. EPA, 2006). We tailored this general model to our study site. First, we filtered the studies from the original database used to fit the model to include only freshwater, non-anadromous species — the species most appropriate for this policy context. Second, we added studies to the database by conducting a literature search for studies published after 2004, the date of the original analysis. Third, we fit a new MRM tailored to freshwater fishing sites. In selecting variables and fitting the model, we used the previous MRM study (Johnston et al., 2006; U.S. EPA, 2006) as a guide, following generally accepted practices (Bateman and Jones, 2003; Bergstrom and Taylor, 2006; Nelson and Kennedy, 2009; Rosenberger and Loomis, 2001; Stanley et al., 2013). After model fitting, the new model contained many of the same variables as the previous model, with some changes relevant to the revised data set. Besides eliminating salt water and anadromous species, the most notable changes are that our model includes only one methodological variable and does not include regional variables, while the earlier study included a set of methodological variables and some regional variables. These changes reflect the smaller data set, which has less variation in methods; and the fact that regional variations were highly correlated with fresh water species, as discussed below.

To update the database, we searched the literature (following the procedures used by Johnston et al., 2006) and identified 179 potentially relevant studies published between 2004 and 2012. After screening, we found four new studies (providing 15 observations) that were relevant to our analysis and included the data necessary for estimating the model. The criteria for inclusion in the database were: (1) to assure commodity consistency, the study estimated willingness to pay (WTP) by recreational anglers for catching an additional fish, or provided sufficient information to estimate WTP per fish; (2) to assure welfare consistency, the study estimated Hicksian welfare measures; and (3) to control for policy and social context factors, the study was conducted in the United States.

Our final database included 19 studies and 108 observations (Table 1). The 19 studies include 9 journal articles, 3 reports, 2 working papers, 1 conference proceedings paper, and 4 dissertations. Data for the studies were collected between 1986 and 2011. Studies provided from 1 to 19 observations. Eleven of the studies used stated preference methods (9 contingent valuation and 2 conjoint analysis), and 8 used

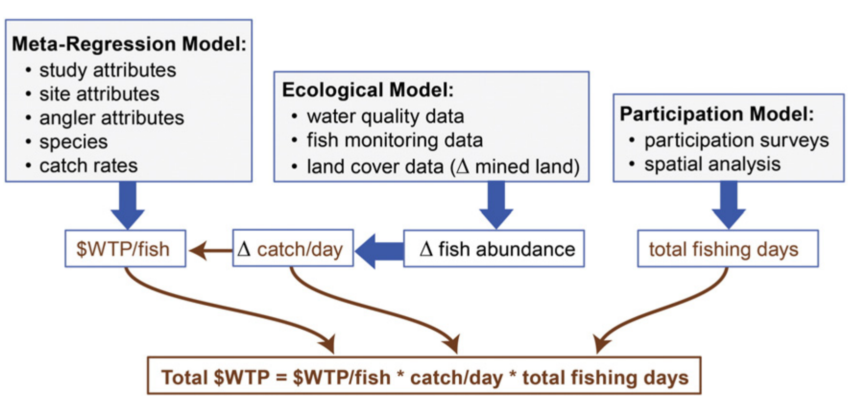

Fig. 2. Relationships between models and data used in the analysis.

Table 1
Studies included in the meta-analysis.

Author(s) and year	Type of publication	Number of observations	State(s)	Study methodology	Species	Marginal value per fish (2012$)
Besedin et al. (2004)	Conference proceedings	10	MI	RUM	Bass	$16.34 to $21.30
					Perch (other)	$2.22 to $3.67
					No target (other)	$1.97 to $4.16
					Walleye–pike	$12.66 to $26.55
Bingham et al. (2011)	Journal article	8	NJ	RUM	Bass	$5.06 to $8.86
					Panfish (other)	$4.12 to $8.86
					No target (other)	$3.80 to $4.43
					trout	$9.49 to $17.17
Breffle et al. (1999)	Report	6	WI	Conjoint analysis	Perch (other)	$0.98 to $1.95
					Walleye	$5.13 to $10.38
					Bass	$17.04 to $34.18
Dalton et al. (1998)	Journal article	2	WY	Contingent valuation	Trout	$34.99 to $63.95
Douglas and Harpman (2004)	Journal article	2	UT, AZ	Contingent valuation	No target (other)	$22.53 to $26.99
Johnson (1989)	Dissertation	5	CO	Contingent valuation	Trout	$1.08 to $2.14
					Rainbow trout	$3.21
Johnson et al. (1995)	Journal article	19	CO	Contingent valuation	Trout	$0.68 to $3.65
Lee (1996)	Dissertation	5	WA	Conjoint analysis	Trout	$1.40 to $4.76
Loomis (2005)	Report	3	ID, WY	Contingent valuation	No target (other)	$15.22 to $28.23
Lupi (1997)	Dissertation	9	MI	RUM	Lake trout	$7.45 to $13.85
Lupi and Hoehn (1998)	Working paper	3	MI	RUM	Lake trout	$12.58 to $17.28
Lupi et al. (1997)	Report	7	MI	RUM	Bass	$10.62
					Catfish/carp (other)	$1.74
					Pike	$2.91
					Lake trout rainbow	$8.22
					trout	$12.58 to $19.61
					Walleye	$4.55
Milliman et al. (1992)	Journal article	1	WI	Contingent valuation	Perch (other)	$0.41
Morey et al. (2002)	Journal article	2	MT	RUM	Trout	$14.44 to $246.33
Murdock (2001)	Dissertation	7	WI	RUM	Bass	$5.26 to $24.21
					Muskie (pike)	$201.81
					Pike	$19.50
					Trout	$40.65
Pendleton and Mendelsohn (1998)	Journal article	3	ME, NH, VT, NY	RUM	Trout	$5.37 to $32.89
					Rainbow trout	$29.07
Rosenberger (2004)	Journal article	2	WV	Contingent valuation	Rainbow trout	$1.66 to $2.24
Whitehead and Aiken (2000)	Working paper	6	USA	Contingent valuation	Bass	$5.72 to $12.90
Williams and Bettoli (2003)	Report	8	TN	Contingent valuation	Trout	$0.77 to $11.73

revealed preference Random Utility Model (RUM) methods. Thirty-six observations, from six studies, are values for stocked species.

Table 2 presents descriptive statistics for variables included in the final model. The dependent variable is the natural log of WTP per fish, converted to 2012$ using the Consumer Price Index (U.S. Bureau of Labor Statistics). Values per fish in the original studies included in our MRM ranged from $0.41 to $246.33, with a mean of $13.70 and median of $5.91, resulting in log values ranging from −0.88 to 5.51, with a mean of 1.76. The age and number of trips variables were included as categorical rather than continuous variables, as in U.S. EPA (2006), because there was not enough variation in the continuous measure to estimate parameters at that level of precision. The mean angler age in the data was 44.5 (based on 27 observations with data); based on this finding, we created two age categories: 45 and up and less than 45. The mean sample number of trips per year (based on 58 observations with data) was 20; we thus categorized trips into less than 20 and 20 and up. The variable less than 20 was not significant and not retained in the final model, so was not included in the tables. The catch rate variable was measured as fish caught per day. For studies that estimated fish per hour, estimates were converted to fish per day using average hours fished per day from the original study, or 4 h (the overall daily average) if not reported in the original study.

To specify and test the model, we first checked the data for influential observations, using tests of residuals and stem and leaf plots of the residuals. These tests did not identify any observations with undue influence on the estimates. Next, as recommended by Nelson and Kennedy (2009), we estimated the weighted mean WTP per fish, using sample sizes from the original studies as weights. The preferred weight is the inverse variance of the estimate, but since this was not reported for most of the studies, we used the sample size, again, as recommended by Nelson and Kennedy (2009). The weighted mean value was slightly lower ($12.34 vs. $13.70), and the confidence interval was tighter than for the unweighted mean. Based on this result, we used the weighted form in the meta-regression.

In early tests of explanatory variables, we found that certain variables were highly correlated. Species distributions are not geographically random and studies tend to be concentrated in certain water bodies. For example, all lake trout studies were conducted in the Great Lakes. Further, studies from the Midwest and in the Great Lakes are highly correlated, with most Midwest observations conducted in the Great Lakes. As a result of these correlations, we were unable to account for regional differences in value in the model. We tested various model specifications, including a random effects panel model, defining panels as all observations from a single dataset. The Breusch–Pagan test indicated that random effects were not significant. A weighted OLS model without robust errors tested positive for heteroskedasticity, so we selected a weighted OLS model, using sample size as weights, with clustered robust errors, clustered by study, as the best model fit.

We conducted a series of model robustness tests, as recommended by Boyle et al. (2013), and found that model coefficients were robust across various model specifications and tests. Following Hoehn (2006) and Boyle et al. (2013), we tested for sample selection bias, by first estimating a regression that explained the probability of at least one study being conducted in each state, with the following regressors: percent of the state in inland waters, state per capita income, number of fishing licenses, population density, and fish and wildlife spending in the state. From this equation we estimated the Inverse Mills Ratio, which was then added to the WTP model, and found to be insignificant,

Table 2
Summary statistics for meta-regression variables.

Variable name	Definition	Mean (std. dev.) [range]
log_WTP	Dependent variable. Natural log of willingness to pay to catch an additional fish (in 2012$).	1.761 (1.246) [−0.88–5.51]
st_pref	Binary (dummy) variable; = 1 for stated preference studies, = 0 otherwise.	0.546 (0.500) [0–1]
year_indx	Index for the year a study was conducted, calculated as the study year minus 1985, the earliest year in the data set.	9.759 (5.394) [1–19]
inc_thou	Average household income of survey respondents in thousands of (2012) dollars. If the study does not list income values, this was imputed from Census data for the appropriate geographic area.	58.422 (17.024) [27.35–130.28]
age_lt45	Binary (dummy) variable; = 1 if the mean age of sample respondents was less than 45 (the mean for all studies in our sample), = 0 otherwise.	0.398 (0.492) [0–1]
age_45up	Binary (dummy) variable; = 1 if the mean age of sample respondents was 45 or greater, = 0 otherwise.	0.130 (0.337) [0–1]
trp_20up	Binary (dummy) variable; = 1 if the mean number of fishing trips for sample respondents was 20 or more per year (20 was the mean trips per year for all studies in our sample), = 0 otherwise.	0.204 (0.405) [0–1]
nonlocal	Binary (dummy) variable, = 1 if no respondents in the sample were local residents.	0.019 (0.135) [0–1]
bass_fw	Binary (dummy) variable, = 1 if target species was freshwater bass, = 0 otherwise.	0.139 (0.347) [0–1]
pike_walleye	Binary (dummy) variable, = 1 if target species was pike or walleye, = 0 otherwise.	0.093 (0.291) [0–1]
rainbw_trout	Binary (dummy) variable, = 1 if target species was rainbow trout, = 0 otherwise.	0.056 (0.230) [0–1]
laketrout	Binary (dummy) variable, = 1 if target species was lake trout, = 0 otherwise.	0.120 (0.327) [0–1]
unspec_trout	Binary (dummy) variable, = 1 if target species was an unspecified trout species, = 0 otherwise.	0.417 (0.495) [0–1]
Other species	Other freshwater species not included in the above categories, including panfish, perch, catfish, carp, and "no target" (this is the omitted base case in the model)	0.176 (0.383) [0–1]
lake_res	Binary (dummy) variable, = 1 if angling took place in a lake or reservoir (other than Great Lakes), = 0 otherwise.	0.056 (0.230) [0–1]
catch	For studies that present catch rate on a per hour, per day, or per trip basis, this is the baseline catch rate for the target species, converted to fish per day; otherwise this variable is set to zero.	2.298 (2.86) [0–14]
spec_catch	Binary (dummy) variable, = 1 if baseline catch rate was specified in the study, = 0 otherwise.	0.861 (0.347) [0–1]
stock_yes	Binary (dummy) variable, = 1 if the study valued stocked fish, = 0 otherwise.	0.333 (0.474) [0–1]
_cons	Model intercept.	

indicating no evidence of sample selection bias. This finding is consistent with the results found in Boyle et al. (2013).

Model coefficients and significance were generally robust to tests of horizontal (omitting studies) and vertical (omitting model parameters) robustness. In the horizontal robustness tests, no studies were found to have single influential observations, based on the Cook's D statistic; and five of the 19 studies were found to be influential, based on F-tests of all parameters as a group. Each of these influential studies was removed in turn from the model, and effects on parameters were tested. The mean absolute deviations (MADs) in parameter values, which are estimated by removing each individual influential study from the database, one at a time, are shown in Table 3, and range from 0.02 to 0.34. In the vertical robustness tests, we estimated the regression with each possible linear combination of variables, and examined whether individual coefficients remained statistically significant and whether their estimates crossed zero. Only the catch rate and income variables passed these stringent tests; however, all but four of the coefficients (the intercept, age_45up, stock_yes, and unspec_trout) passed the less stringent test using the interdecile range (which tests whether the 10th and 90th percentile of values cross zero). The catch rate variable was robust to all specifications.

3.2. Spatial Trip Demand Analysis

We developed a model to estimate angler activity by location using available national survey datasets. In doing the estimation, we focused on local day trips (as opposed to overnight trips), because we expect that these trips provide the bulk of visits to sites in the study area, which is not a major tourist destination. This assumption is consistent with survey data that estimate that 94% of all fishing days in WV are fished by state residents (U.S. Fish and Wildlife Service (USFWS), 2011b, Table 3).

Our model of trip-taking behavior used an approach commonly applied in biological and geographic sciences for distributing organisms spatially as a function of initial densities (by location) and movement patterns. Such models use a dispersal kernel to represent the probability of organism dispersion as a function of distance from the origin point. An alternative approach, travel time along networks (e.g., roads, streams) is likely to be a more accurate means to estimate human movement (Xie and Yan, 2008), but creates large computational burdens in cases such as ours in which users have large numbers of potential origin and destination points.

Spatial dispersion models have been used in many applications, particularly estimating spread of disease (Mundt et al., 2009) and invasive species (Shigesada et al., 1995). While these models commonly attempt to incorporate complex effects such as rare events of long-distance dispersal (Nathan, 2006), stochasticity (Keeling et al., 2001), and feedbacks (Baker et al., 2012), recent work has suggested that the predictive ability of these models is limited (Clark et al., 2003; Hastings et al., 2005). Thus, although it is obvious that simple models have high error, it is not clear that increased model complexity leads to generalizable models with reduced error (Robinet et al., 2012).

Since we needed a model to apply across a large geographic region, we used a relatively simple method to generate a dispersal kernel to generally characterize angler trip-taking behavior. Our approach consisted of three main steps: (1) estimate number of days demanded by origin (DDO) (i.e., residences); (2) generate a probability density function (PDF) representing the expected distribution of anglers as a function of distance from home; and (3) apply the PDF to the DDO map to distribute angler days across the landscape and provide estimates of days demanded by location (DD). Steps 1 and 2 used local,

Table 3
Mean absolute deviations in parameter values.

Coefficient	MAD	Min	Max
lake_res	0.34	0.01	1.15
age_45up	0.26	0.01	0.54
st_pref	0.21	0.00	0.46
trp_19up	0.21	0.05	0.45
stock_yes	0.17	0.02	0.35
ln_year	0.11	0.01	0.21
spec_catch	0.11	0.02	0.21
_cons	0.10	0.02	0.18
catch	0.09	0.01	0.26
unspec_trout	0.09	0.01	0.18
inc_thou	0.07	0.02	0.17
nonlocal	0.06	0.03	0.09
age_lt45	0.05	0.00	0.11
rainbw_trout	0.05	0.00	0.11
laketrout	0.04	0.00	0.08
bass_fw	0.03	0.00	0.09
pike_walleye	0.02	0.00	0.04

state and national survey data as inputs to these models. Step 3 created a map of estimated demand for recreational fishing by map pixel. We summed demand estimates by 10-digit Hydrologic Unit (HUC-10 watershed) before use in the economic value estimation.

3.2.1. Developing the Days Demanded by Origin (DDO) Map

The DDO map represents the number of recreational angler days that would be generated by location (30-m map pixel) based on population distribution, demographic-specific participation rates, and average days per participant, using the steps described below.

3.2.1.1. Population Distribution. The US Census Bureau population census provides relatively detailed population distribution data; however, the spatial detail is often low in rural areas. In rural areas, blocks and block groups (the smallest census reporting unit) can be large (100 s of mi^2), even though people may be concentrated in a few areas. To create more precise locations of population, dasymetric mapping can be used. In this technique, landscape features that are likely to indicate the presence of residences (e.g., roads, developed land use) are used to map population to its most likely location within a block group (Eicher and Brewer, 2001; Fisher and Langford, 1995; Langford and Unwin, 1994; Mennis, 2003).

We used a dasymetric dataset based on the 2010 US Census data, created by U.S. EPA for the contiguous U.S. (U.S. EPA, 2013), which used roads, land cover, and other data indicating presence of residences to distribute population and socio-demographic characteristics from census block groups to 30-m map pixels. We defined the source area for anglers as the study area plus a 100 mile buffer. The 100 mile buffer was set to capture anglers who would be likely to travel to the study area based on observed travel distances for anglers in this region of the country (data are described in the 2-D PDF estimation methods).

3.2.1.2. Freshwater Fishing Participation Rates. Many demographic factors have been shown to influence outdoor recreation participation rates including gender, age, race, ethnicity, income, and population density (Bockstael et al., 1987; Bockstael et al., 1989; Bowker and Leeworthy, 1998; Bowker et al., 2006; U.S. Fish and Wildlife Service (USFWS), 2011a). As a result, spatial variation in demographic characteristics (i.e., age distribution, ethnicity) can generate locational differences in recreational demand. However, when a given demographic factor is spatially homogeneous, it does not contribute to differences in spatial distribution of recreational demand. For example, if the proportion of males to females in the population is relatively constant spatially, then using the average participation rate across both genders will generate the same demand by location as if the participation rate per gender were estimated and then applied to the population. Therefore, we estimated participation rates using demographic factors that varied spatially at the scale of our analysis.

To estimate participation rates, we used the raw data from the U.S. Fish and Wildlife Service's (USFWS) National Survey of Fishing, Hunting, and Wildlife-Associated Recreation (FHWAR), which is a national phone survey (U.S. Fish and Wildlife Service (USFWS), 2011a, 2011b). Rather than use average participation rates by state, which is the finest scale appropriate for the sampling density, we used the survey data to estimate participation rates for four demographic groups that exhibit spatial variability: (1) urban white non-Hispanic, (2) urban non-white and Hispanic, (3) rural white non-Hispanic, and (4) rural non-white and Hispanic. We omitted highly correlated demographic variables to create a parsimonious model of participation rates that could be readily transferred across regions.

We used different data sets to estimate participation rates for white and non-white groups. For whites, we used weighted observations from the Appalachian region including the states of VA, WV, KY, TN, and NC. For non-whites, we used weighted observations from the continental US data, because too few observations were available for the case study region. These regional or national estimated participation rates were then available to use at scales finer than the state because they could be linked to locally variable demographics. We applied the participation rates to the dasymetric population data to generate a map of total anglers based on location of residences. The dasymetric data provided total population. To estimate the adult population (18 and over), we reduced the total population in the dasymetric pixel data by the proportion of the state-level population that was under age 18.

3.2.1.3. Days per Angler. The average number of fishing days per freshwater fishing participant per year was derived from the FHWAR data (U.S. Fish and Wildlife Service (USFWS), 2011a) using the same demographic groups used for assessing number of participants. We multiplied the survey-derived weighted average days per participant by number of participants to generate estimates of total days per year of freshwater fishing in our study region. We produced a 30-m grid of days demanded and aggregated cells to 480-m cells to enhance processing efficiency.

3.2.2. Fitting the Probability Density Function

Once the DDO map was developed, the next step was to estimate how the recreation days identified in that map would be distributed across the landscape. A PDF was fit to data and then used to estimate the dispersion of anglers across the landscape. We used three steps:

1. Create the 1-dimensional (1-D) PDF showing probability density as a function of distance from the origin point;
2. Create the 2-D probability surface — A matrix in which the 1-D PDF is integrated over individual map cells in eight directions (8 nearest neighbor cells) to create a 2-D estimator;
3. Apply the 2-D probability surface to the DDO map (as a moving window) to generate the days demanded (DD) by location (map cell) map.

These three steps were applied separately to urban and rural recreator data due to different travel behavior between groups. Once the DD maps were created for urban and rural anglers, the data were added together to create a single DD map for the study region.

3.2.2.1. Develop the 1-D PDF. The 1-D PDF represents the probability that a recreator will travel a given distance from her origin point and can be applied to represent the behavior of a population of recreators. To generate the PDF, we used survey data from the National Visitor Use Monitoring (NVUM) program (USDA Forest Service, 2011). The survey is conducted onsite at all National Forest and Grassland sites on a four-year cycle and provides a national data set representing travel distances by recreation type among other variables. We selected observations from the NVUM in which respondents identified freshwater fishing as the main purpose of their trip (fiscal years 2005–2009), separated observations into urban and rural dwellers, and excluded travel distances greater than 500 miles. We used observations from the nation because we did not have enough observations to represent travel distances for each recreation type for our study area or localized region.

A gamma distribution provided the best fit to the data (Fig. 3). The major distinction between the urban and rural anglers was that fewer urban dwellers fish close to home, presumably because of lower availability or lower quality of sites, compared to rural dwellers. In the PDFs, this effect translates into a peak in the PDF that is farther from the origin for urban dwellers, relative to rural dwellers.

We corrected the urban and rural PDFs to account for the fact that distances measured on a network of roads are not equivalent to straight-line Euclidian distances. A “detour index” (Boscoe et al., 2012) has been developed to characterize the difference between these two measurements for US road density (excluding Alaska). We divided the travel distances provided in the survey by the detour index of 1.417, so that the numbers were scaled down to represent their equivalent Euclidian distance. The PDF was fit to these scaled numbers to avoid overestimating distance traveled.

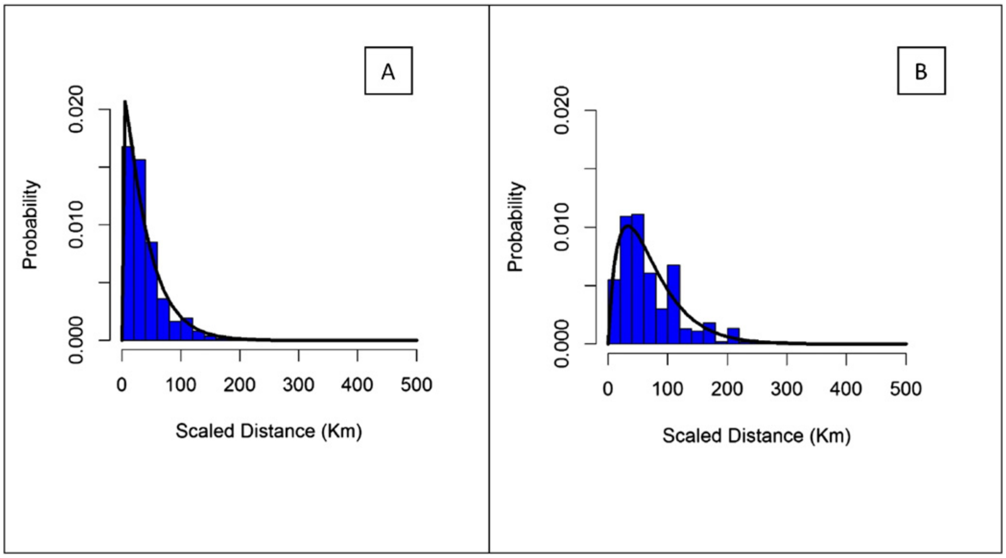

Fig. 3. Histograms of distance traveled to recreate for rural (a) and urban (b) recreational freshwater anglers and fitted gamma probability density functions.
Source data: USDA Forest Service (2011).

3.2.2.2. Develop the 2-D Model. The urban and rural 1-D PDFs were translated into 2-D probability surfaces that represent the probability of travel in all directions from a given origin point. R code was used to create a matrix of PDF values by calculating a distance from the origin and calculating the probability of travel to that cell, using the gamma dispersal function. The resulting surface was sized at 150 miles (240 km), which is consistent with the 1-D PDF results but truncates the distribution by removing the tails. Because the probabilities of travel outside this window are extremely small, a minimal number of long trips are ignored to improve processing time. After all cell values were calculated, the probability surface was normalized so that the probabilities in all cells sum to 1. The resulting probability surfaces show generalized travel patterns that are suggested by the survey data on travel distances of urban and rural anglers (Fig. 4).

3.2.3. Apply the 2-D Kernel Density Estimator to the DDO Map to Generate the Days Demanded (DD) Map

The final step in estimating the distribution of freshwater angler days demanded in our case study area was to apply the 2-D probability surface to the DDO map to estimate demand for fishing by location. In this step, the 2-D model was used as a moving window and its center was placed, one-by-one, on each cell of the DDO map. The population count at the center of the moving window was distributed according to the 2D probability surface. In other words, if 50 days were demanded at a given cell (based on participation rates of the population present in that cell), those days were spread outward to the adjacent cells within the window according to the probabilities of the 2-D probability surface. The process was repeated at each cell of the DDO map. Finally, the results of each instance of spreading days outward from each cell to the entire 2-

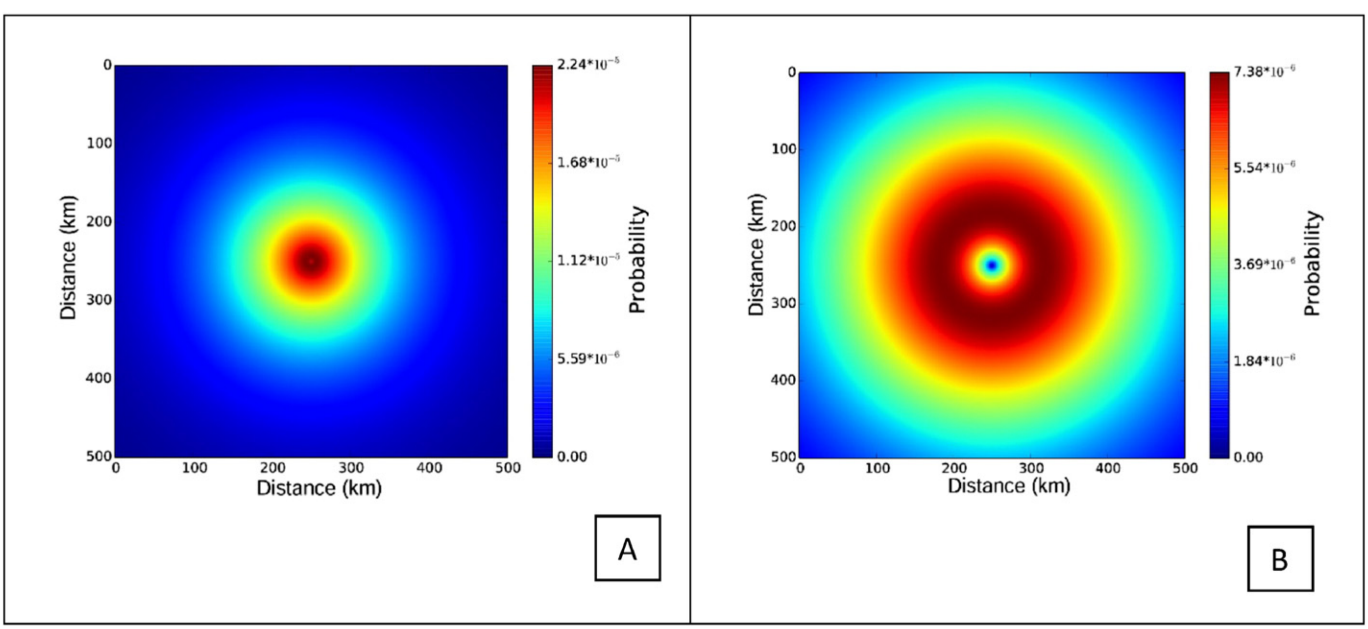

Fig. 4. Two dimensional probability surface for rural (a) and urban (b) freshwater anglers. These surfaces represent the probability of travel from any given point of origin, in any direction, based on survey data of travel distances, under assumptions of spatial isotropy (identical conditions in all directions) but correcting for non-linear travel time using the detour index (as described in text). Urban and rural freshwater anglers exhibit different travel patterns since urban dwellers travel farther than their rural counterparts to engage in fishing.

D window were summed together to generate the days demanded (DD) maps for urban and rural anglers. This entire process was automated in Python using the NumPy library (van der Walt et al., 2011).

The days demanded for rural and urban anglers (Fig. 5) were added together to create the final DD surface. The surface represents the total number of angler days demanded by location. The figure shows the broad patterns in trip density that develop, such as concentric circles, that reflect effects of cities or other population concentrations. The data in this DD surface were summed by HUC-10 watershed to reduce error associated with cell-specific calculations (e.g., that might be introduced by assuming spatial isotropy) and to match the scale of other data used in the benefit transfer function.

We verified the resulting estimated angler days at the scale of the entire case study area by comparing the total days demanded in the DD map

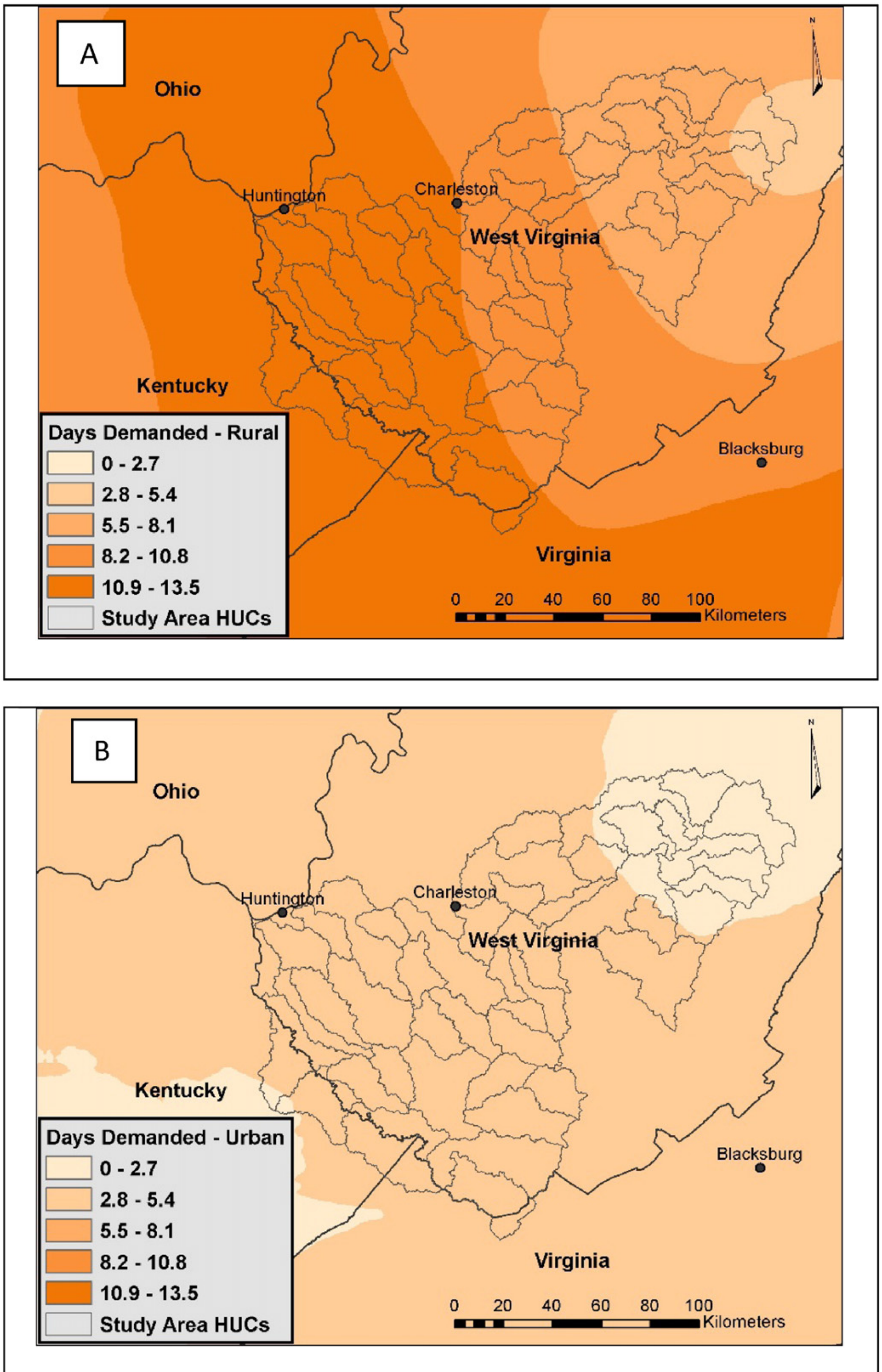

Fig. 5. Distribution of freshwater fishing days demanded (DD) for rural (A) and urban (B) anglers.

to the total days in the DDO. This confirmed that the total number of days was consistent before and after the probability surface was applied. We also compared the number of fishing days to survey totals for the State of WV. According to the U.S. Fish and Wildlife Service (USFWS) (2011b), p. 7), anglers (from in and out of state) fished 4.5 million days within West Virginia in 2011 (305,000 people). In comparison, the total fishing days that we estimated for this region is 1.18 million days or 26% of annual days for WV. The study area represents about one quarter of the state area and population, which is consistent with our estimate that 26% of all fishing days occur in the case study region.

3.3. Model Integration

We aggregated both the ecological and spatial demand results to HUC-10 watersheds which created a final set of 45 HUC-10 watersheds with average size 460 km^2. We used this scale of analysis because it maintains the connections of the stream network and is a reasonable range for representing a set of nearby sites that an individual angler might use (USDA Forest Service, 2011). We then applied the ecological and spatial demand results to estimate potential welfare effects on recreational anglers from mountaintop removal mining, for the two scenarios (20% and 100% of available mine permits become active).

To evaluate the aggregate economic effects of changes in recreational fishing for the two mining scenarios, we required the following information for each watershed in the study area:

1. proportion of total angler catch made up of each of the affected recreational species
2. baseline catch rates per day fished
3. change in catch rates under each scenario
4. number of days fished
5. WTP per marginal fish.

As further described below, each of these data sources had to be developed from the existing models and available data. The proportion of total catch represented by each affected species was developed using proportions in the fish monitoring data. Baseline catch rates were derived from the literature and local data sources and the two sources were compared in sensitivity analyses. Change in catch rates by scenario was estimated by assuming that the changes in catch by species were proportional to the changes in species abundance estimated by the ecological model. Number of days fished came from USFWS survey data. Finally, the marginal WTP per fish was estimated by applying the MRM in combination with all the other data.

Ideally, we would estimate the net present value of changes over time, as mines come online and are reclaimed. However, the fisheries model was not dynamic, so we present a static snapshot of maximum annual impacts for each scenario.

Baseline total benefits from recreational angling in the study area were calculated as:

$$(\$\mathrm{WTP/year})_b = (\mathrm{WTP/fish})_b * (\mathrm{fish\ catch/day})_b * (\mathrm{days\ fished/year})_b.$$

Policy losses from each mining scenario were calculated as:

$$(\$\mathrm{WTP/year})_p = (\mathrm{WTP/fish})_p * \Delta(\mathrm{fish\ catch/day})_p * (\mathrm{days\ fished/year})_p$$

where the change in catch per day is calculated as:

$$\Delta(\mathrm{fish\ catch/day})_p = \Delta(\mathrm{catch\ rate/day})_p * (\mathrm{fish\ catch/day})_b$$

and the change in catch rate per day is calculated as:

$$\Delta(\mathrm{catch\ rate/day})_p = \Big((\mathrm{fish\ abundance})_p - (\mathrm{fish\ abundance})_b\Big)/(\mathrm{fish\ abundance})_b.$$

The b subscript signifies the baseline (current status), and the p subscript signifies the policy scenario, with either 20% or 100% of existing leases mined.

4. Results: Integrated Policy Application

4.1. Ecological Model Results

The predicted changes in fish abundance due to mining activities for HUC-10 watersheds in the study area for the two scenarios are shown in Fig. 6 and Fig. 7. Details may be found in Petty et al. (2014). Across the study area (45 HUC-10 watersheds), the ecological model predicted that for the partial mining scenario, gamefish abundance would decrease by an average of 0.87%, ranging from 0 to 3.7%. For the full mining scenario, the model predicted that abundance would decrease by an average of 4.24%, ranging from 0.14% to 10.47%.

4.2. MRM Results

Table 4 shows the final model results including all retained variables and their coefficients. Because the dependent variable is the natural log of WTP, the coefficients are interpreted as the approximate percent change in WTP per fish for a one-unit change in the explanatory variable. The log-linear form allows for non-linearity of effects, and also implies multiplicative rather than additive effects of the independent variables on WTP. The model R-squared is 0.71, and most coefficients are statistically significant at the 5% level or better.

The dummy variable for stated preference studies is negative and significant at the 5% level, indicating that revealed preference studies tend to produce higher values. The year index coefficient is positive and significant, indicating an upward trend in real value over time, which may be a result of increasing scarcity of recreational fish, or may reflect other factors that have changed systematically over time, such as changes in preferences or in study methods. As expected, anglers with higher incomes are willing to pay more per additional fish. The age variable coefficients indicate that willingness to pay is generally higher for anglers with lower than the sample average age. Anglers who take more trips per year are predicted as willing to pay less per additional fish than those who take fewer trips. Values for fish caught on trips to nonlocal areas are significantly higher than those caught locally. Values by species indicate that rainbow trout is the highest valued freshwater species, followed by lake trout, bass, pike and walleye, and other trout. All of the included species are valued more than the base case “other” species group. Higher catch rates result in lower values per fish, which is consistent with diminishing marginal returns to catch. Stocked fish are valued less than fish that are not stocked.

These results are similar to those in U.S. EPA (2006), although the comparison is complicated because, unlike this study, the earlier study includes saltwater and anadromous species. Another difference is that we include only two methodological variables—a dummy for stated preference approaches, and the year index, while U.S. EPA (2006) included multiple variables. Both studies found that stated preference studies produce smaller values per fish than RUM studies. However, in U.S. EPA (2006), the researchers interacted the year_index with the method, making comparisons difficult. We did not find a significant interaction among the method term and the year_index. Further, our results indicate an increasing trend in values over time, while the U.S. EPA (2006) results indicate that trends may vary by method. Our results suggest declining WTP per fish with age, while the U.S. EPA (2006) results indicate the opposite effect of age. However, the coefficient on the higher age group is not significant in our model. Both models find declining value with more trips taken; both find that nonlocal anglers have much higher values; and both find decreasing value per fish as catch rate increases.

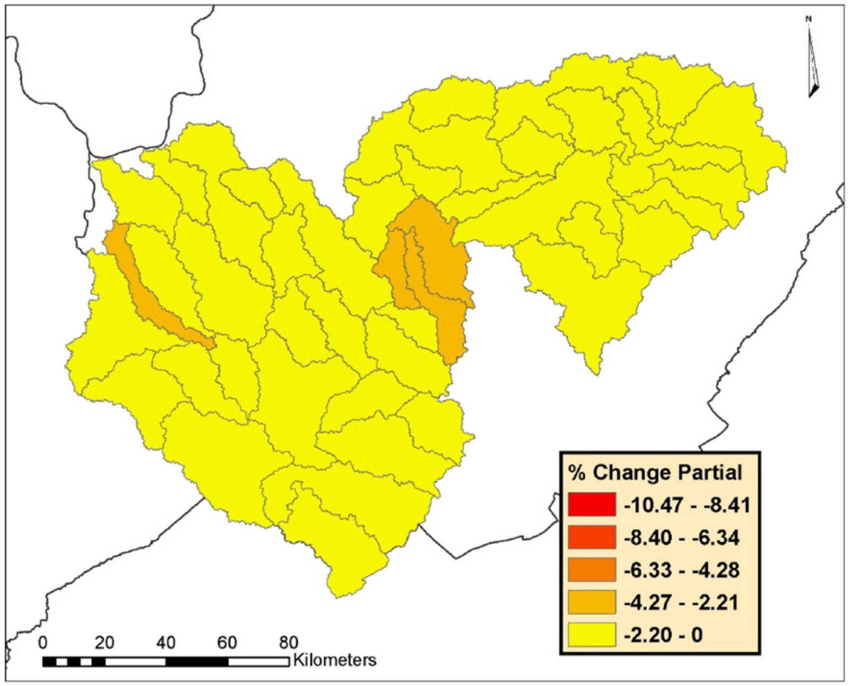

Fig. 6. Ecological model results: percent change in game fish abundance for the partial mining scenario by HUC-10 watershed.

4.2.1. Willingness to Pay per Fish

We calculated the WTP/fish with parameters appropriate to the study area (Table 5 and Table 7), using the following formula:

$$WTP = e^{(x'\beta + \sigma 2/2)}$$

where WTP is the predicted willingness to pay per fish under the policy scenario; $x'\beta$ is the sum of coefficients times policy parameters; and σ^2 is the mean squared error, or residual variance, from the regression equation (Cameron and Trivedi, 2010).

The income estimates were derived from the US Census Bureau data for West Virginia, by choosing the median income for the county that enclosed the majority of each watershed. Results for county-level income were compared to state median income to demonstrate the sensitivity of results to this variable.

4.2.1.1. Estimates of Fish Caught. A key variable that determines economic effects of a fishery change is the baseline average catch rate, since reductions where current catch rates are high will generally have lower economic impacts than reductions where catch rates are low, all else equal. Since we did not find a systematic survey to provide catch rates for the

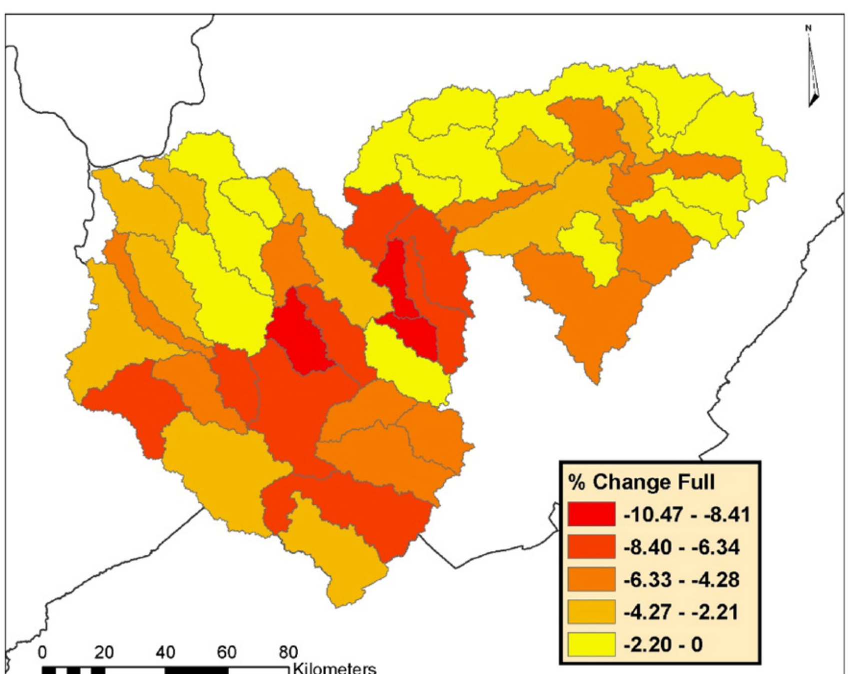

Fig. 7. Ecological model results: percent change in game fish abundance for the full mining scenario by HUC-10 watershed.

Table 4
Meta-regression model results.
Dependent variable: ln(WTP/fish − $2012).

	Coef.	Robust std. err.	t	P > t	95% conf. interval	
st_pref	−0.4933*	0.2137	−2.3100	0.0330	−0.9423	−0.0442
year_indx	0.0933**	0.0236	3.9500	0.0010	0.0436	0.1430
inc_thou	0.0288**	0.0080	3.5800	0.0020	0.0119	0.0457
age_lt45	0.9478**	0.2458	3.8600	0.0010	0.4314	1.4643
age_45up	−0.2853	0.4933	−0.5800	0.5700	−1.3216	0.7510
trp_20up	−0.6143	0.2973	−2.0700	0.0530	−1.2390	0.0103
nonlocal	3.7319***	0.4391	8.5000	0.0000	2.8094	4.6545
bass_fw	1.2070*	0.5036	2.4000	0.0280	0.1491	2.2650
pike_walleye	1.1625**	0.3435	3.3800	0.0030	0.4410	1.8841
rainbw_trout	1.9668***	0.4406	4.4600	0.0000	1.0412	2.8925
laketrout	1.6815***	0.2786	6.0400	0.0000	1.0962	2.2668
unspec_trout	1.0151**	0.2440	4.1600	0.0010	0.5026	1.5277
lake_res	1.2952*	0.5577	2.3200	0.0320	0.1236	2.4669
catch	−0.1024**	0.0334	−3.0700	0.0070	−0.1725	−0.0322
spec_catch	0.6916**	0.2003	3.4500	0.0030	0.2708	1.1124
stock_yes	−0.5793*	0.2036	−2.8500	0.0110	−1.0070	−0.1516
_cons	−2.0281*	0.7528	−2.6900	0.0150	−3.6096	−0.4465

Number of obs = 108.
$F(16, 18) = 204.8$; Prob > F = 0.0000.
R-squared = 0.71.
Root MSE = 0.5498.
* Significant at the 5% level ($p < 0.05$).
** Significant at the 1% level ($p < 0.01$).
*** Significant at the 0.1% level ($p < 0.001$).

study area, we applied the average catch rates derived from our literature database. Average catch rates were 0.58 fish per day for bass, 4.4 fish per day for other species and 3.2 fish per day for trout, for inland freshwater fishing.

To test the reliability of applying these numbers locally, we gathered available, but limited, data from local government officials and government reports. The WV Department of Natural Resources tracks bass tournament catch rates and found that in 2011, the hourly catch rates for rivers was 0.21 bass/h and for lakes and rivers combined was 0.20 bass/h (Jernejcic, 2012, pers comm). Over the past decade, the combined catch rate for lakes and rivers was 0.15 bass/h. Several WV DNR personnel suggested that tournament catch rates were likely to be about 3–4 times lower than catch rates for anglers outside of competition because tournament anglers report only the largest fish they are catching, and release many fish that are not reported.

Therefore, if we assume a 4 h fishing day and a 3.5 multiplier to represent non-tournament anglers, the 2011 rate for non-tournament bass anglers would be 2.8 fish per day if using 2011 numbers and 2.1 fish per day using the decadal average. This estimate is significantly higher than the catch rates found in the literature and may be biased by the high skill level of tournament anglers, relative to the average angler. Therefore, if we ignore the 3.5 multiplier, the mean daily rate (0.6 fish/day to 0.84 fish/day) is similar to those found in our data. In the only other applicable data set that we found, Caudill (2007) estimated daily catch rates in the Southeast region for the years 2002–2005 using a mix of data and best professional judgment to arrive at the following estimates: largemouth bass = 1.58 fish per day; all other species = 2.0 fish per day (based on a 4-h day). Again, the catch rate for bass is significantly higher than that of our data set, while the catch rate for other species falls within the range of our data. We tested the highest estimate for bass catch rate of 2.8 fish/day in sensitivity analysis of WTP values.

Table 7 presents the estimated baseline willingness to pay (WTP) per fish, in 2012$, using the mean catch rate from the meta-analysis data and the local WV catch estimates (which are available for bass only). Values for freshwater bass species range from around $15 to around $22 per additional fish caught, depending on assumptions about baseline catch rates and income. In contrast, other species (panfish, perch, catfish, carp, and "no target") range from around $3.80 to around $4.50 per additional fish caught.

4.3. Total Recreational Angler Demand

Using the DD map, we aggregated the total days demanded for freshwater fishing per HUC-10 watershed. The annual recreational fishing days range from 6490 to 51,900 per watershed (Fig. 8). Watersheds that are closer to urban or more populous areas showed higher demand, as would be expected.

4.4. Change in Catch

Assuming current conditions are representative of a no-action baseline, we applied the model using expected changes in catch rates for the two scenarios. To do so, we assumed that catch rates will change by the same proportion as the changes in fish abundance predicted by the ecological model. These changes were applied to the catch rates shown in Table 6, and WTP/fish was re-estimated using the new catch rates to represent the marginal value of a fish caught given average baseline catch rates.

Table 5
Independent variable assignments for meta-regression model application.

Variable	Assigned value	Explanation
st_pref	0	Assume revealed preference study (accepted standard practice for use values for recreational fishing)
year_indx	19	Sample maximum from the data
inc_thou	Varies by county; or 41.51 for state median	West Virginia median county or state income (thousands of 2012$)[a]
age_lt45	.53	Average for W VA anglers[b]
age_45up	.47	Average for W VA anglers[b]
trp_20up	.323	Average for W VA anglers[b]
nonlocal	0	Assume trips are local (within 150 miles)
bass_fw	0 or 1	1 to evaluate values for bass; 0 to evaluate values for "other" species
pike_walleye	0	Species not affected in the study region
rainbw_trout	0	Species not affected in the study region
laketrout	0	Species not affected in the study region
unspec_trout	0	Species not affected in the study region
lake_res	0	All water bodies in study region are rivers or streams
catch	Varies	See Table 6
spec_catch	1	To represent studies that included catch rates in their analysis
stock_yes	0	Affected species are not stocked
_cons	1	Intercept

[a] Source: 2011 American Community Survey 2007–2011, U.S. Census.
[b] Source: 2006 National Survey of Fishing Hunting and Wildlife-Associated Recreation data.

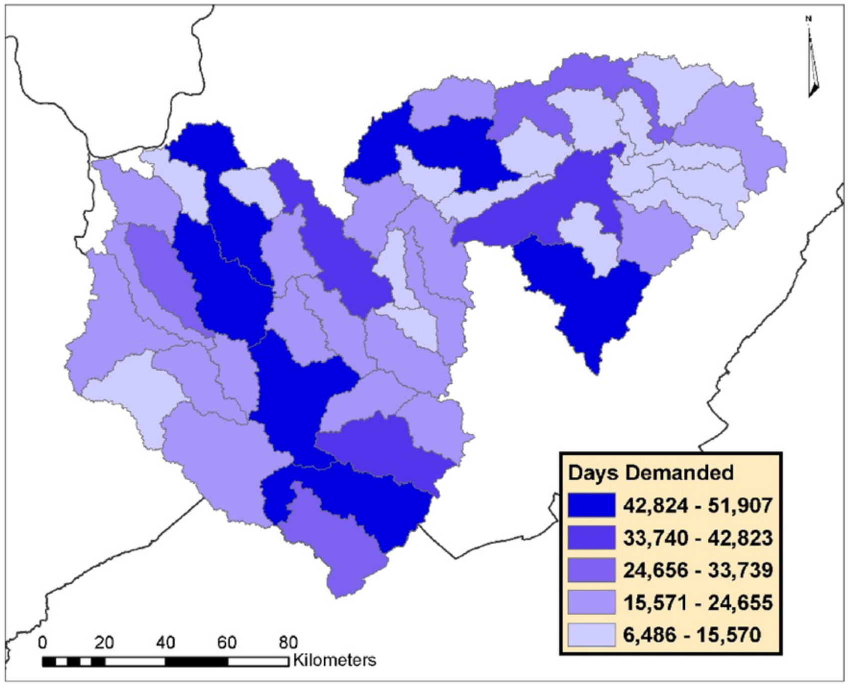

Fig. 8. Total estimated freshwater fishing days demanded by HUC-10 watershed. Spatial variability in days demanded is due to spatial distribution of residences (origin points) within and adjacent to the case study area, demographic characteristics that influence participation rates by location, and different willingness to travel for fishing on the part of urban and rural participants.

4.5. Estimates of Total Value

To estimate total annual social value for the baseline (current conditions), we multiplied the value per fish (Table 7) times catch per day (Table 6) times the total days demanded, for each 10-digit HUC in the study area. These values were then weighted by the proportion of bass and other species in each watershed and summed to get total values for each catch rate and income level. The total baseline willingness to pay for recreational angling in the study area is shown in Table 8. The current total value for recreational angling in the study area is estimated as $5.5 million to $46.9 million per year, depending on the annual number of fish caught in the region and income. A more accurate estimate of catch would greatly improve the precision of these estimates.

For each of the two scenarios, we: (1) estimated the change in catch rates per angler per year and the change in projected total catch rates (across all anglers) for each watershed, (2) estimated WTP/fish using the projected changes in catch rates, (3) estimated the change in WTP/year by species, and (4) estimated the species-weighted total reduction in WTP/year for each scenario and combination of inputs. From these calculations, we estimated that changes in value for the partial (20%) mining scenario range from losses of $39.5 thousand to $377.9 thousand per year (Table 8). Estimated changes in value for the full (100%) mining scenario ranged from losses of $209.6 thousand per year to almost $2.1 million per year (Table 8). The spatial distribution of WTP values showed that economic impacts tend to be greater in the southern portion of the study area for both scenarios (Fig. 9 and Fig. 10). This pattern can be largely explained by greater ecological impacts in these streams and rivers (Fig. 6 and Fig. 7); however, part of the effect is also due to expected differences in fishing participation across watersheds.

Table 6
Baseline catch rates per day by species.

Species	Catch rates from the meta-analysis data: N	Median	Mean	Min	Max	Local WV estimates: Mean
Bass	8	0.57	0.58	0.27	0.88	0.6–2.8
Other species	25	3.52	4.44	0.37	14	2.0

5. Discussion and Conclusions

The challenges of applying benefit transfer models to policy sites are often underestimated. Data for MRM variables may not be available and results can be sensitive to variables that are estimated with high uncertainty. Although benefit transfer is generally considered to be a relatively easy approach to generating a monetary value of a good or service, practitioners often face severe data limitations. They not only lack the values needed to develop the MRM, but lack local data for estimating the policy-relevant variables needed to apply the model. We presented some options for estimating the data needed to apply MRMs in ways that were scale-appropriate and sensitive to local conditions. However, overall, valuation results were sensitive to variables with high uncertainty in the ecological and socio-demographic data. Therefore, improving the ability to characterize local conditions with available data would enhance the robustness of value estimates.

Through our comparison of median income calculated at two different scales, we showed that valuation results were sensitive to the spatial scale of socio-demographic measurements. Further, our comparison of fish catch rates showed that values are sensitive to assumptions about

Table 7
Estimated willingness to pay per fish for West Virginia with alternative trip catch rates (2012$).

Species	Using mean catch rate from meta-analysis data	Using high catch rate from WV data
Bass, using median income by county for the study area	$18.93	$15.09
Bass, using state median income	$22.21	$17.71
Other species, using median income by county for the study area	$3.82	N/A
Other species, using state median income	$4.48	N/A

Table 8
Total WTP for recreational fishing for the baseline and loss in WTP for partial and full mining scenarios showing sensitivity to income and catch rate assumptions.

WTP (thousands 2012$)					
	Catch	Low	Medium	High	Extra high
Baseline (current level of mining)					
Income	County median	$5,523	$15,400	$20,500	$39,700
	State median	$5,678	$18,100	$24,200	$46,900
Partial mining scenario					
Income	County median	$(39.5)	$(120.5)	$(163.1)	$(326.9)
	State median	$(45.7)	$(139.0)	$(188.3)	$(377.9)
Full mining scenario					
income	County median	$(209.6)	$(627.8)	$(864.7)	$(1,761)
	State median	$(248.2)	$(741.2)	$(1,021)	$(2,085)

catch rate, one of the hardest variables to estimate precisely without creel survey data. We expect that other variables will be similarly sensitive when landscapes exhibit high spatial diversity of important characteristics. In particular, spatial variability in the magnitude of ecological effects by location, number of affected users, and angler characteristics will drive the magnitude of welfare losses for recreational fishing.

An important aspect of the analysis is the heterogeneity of ecological impacts (Petty et al., 2014). If, as mining occurred, damages were concentrated in a few areas, anglers may be able to find substitute sites, thereby minimizing welfare effects. However, our analysis showed that within the mountain-top mining region, ecological impacts were heterogeneous but showed net losses everywhere. This result of widespread harm supports the benefit transfer assumption that substitution effects are minimal. The result further suggests that cumulative impacts to fisheries could be a future concern if species lose areas of high quality habitat that may serve as source populations to more degraded streams.

5.1. Sensitivity to Ecological Model

Our ability to capture the ecological production function that relates water quality to fish abundance and fish quality had a large impact on results. The boosted regression trees predicted relatively modest effects on game fish abundance from the partial mining scenario (~1% average and 4% maximum decline in game fish) and only slightly more substantial effects from the full mining scenario (~4% average and 10% maximum decline). These results are consistent with other studies that have showed declines in fish species in response to mountaintop mining (e.g., Stauffer and Ferreri, 2002; Hopkins and Roush, 2013). A recent targeted study of the effects of mountaintop mining on fish assemblages in a West Virginia watershed found mixed effects on game species but an overall decline in number of species and total abundance in mining-affected sites, as compared to reference sites (Hitt and Chambers, 2014). Although the statistical models relating mining and fish abundance used in our analysis were based on all available data, the data have limitations because they were not collected specifically to address the question of mining impacts. Further, these data may be influenced by the timing of sampling, or by metacommunity processes and dynamics (e.g., Freund and Petty, 2007; Hitt and Angermeier, 2011). The use of our statistical models to consider future mining scenarios is based on the assumption that these relationships would be valid under future conditions. However, it is possible that the cumulative effects of the impairment of many stream segments could lead to a more significant regional response of the fish assemblages (Freund and Petty, 2007).

5.2. Sensitivity to Local Conditions

Other sources of uncertainty stemmed from the assumptions of the typical catch rate in these streams. We did not have data specific to these systems, so we used averages from the literature, which seemed to be a reasonable fit based on our conversations with local fisheries managers. However, because the results depend heavily on expected catch, we presented a range of values to test the sensitivity of this assumption. The results are also sensitive to angler income. Because we did not have sufficient data to estimate the mean income of anglers, we conducted sensitivity analysis based on income, presenting values calculated using both the county and state median incomes.

This analysis demonstrated approaches to capturing ecological changes in terms of social welfare effects. Using the conservative assumptions of median county income and mean catch rates, we estimate a total welfare loss due to changes in freshwater fish abundance of

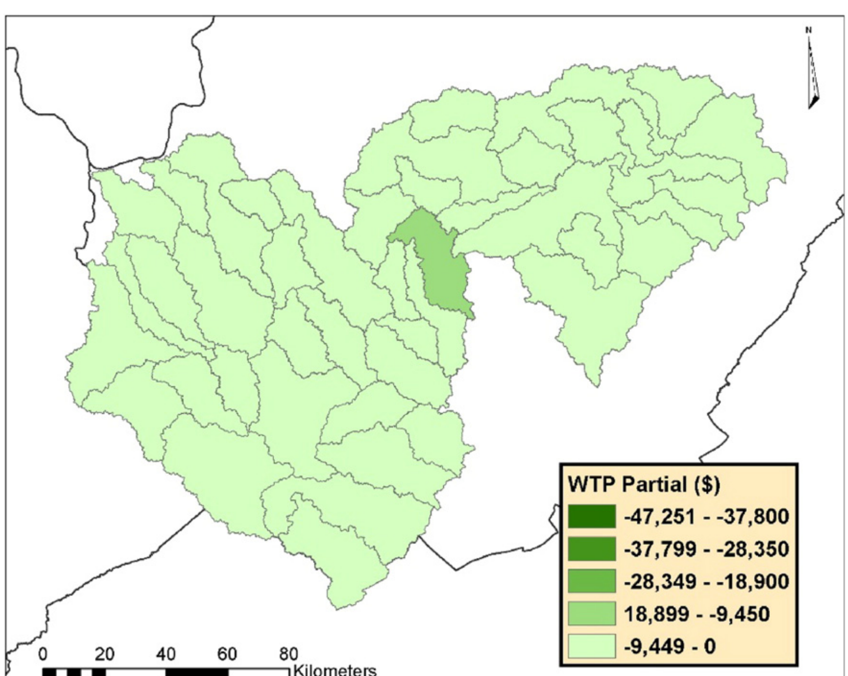

Fig. 9. Change in annual WTP (2012$) for freshwater fishing in partial mining scenario by HUC-10 watershed (using median county income and medium catch rate).

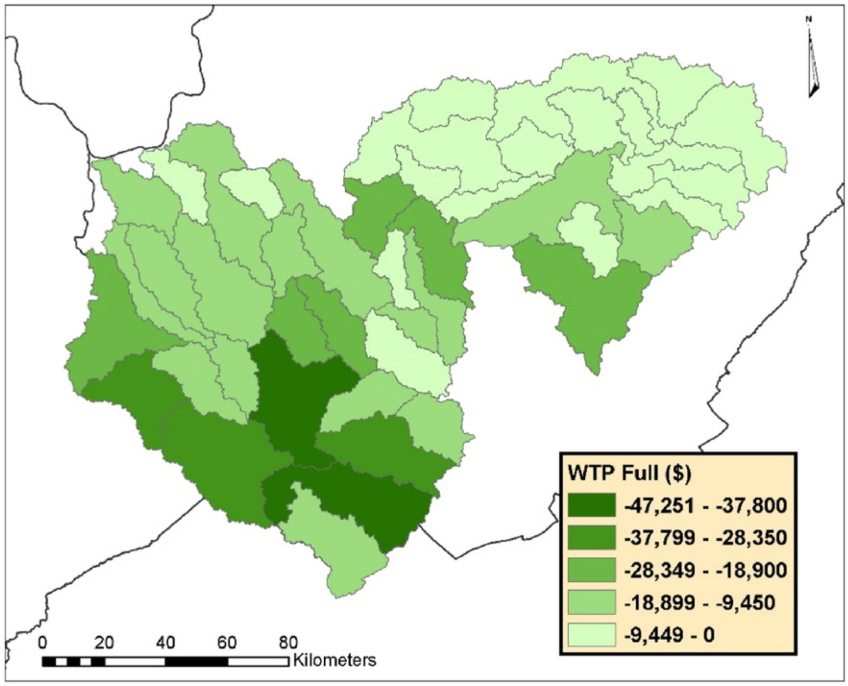

Fig. 10. Change in annual WTP (2012$) for freshwater fishing in full mining scenario by HUC-10 watershed (using median county income and medium catch rate).

$120,500 per year for the partial mining scenario and $627,800 per year for the full mining scenario. These modest estimates do not take into account reductions in participation that might occur if areas become unattractive to some anglers because of a stigma that they are unsafe or if they lose aesthetic appeal. Further, these numbers only begin to provide an estimate of the ecosystem service effects of mining since recreational fishing is only one use of the area.

Changes in social welfare as a result of mining are a function of both ecological change and how much users or beneficiaries are affected by those changes. Here we have focused on recreational freshwater fishing because it is a popular activity, it is impacted by the mining scenarios, and we can measure the welfare effects of a change by building on available data and studies. The economic meta-analysis function that we developed here can be readily transferred to other regions as long as the appropriate data on fishing use rates by location, average catch, and ecological changes can be gathered or estimated using the techniques described here or other approaches. For both the ecological and economic models, we used national data sets, literature values, and transferable modeling techniques in order to create a reusable process for transferring the meta-analysis to any region in the U.S.

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