FINAL REPORT

Title: Demand for prescribed fire on private lands in the Mid-Atlantic United States

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Abstract

Fire is an important process that shapes the structure and composition of many North American forest ecosystems. In the absence of fire, fire-dependent tree species can be gradually replaced by fire-sensitive species. There is an increasing interest by natural resource professionals to restore important fire-dependent ecosystems in order to enhance the provision of ecosystem services. Restoring fire across eastern US landscapes is complicated by a diverse mix of public and private land ownerships. In the Mid-Atlantic region, most prescribed burning occurs on public lands. However, three-fourths of forestlands in this region are privately owned which means the potential for private lands burning is significant. To help inform policies that support prescribed burning on private lands we conducted a regional survey of private landowners regarding their knowledge and interest in prescribed burning. The survey assessed landowner knowledge and perceived risk of burning, trust in fire practitioners, and willingness to pay for using prescribed fire as a management tool. We also examined regional variation in landowner responses using a spatial analysis technique called hot spotting. Overall, many respondents had limited experience with prescribed fire, but many also had low-risk perceptions about prescribed fire and positive attitudes towards prescribed fire implementors. Results showed that private landowners see burning as a tool that can help them obtain important ecological (e.g., forest health) benefits and support cultural values about forest stewardship. The hotspot analysis indicated that respondent's opinions were spatially correlated. Respondents from the most northern (New York) and southern (Virginia) regions of the study area were statistically different from the rest of the study area. New York landowners were less knowledgeable about prescribed burning and had higher risk perception, whereas Virginia landowners had greater knowledge experience and lower risk perceptions. This outcome is reasonable as prescribed fire is commonly used in Virginia and uncommon in New York. Pennsylvania landowners were unique, however, because even though knowledge about prescribed fire was low, they had a much higher willingness to pay compared to Virginia which already uses prescribed fire. This suggests that landowners in Pennsylvania are highly motivated to use prescribed fire but may be overestimating the potential benefits due to lack of experience. Education, technical support, financial assistance and access to professionals will be important for helping private landowners use prescribed fire to achieve important management objectives.

Keywords: Willingness to pay, Prescribed burning, Private Landowners, Hotspot Analysis, Spatial Autocorrelation

Goals/Objectives

This project builds on a 2021 survey study conducted in Pennsylvania by Arun Regmi to help inform the design of an extension education program about private lands burning. The study in this report now includes respondents from several states in the Mid-Atlantic region to help inform the design of landowner education programs more broadly.

Research Questions

1. Do landowners in the Mid-Atlantic region see prescribed fire as a valuable land management tool?
2. Which factors influence landowner decisions to burn?
3. Are there regional differences in landowner perspectives about prescribed fire?

Introduction

Fire is a primary driver forming the structure and composition of many North American forest ecosystems. Prescribed fire is widely used as a management tool throughout the US for a variety of reasons such as to reduce wildfire hazards, improve wildlife habitat, enhance aesthetics, encourage forest regeneration, and maintain fire-dependent ecosystems (Phillips et al., 2012). Prescribed fire is more commonly used in many southern and western states in the US. However, there is an increased interest in the Mid-Atlantic US towards the comprehensive use of prescribed fire for ecological restoration, regeneration of oaks and other fire-tolerant species, and wildlife habitat management (Clark et al., 2014; Hiers et al., 2020). Restoring fire in the eastern US is complicated by a diverse mix of public and private land ownerships (Ryan et al., 2013). A recent study found the public in the mid-Atlantic region are generally supportive of prescribed fire and demonstrated high trust in state agencies that use fire (Wu et al., 2022). However, forest landowner opinions about using prescribed fire on their land and possible barriers to burning in this region are still not well understood.

About 64% of the Mid-Atlantic region is covered by forests, and 70% of forests are privately owned. This region also highly diverse with at least 135 tree species and several dominant forest types (i.e., oak-hickory, oak-pine, and northern hardwoods; Phillips et al. 2012). Most burning in the Mid-Atlantic region occurs on public lands. Federal and state agencies, and some non-governmental organizations (e.g., The Nature Conservancy) use prescribed burning mainly for habitat restoration and to promote landscape level biodiversity. Private forests are rarely prescribed burned, which means the potential for adding prescribed fire as a land management tool on private lands is significant for advancing forest management in the region.

To help design more effective policies that support prescribed burning on private lands, a better understanding of the key barriers to behavior change (e.g., knowledge, preferences, attitudes) are needed. Exploring landowner choices within economic, cultural and political contexts can also help explain behavioral intentions towards prescribed fire and the potential for a prescribed fire economy. Findings can help policymakers design more effective landowner education and outreach programs and advocate for policies that promote burning on private lands. Landowner perspectives of prescribed fire may also vary across the region due to differences in forest ownership goals, legal, geographical, and ecological complexities. Therefore, understanding spatial variation in landowner perspectives can help inform more targeted interventions.

Study Objectives

1. Evaluate landowner knowledge, attitudes, and willingness to pay (WTP) for prescribed burning programs in the Mid-Atlantic region.

2. Understand spatial variation in landowner perspectives of prescribed burning across the region using spatial analysis techniques. The spatial analysis is a new addition to this project.

Approach and Methods

Study Sites

The study was conducted in four states across the Mid-Atlantic US including New York, Pennsylvania, Maryland, and Virginia (Figure 1). Historically, the Mid-Atlantic region consists of different fire regimes. It has been proposed that in the northern part of the mid-Atlantic region, fire occurred infrequently with low to medium severity while in the southern part of this region fire burned more frequently with low severity (Stolte, 2012). In terms of total acres burned by state and federal agencies Virginia is ahead of the rest of the states. In 2022 Virginia burned over 30 thousand acres of forests while Pennsylvania and Maryland have burned about 12 and 11 thousand acres of forests, respectively (NIFC, 2022). Prescribed burning in New York is rare (about 1,000 acres) compared to rest of the states but is nonetheless increasing over the years (Melvin, 2020).

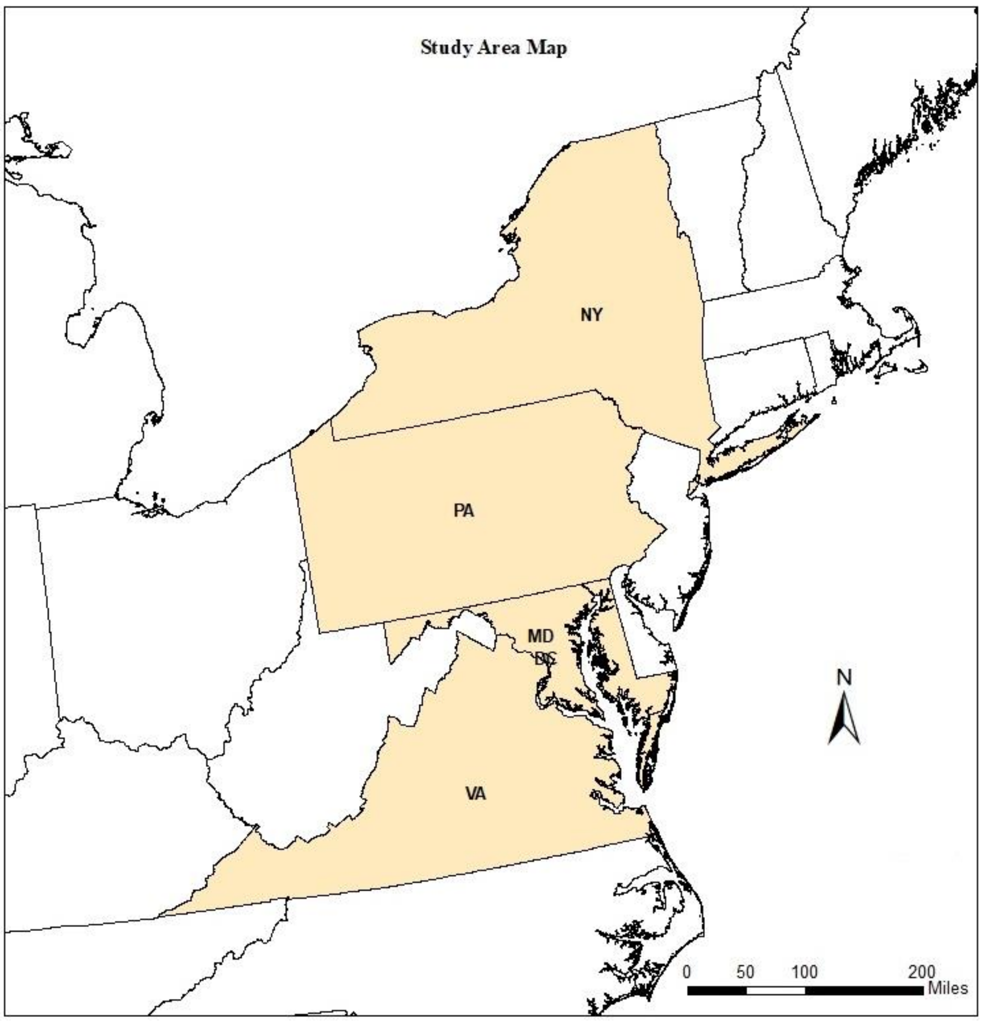

Figure 1 Study Area Location in the United States Map includes four Mid-Atlantic states: New York, Pennsylvania, Maryland, and Virginia

Theoretical Approach

Social network theory endeavors to describe the processes by which society evolves (Lusher et al., 2013). The Social Process Triangle is useful for assessing social situations and the complex factors behind them to create strategies to address social issues in communities and organizations (Figure 2.)

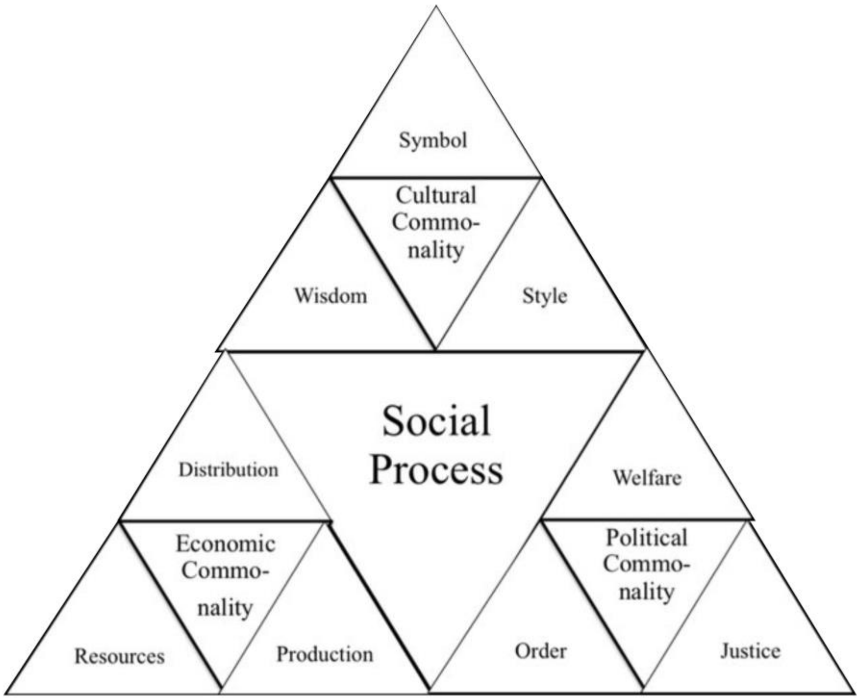

Figure 2. Social Process Triangle

Following this conceptual model, we expect that landowner willingness to consider using prescribed fire is likely a function of the cultural, economic, and political context in which decisions are made. Landowner perspectives of prescribed fire may also vary across the region due to heterogeneity in ownership objectives, legal provisions, and complex ecological and geographical conditions.

Political Context

The Mid-Atlantic region faced almost a century of fire suppression on the landscape. After realizing the negative impacts of fire exclusion, the Mid-Atlantic states started to provide a legal framework for prescribed burning by passing related act and policies. Prescribed fire laws provide civil and criminal protection to prescribed fire implementors who burn under the set standards. Prescribed fire acts were passed in Pennsylvania (PA) in 2009, New York (NY) in 2009, and Maryland (MD) in 2010 while Virginia (VA) started passing a series of laws related to fire in 1998. Specific burning laws of Virginia are found in Title 10.1 of the Code and article 1150. Standard (i.e., simple negligence) liability laws are used in PA, MD, and VA (Melvin, 2018), but NY has strict negligence liability laws. Prescribed fire councils have been established in PA and VA to help promote prescribed burning in the state (Melvin, 2018). It is still unclear how these policies encourage or discourage landowners who may consider using prescribed burning on private lands. Even with liability laws in place, burning on private lands may also still be limited if political officials are risk adverse (Schultz et al., 2018).

Cultural Context

Cultural values about prescribed fire are often a function of people's knowledge, beliefs and attitudes. Most studies evaluating attitudes, knowledge and trust have only assessed public and land manager perceptions, not landowners (McCaffrey, 2006; Blanchard and Ryan, 2007; Kreuter et al., 2008; Elmore et al., 2009; Piatek and McGill, 2010; Fischer, 2011; Kobziar et al., 2015; Weir et al., 2019; Jarrett et al., 2009; McCaffrey, 2004). Very few studies have conducted these same assessments in the mid-Atlantic area (Dupéy and Smith, 2018; Wu et al., 2022). Even though prescribed fire is rarely used on private lands, we expect that some landowners may view prescribed burning as a way to maintain cultural values about land stewardship. Some may use fire to manage the landscape for hunting or gathering resources while others may see it as a way to preserve cultural heritage, enhance aesthetic and recreational values (Schultz et al., 2018).

Technical assistance and training programs are a useful strategy for shaping cultural values about fire and land stewardship. Virginia already has an established system to conduct prescribed fire on private lands. This includes a landowner education program ran by Virginia Tech and a certified prescribed burning managers program ran by Virginia Department of Forestry. They also have comparatively more fire professionals to conduct burning (e.g., burn bosses, consultants). The Pennsylvania Prescribed Fire Council is just starting to provide learning opportunities for landowners in the state, but opportunities are still very limited in Pennsylvania and the other study states.

Economic Context

In the southern US, where prescribed fire is an established land management tool, the average cost of prescribed burning is around $31.12 per acre (Maggard, 2021). The cost of burning in the Mid-Atlantic states has not been formally documented, however, interviews with practitioners suggest that costs can range from $40 to $400 per acre or more depending on the total acres burned and availability of trained work forces (Regmi et al., 2023). The limited number of trained burning professionals in this region could be one reason why costs are high (i.e., increased competition). At these prices, some landowner may need cost-share assistance to help achieve burning goals. High liability costs could also discourage landowner participation even when incentives are provided (Schultz et al., 2018).

Survey Design

We used a multi-stage process to design, test, validate, and distribute a survey to private landowners across the Mid-Atlantic US (Dillman et al. 2014). To help develop survey questions, semi-structured interviews were conducted with 25 participants representing diverse stakeholder groups including landowners. The final survey contained 68 questions and consisted of four sections: 1) information on land ownership and management objectives, 2) questions to measure knowledge, perceived risk, and trust, 3) choice experiment questions and 4) landowner demographic questions. Survey pre-testing was conducted with more than 20 participants including forest owners and state agencies and other research professionals.

Attitude and Knowledge Scales

Five-point Likert scale questions (1=strongly disagree, 5=strongly agree) were used to measure respondents' knowledge and experience with prescribed fire, trust in prescribed fire implementers, and perceived risk of prescribed fire. Scaler statements were developed based on findings from related studies (e.g., Blanchard and Ryan 2007; Elmore et al. 2010; Busam and Evans 2015). Respondent total scores were used as covariates in the regression model on landowner choices (see Appendix E for statements used in scalar tools).

Choice Experiment Design

A choice experiment (CE) approach was used to understand landowner motivations and willingness to pay (WTP) for prescribed fire programs. The CE method has been extensively used in environmental research to evaluate the monetary value of non-market goods and services. This method involves asking respondents to make a choice for a series of hypothetical management programs (often called a choice set) made up of a combination of attributes and their levels. The CE approach is based on random utility theory which provides the necessary link between the statistical model (i.e., observed landowner behavior) and an economic model of utility maximization (Hanley et al., 1998).

A total of 16 choice sets were designed using the Taguchi orthogonal array (OA). Preliminary surveys, interviews, and focus group discussions revealed the need to rank a wide range of potential program options and benefits. The attributes and levels used in the choice experiment were designed to represent what landowners may consider when deciding to adopt fire as a new management tool (Table 1). For example, preferences for levels describing Ecological Outcomes and Management Benefits are expected to be dependent on the respondent's management objectives. Preferences for Support Resources are expected to be dependent on what the respondent considers important barriers to burning. Preferences for levels describing changes in Institutional Factors indicate potential barriers that could be controlled by policy. A price attribute was also included in the design to estimate a marginal WTP for the other attributes. According to interviews and focus groups, the price of burning in Pennsylvania can be highly variable ranging from $20 to $400 per acre. These values informed the prices on offer in this study.

Table 1 Factors and Levels used in the choice experiment.

Attributes	Levels	Coding
Ecological outcomes	Promote oak regeneration	EO_0
	Improve wildlife habitat	EO_1
	Restore rare vegetation communities	EO_2
	Maintain forest health, resilience, and diversity	EO_3
Management benefits	Reduce management costs	MB_0
	Control invasive plant species	MB_1
	Reduce ticks	MB_2
	Reduce tree and plant pests	MB_3
Resources for landowners	Landowner training to enhance prescribed fire skills	RL_0
	Prescribed fire associations to coordinate landowners	RL_1
	State agency coordination	RL_2
	Financial assistance (e.g., cost-share)	RL_3
Reduction in barriers	Reduce legal liability of an escaped fire	RB_0
	Access to qualified consultants	RB_1
	Access to qualified burn bosses	RB_2
	Relaxed standards	RB_3
Cost of burning (US$)	$20/acre, $50/acre, $125/acre, $200/acre	

To reduce respondent fatigue only 8 of the 16 choice sets were presented to each respondent at any given time (see Appendix D for sample question). A 10-point certainty scale

(1=Extremely uncertain, 10=Extremely certain) was included with each WTP question to help control hypothetical bias (see Appendix D) (Vossler et al., 2003). A follow-up scaler question was asked after all choice questions to understand reasons for not accepting any of the giving programs.

Data Collection

A regional survey was conducted to collect the data. The survey was designed and distributed using mixed modes (i.e., mail and web) following Dillman et al. (2014). The primary method for collecting responses was a push-to-web method that involved mailing a survey invitation postcard to respondents asking them to access the survey through a secure web link or QR code. Most of the data (55%) was collected using this method. A mail survey (25%) was also used for those who did not want to reply to a web survey. This involved mailing a survey questionnaire along with a cover letter to respondents. The mailing addresses of private forest landowners was provided by collaborating with several private organizations and state agencies such as the Centre of Private Forest in Pennsylvania, the Pennsylvania Bureau of Forestry, the New York Forest Owners Association, and the Maryland Tree Farm Program. Some organizations were only willing to distribute information about the survey using their list-serve rather than sharing members names and addresses for a direct mailer. In this case we created an opt-in method (20%). In this method a link to the project website was distributed via collaborators' organizational list serve. Visitors to the website could read about the project and sign up to be a survey participant. Respondents could either take the survey online or request a paper copy of the survey. Listservs used in this study include the Virginia Landowner Education Program's newsletter listserv and the Virginia Fire Council listserv. The Qualtrics software was used to design and distribute the web survey. To improve the response rate, a series of follow-up communications such as mailing reminder postcards or emails were sent to those who didn't respond the first time. A sample of mail surveys, push-to-web postcards, and sign-up websites are presented in the Appendix D.

Data Analysis

Responses to attitude scales were analyzed by calculating a mean response to individual statements and grand means for the whole set of statements. The grand means are reported as descriptive statistics and the total score was used as covariates in the model. The certainty score associated with each WTP question was used to address the potential hypothetical bias. Respondents who accepted the choice set at the proposed price and had a certainty score of ≤ 5, had their responses changed to reject the program, because of their lack of certainty about the purchase (Vossler et al., 2003). Effect coding[1] was used to parameterize program attributes and avoid confounding the *Opt-Out* coefficient (Bech & Gyrd-Hansen, 2005).

Mixed logistic regression models were used to establish a relationship between the dependent variable (i.e., willingness to enroll in a prescribed fire program at the offered price per acre) and the independent variables listed in Table 2. Sequential runs of the model were set to retain variables significant at $p<0.01$, $p<0.05$, and $p<0.10$ levels. Model selection was also based on goodness-of-fit measures including the likelihood ratio test and McFadden's Pseudo R-squared (Rolfe, 2000).

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[1] The effects coded variable for an attribute level is set equal to 1 when that level is present in the choice set, and equal to -1 if the reference level is present in the choice set and equal to 0 otherwise.

Table 2 Description of variables tested in mixed logistic regression models.

Name	*Description*	*Data Type*	*Coding*
Choice	Dependent variable	Binary*	1= Accept the program 0 = Reject the program
Ecological Outcomes	Promote oak regeneration	Effect code	Reference level (-1)
	Improve wildlife habitat	Effect code	1= EO_1, and 0 if else
	Restore rare Vegetation	Effect code	1= EO_2, and 0 if else
	Maintain forest health	Effect code	1=EO_3 Reference level
Management Benefits	Reduce Management Costs	Effect code	Reference level (-1)
	Control invasive plant species	Effect code	1= MB_1, and 0 if else
	Reduce ticks that harm humans	Effect code	1= MB_2, and 0 if else
	Reduce tree/plant pests	Effect code	1= MB_3, and 0 if else
Support Resources	Landowner training	Effect code	Reference level (-1)
	Prescribed fire associations	Effect code	1= RL_1, and 0 if else
	State agency coordination	Effect code	1= RL_2, and 0 if else
	Financial assistance: cost share	Effect code	1= RL_3, and 0 if else
Institutional Factors	Reduce legal liability	Effect code	Reference level (-1)
	Access to qualified consultants	Effect code	1= RB_1, and 0 if else
	Access to qualified burn bosses	Effect code	1= RB_2, and 0 if else
	Relaxed standards	Effect code	1= RB_3, and 0 if else
Price	Cost of burning per acre	Categorical	$20, $50, $125, $200
Trust	Trust in prescribed fire implementers (total score)	Continuous	1= low trust, 5= high trust
Risk	Perceived risk of prescribed fire (total score)	Continuous	1= low risk, 5= high risk
Assistance Program	Past use of government assistance	Binary	1=enrolled in an assistance program in the past, 0 if else
Pennsylvania	Respondents corresponding states	Binary	1=respondents from Pennsylvania state, 0 if else
Virginia	Respondents corresponding states	Binary	1=respondents from Virginia state, 0 if else
New York	Respondents corresponding states	Binary	1=respondents from New York state, 0 if else
Maryland	Respondents corresponding states	Binary	1=respondents from Maryland state, 0 if else
Income	Annual household income	Ranked categories	1=< $20k, 2= $20k to <$50k, 3= $50k to <$80, 4= $80k to <$100k, 5= $100k to <$150k, 6=$150k to <$250, 7= $250k & more
Age	Age of respondent (years)	Ranked Categories	1= 18 to 24, 2= 25 to 34, 3= 35 to 44, 4=45 to 54, 5=55 to 64, 6=65 to 74, 7=75 to 84, & 8=85 or older

* Observations were recoded to 0 if the associated response on the ten-point confidence scale was ≤ 5.

The part-worth value (PWV), also known as WTP or marginal utility of each attribute was estimated using the ratios of attribute and price coefficients given by Hanemann (1984) and Parsons and Kealy (1992) in the simplified form (Eq.4):

$$WTP\ (or\ PWV) = -1\left(\frac{\beta_{attribute}}{\beta_{price}}\right) \qquad \textit{Eq. 1}$$

The Krinsky-Robb simulation method as introduced by Hole (2007)[2] was used to estimate WTP standard errors and 95% confidence interval for each variable. Following Rolfe et al. (2000) total WTP for different prescribed fire programs (i.e., different combinations of variables) was estimated using the following equation.

$$Overall\ willingness\ to\ pay\ value\ = -\frac{1}{\beta_{price}}\ (\beta_1 x_1 + \cdots + \beta_i x_i) \qquad \textit{Eq. 2}$$

where β_{price} is the coefficient for the price per acre variable and $\beta_{1\ldots}\beta_i$ represents the coefficients of features of the program on offer, and x_i represents value of desired features (e.g., trust score).

Benefit Transfer Analysis

Equation 2 was also used to conduct a value transfer procedure which predicted an acceptable mean price for prescribed fire for each county based on income level and the variable for state. Values were transferred to each county by matching the income levels in the calculation with the median household income level in each county. The median household income values for each county were obtained from the US Census Bureau.

Spatial Data Analysis

We used geographic information systems (GIS) for mapping geographic locations that were significantly different in terms of landowner knowledge and experience with prescribed burning, their trust in fire implementors, risk perceptions, and WTP for using prescribed fire as a management tool. Mapping can help identify locations for targeted education programs to promote prescribed fire use on a landscape level. We conducted a hotspot analysis, which is a spatial analysis and mapping technique that is widely used to illustrate the clustering of spatial phenomena (Poudyal et al., 2019; Cruz et al., 2020). The hotspot analysis involves two major steps: testing the spatial patterns, or cluster, and mapping clusters (i.e., hotspot mapping).

Data preparation for the spatial analysis was carried out following GIS tutorial from the Spatial analysis workbook (Allen, 2016). We geocoded 430 survey responses using zip codes of the survey respondents and transformed them into individual point data in ArcGIS. Figure 3 illustrates the spatial distribution of survey responses across the study area. Then, we spatially joined the point data with the county shapefile of the study area. The joined shapefile then aggregated all the observations in a county into a mean value for that county. This value was later used as the input field in the hotspot analysis. Survey responses were collected from 164 counties (out of 257 counties total within the study states). The mean number of respondents in each county was 2.57 (min, 1, Max 17). Lastly, we exported shapefile of counties that had observations which was later used as an input feature for the hotspot analysis.

After the data preparation, we tested spatial autocorrelation by computing Global

[2] Hole (2007) introduced a STATA command "*wtp*" based on the simulation of variance and co-variance matrix.

Moran's I statistic. Spatial autocorrelation analysis examines whether closer observations are related to each other. Next, we used the Getis-Ord Gi* hotspot analysis for mapping the cluster. The Getis-Ord Gi* hotspot analysis produces graphical outputs, given a set of weighted features, displaying statistically significant hot spots, cold spots, and areas of no significance using the Getis-Ord Gi* statistic (Allen, 2016). The local Getis-Ord Gi* is essentially a z-score that is calculated based on the values of both the selected geographical feature (e.g., county) of analysis and the features around it.

To conceptualize the spatial relationships in the hotspot analysis we used a fixed distance band instead of using the default distance band. The optimum distance band (or threshold distance) was obtained using the incremental spatial autocorrelation method. In the spatial analysis, the null hypothesis was if there is spatial randomness of the values associated with features (i.e., county). To be a significant hotspot, a feature with a high or low value must be surrounded by other features with high or low values. Hotspots indicate a statistically significant cluster of features with high values (e.g., higher knowledge score) whereas cold spots indicate a statistically significant cluster of features with low values.

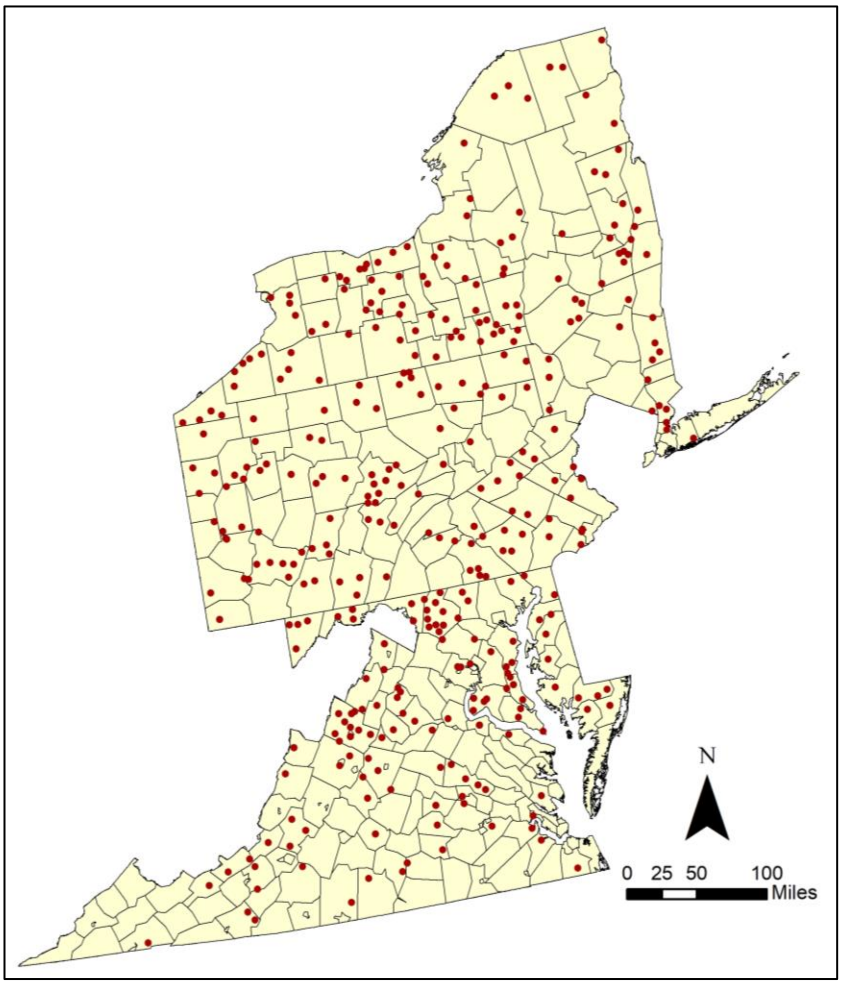

Figure 3 Spatial distribution of survey responses in the study area

Results

Of the 2,050 respondents contacted, 482 surveys were returned with an adjusted return rate of 25%. After adjusting for non-usable responses[3], 430 responses were classified as usable for further analysis. Based on the total landowner population of the study area, expected sample size was 385 with 95% confidence interval and 5% margin of effort. Table 3 contains a summary of the respondent demographic profiles. Among respondents, most were male (85%) and 55 years of age or older (87%). Most respondents (63%) had annual household income levels ≥$80,000. About 78% of respondents had either a bachelor's or equivalent degree or a higher level of education. A majority of respondents reported that they were part of a private association (e.g., landowners association) (59%) while about 47% reported that they enrolled in government assistance programs in the past.

Table 3 Summary of demographic profiles.

Characteristics	Sample	
	Count	Percent (%)
Gender		
Male	363	85
Age		
25 - 34 years	2	1
35 - 44 years	18	5
45 - 54 years	30	7
55 - 64 years	97	22
65 - 74 years	184	43
75 years and above	97	22
Acres owned		
10-19 acres	29	7
20-49 acres	91	22
50-99 acres	110	26
100-199 acres	97	23
200-499 acres	74	17
500 acres and above	22	5
Annual household income		
Less than $20,000	11	3
$20,000 - $49,999	49	12
$50,000 - $79,999	88	22
$80,000 - $99,999	65	16
$100,000 - $149,999	80	20
$150,000 - $ 249,999	75	19
$250,000 and more	31	8
Education		
Less than high school	6	1
High school	43	10
Associates degree	48	11
Bachelor's degree	148	35

[3] Non usable surveys include incomplete surveys, responses from non-landowners (e.g., wildlife managers, biologists, government professionals, etc.), and landowners with less than 10 acres forests.

Master’s degree	121	28
Postgraduate degree	62	15
Assistance program (yes)	203	47
Association member (yes)	252	59

Management Objectives

Results showed that forest owners in the study area own and manage forests for a variety of reasons (Appendix E). Most respondents reported that they manage forests mainly to achieve cultural benefits such as recreation, aesthetics and a sense of place, and to enhance natural heritage rather than producing timber for income generation. Similarly, top management activities reported by many forest owners included controlling invasive plant species, habitat management, controlling tree regeneration, and stand improvement. Results suggest that landowners are more concerned about the overall health of forest ecosystems rather than focusing on specific management objectives. Few survey respondents (14%) had any burning experience. Those that did, reported that burns were often limited to small areas and were conducted primarily to manage warm-season grass, reduce understory fuel, or improve browse for deer.

Willingness to Pay for Prescribed Fire

Respondents’ mean certainty score was 7.55 (out of 10) indicating that respondents were highly confident in expressing their WTP. About 64% of respondents were willing to enroll in at least one prescribed fire program throughout the region. With the corrected certainty level >5, about 48% were willing to pay at least for one program out of eight programs offered. Virginia had the most respondents (58%) who indicated they were willing to pay for at least one prescribed fire program followed by Pennsylvania (57%), Maryland (45%), and New York (32%). About 39% of respondents preferred the lowest cost program ($20/acre), but about 15% of respondents were will willing to pay up to $200/acre for burning (Figure 4).

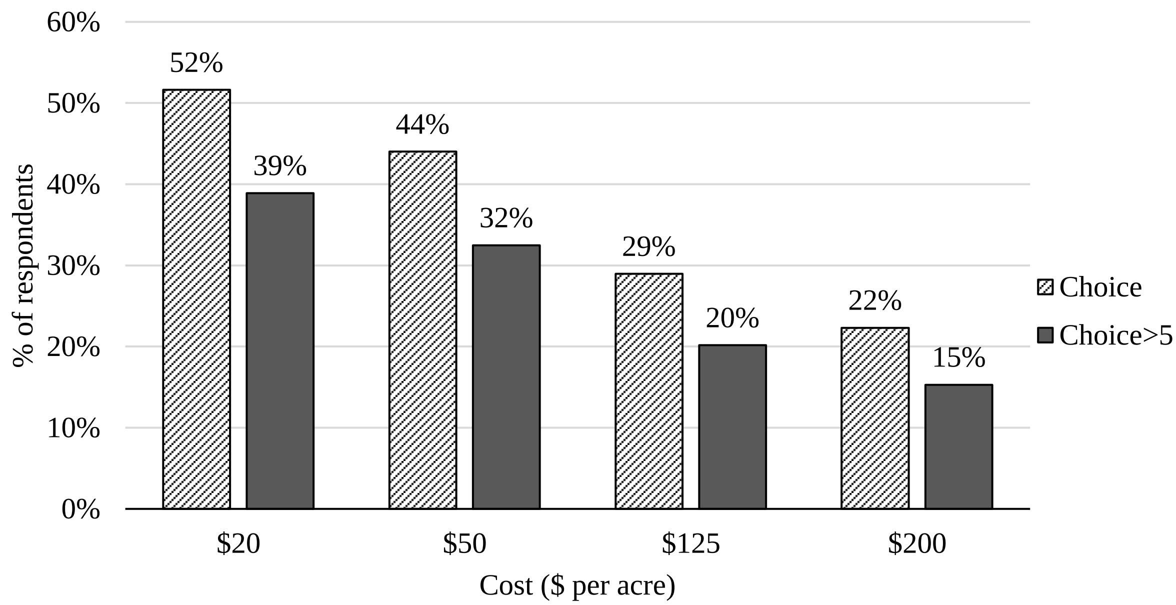

Figure 4 Percent enrollment in proposed prescribed fire programs based on four different price levels. Note: choice denotes all observations without certainty correction, choice>5 denotes certainty scores <6 were converted to no response.

A total of 3,434 WTP observations were used in the model. Out of this dataset, 36% were yes votes. Two models were fitted. Model 1 is the base model using raw data without certainty scale correction. Model 2 utilized certainty-corrected data (i.e., yes responses with a certainty score ≤5 were recoded as “no”). Models were finalized based on pseudo-R squared, *AIC, and BIC* values. Table 4 presents the results of mixed logistic regression analysis.

The demographic variable representing past participation in a landowner assistance program was significant, positive, and had the greatest overall influence on the choice (Table 4). Coefficients for price, risk, and age were negative indicating WTP decreased as levels within these variables increased. State variable Pennsylvania was positively significant in both models and had a substantial impact on choice indicating that landowners in Pennsylvania were willing to pay more compared to other states.

Program attribute coefficients for wildlife habitat management, forest health, cost share, and access to consultant variables were positively significant indicating their presence increased the mean value of prescribed fire. Coefficients for rare vegetation were negative indicating their presence decreased the mean value of prescribed fire. In addition, variables controlling invasive species and state coordination had a positive impact on mean WTP the value in model 1 while these variables were not significant in model 2. Similarly, the variable prescribed fire association was negatively significant only in model 1.

Table 4. Mixed logistic regression model of factors affecting landowner willingness to pay for prescribed fire programs in the Mid-Atlantic region.

Variables	Model 1 Original choice data		Model 2 Certainty corrected (choice>=6)	
	Coeff.	se	Coeff.	se
Trust	0.235***	(0.056)	0.174***	(0.058)
Perceived risk	-0.124***	(0.030)	-0.139***	(0.031)
Age Category	-0.831***	(0.164)	-0.896***	(0.167)
Assistant program	1.139***	(0.353)	0.954***	(0.359)
Income category	0.206*	(0.110)	0.203*	(0.112)
Pennsylvania	0.708*	(0.403)	1.555***	(0.413)
Virginia	0.504	(0.436)	0.855*	(0.447)
Price	-0.0182***	(0.001)	-0.0174***	(0.001)
Wildlife Habitat	0.182*	(0.104)	0.207*	(0.108)
Rare Vegetation	-0.329***	(0.105)	-0.349***	(0.111)
Forest health/resilience	0.243**	(0.101)	0.239**	(0.107)
Control Invasive	0.227***	(0.088)		
Prescribed Fire Associations	-0.272***	(0.105)		
State Coordination	0.317***	(0.102)		
Cost Share	0.328***	(0.101)	0.333***	(0.089)
Access to Consultants	0.144*	(0.085)	0.179**	(0.089)
Constant	2.102	(1.622)	2.201	(1.662)
lnsig2u	2.243	(0.130)	2.201	(0.138)
Sigma_u	3.0698	(0.199)	3.006	(0.207)
Pseudo-R^2	0.19		0.18	
AIC	2744		2454	
BIC	2855		2546	
N	3434		3434	

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 reports the calculated part-worth values for each model variable (also referred to as mean WTP value). These dollar values represent the utility or satisfaction associated with each variable, relative to the other variables on offer. Results shows that some program attributes are more preferred than others. Prescribed fire programs with the most value included those that helped with wildlife habitat management, forest health and resilience, and controlling invasive species. More valuable programs also helped landowners coordinate with state agencies, offered cost share and enhanced access to consultants (see Model 2, Table 5). Landowners expressed a lower WTP or preference for rare vegetation management and prescribed fire associations. Besides program attributes, findings indicate that some categories of landowners are more supportive of prescribed fire than others. For example, landowners who have high trust in prescribed fire practitioners and have low risk perception were willing to pay more for fire. Likewise, younger landowners, and landowners with higher income level and prior involvement in landowner assistant programs were also willing to pay more for prescribed fire compared to their counterparts.

Table 5 Willingness to pay values calculated for significant variables in the mixed regression models, along with the 95% confidence intervals.

Variables	Model 1 Original choice data		Model 2 Certainty corrected (choice>=6)	
	WTP ($)	95% CI	WTP ($)	95% CI
Trust	12.93	[6.85; 19]	9.99	[3.45; 16.53]
Perceived risk	-6.79	[-10.02; -3.55]	-8.02	[-11.58; -4.45]
Age Category	-45.63	[-63.45; -27.81]	-51.54	[-70.78; -32.3]
Assistant program	62.56	[24.32; 100.79]	54.90	[14.18; 95.61]
Income category	11.29	[-0.57; 23.15]	11.71	[-0.99; 24.41]
Pennsylvania	38.87	[-4.59; 82.33]	89.47	[42.41; 136.52]
Virginia	-	-	49.19	[-1.39; 99.76]
Program Attributes				
Wildlife Habitat	9.99	[-1.3; 21.27]	11.89	[-0.31; 24.09]
Rare Vegetation	-18.05	[-29.41; -6.7]	-20.06	[-32.62; -7.5]
Forest health/resilience	13.35	[2.52; 24.18]	13.73	[1.68; 25.77]
Control Invasive	12.50	[3.03; 21.97]	-	-
Prescribed Fire Associations	-14.95	[-26.18; -3.72]	-	-
State Coordination	17.44	[6.45; 28.43]	-	-
Cost Share	18.00	[7.06; 28.95]	19.18	[9.05; 29.32]
Access to Consultants	7.89	[-1.25; 17.03]	10.29	[0.2; 20.39]
Overall WTP	14.56	[12.92; 16.19]	6.24	[5.46; 7.02]

Reasons for Rejecting Programs

Respondents who rejected any of the provided choice sets were asked to report possible reasons behind the rejection. Most respondents reported that liability concerns and the cost of burning were the major reason for not accepting the program on offer (Table 6). About 70% of respondents agreed that they were concerned about liability due to escape fire while a majority of respondents (53%) agreed that burning cost was prohibitive. Limited information and weather for burning were not major reasons for rejecting the programs. In addition, respondents were also asked to describe other reasons besides the listed statements. Some other frequently mentioned reasons for rejecting programs were air pollution, limited resources (e.g., burn boss), topography, and limited information.

Table 6 Percentage and mean response to statements on reasons for rejecting programs scales (1= strongly disagree, 5= strongly agree)

Statement	**N**	**Disagree (1-2)**	**Neutral (3)**	**Agree (3-5)**	**Mean**	**SD**
I am concerned about liability of escape fire	193	21	9	70	3.68	1.30
I found burning cost prohibitive	193	23	23	53	3.40	1.26
I do not have sufficient information to recognize the value and benefits of prescribed fire	193	47	19	34	2.70	1.43
I am not interested in burning	193	50	16	34	2.66	1.53
Weather is not favorable for burning in my area	192	45	41	14	2.44	1.16

Attitude and Knowledge Scales

Respondents often disagreed with statements describing different levels of knowledge and experiences with prescribed fire (Table 7). As such, the grand mean score on the knowledge scale was relatively low (grand mean 1.86, SD 1.30) indicating many respondents have limited experience or formal knowledge about prescribed fire use and behavior. For example, most (75%) respondents disagreed with the statement that they have experience conducting prescribed fire and only about 13% agreed with the statement. Despite having low knowledge, most respondents disagreed with the statements describing the potential risk associated with prescribed fire. The grand mean for risk perceptions was also low (grand mean 2.20, SD 1.06) indicating that most respondents do not consider prescribed fire as having large potential for hazard or harm. Among the nine statements, respondents were more concerned about the potential harm to human health due to poor air quality resulting from smoke. Most respondents agreed with the statements in the trust scale. The grand mean for trust was higher than other grand means (grand mean 3.78, SD 1.11) indicating most respondents generally trusted the people and organizations who implement prescribed fire. Expressions of trust were also higher for professional fire implementers (e.g., state agencies and consultants, about 82% of respondent agreed) compared to trained landowners who implement prescribed fire (about 45% of respondents agreed) (Table 7). Comparatively, more (31%) landowners disagreed with the trust statement "*I trust that trained landowners have the skills needed to conduct a burn safely*".

Table 7 Mean response to statements on the knowledge, risk, and trust scales (1= extremely low disagree, 5= extremely high).

Measurement items	Mean	SD
Knowledge		
I know people who have used prescribed burning	2.81	1.68
I have taken higher education classes on ecosystem management and prescribed burning	1.83	1.34
I have taken a training course on ecosystem management and prescribed burning	1.79	1.33
I have experience conducting a prescribed burn	1.70	1.27
I have been trained to conduct a prescribed burn	1.64	1.25
I have enough experience and qualifications to be a burn boss	1.39	0.94
Grand Mean	*1.86*	*1.30*
Risk Perceptions		
Prescribed fire often harms human health (e.g., smoke and air quality)	2.61	1.13

Prescribed fire could harm native plants and trees	2.49	1.14
Prescribed fire can cause soil erosion	2.28	1.04
Animals are usually unable to find safety during prescribed fires	2.17	1.02
Prescribed fire often harms wildlife and destroys their habitat	2.14	1.06
Prescribed fire can reduce water quality	2.08	0.95
Prescribed fire reduces aesthetic/recreational benefits important to me	2.08	1.05
Prescribed fire typically causes damage to private property	2.03	1.04
Prescribed fire and wildfires are equally dangerous to the public's safety	1.94	1.11
Grand Mean	*2.20*	*1.06*
Trust in Implementors		
I trust that trained resource management professionals have the skills needed to conduct a burn safely	4.17	0.98
I trust state agencies will do a good job setting the prescribed fire standards	3.96	1.08
I trust state agencies to run programs that promote the use of prescribed fire on private lands	3.89	1.14
I trust that trained landowners have the skills needed to conduct a burn safely	3.10	1.24
Grand Mean	*3.78*	*1.11*

Results of Spatial Analysis

The null hypothesis-related to complete spatial randomness of the values representing respondents' survey responses associated with each county-was rejected for five of the variables used in the analysis (i.e., trust, knowledge, risk, choice, and use). This indicates that data representing landowner perspectives about prescribed fire are indeed clustered for the variables described in Table 8. In other words, there exists a spatial autocorrelation in landowner perspectives (i.e., correlation of a variable with itself due to the spatial location of the other observations). All z-scores were greater than 2.58 suggesting that there is less than one percent likelihood that the clustered pattern is a result of random chance. We found that forest landowners WTP decisions are more clustered into spatial locations than if they were randomly distributed.

Table 8 Result of spatial autocorrelation test based on Moran's I index

Variable	**Description**	**Moran's I Index**	**Z-score**	**p-value**
Choice	Decision to pay for program (binary-yes/no)	0.066	4.3	0.000
Knowledge	Knowledge and experience of prescribed fire (total score)	0.128	6.87	0.000
Risk	Perceived risk of prescribed fire (total score)	0.054	2.32	0.020
Trust	Trust in people and organizations who implement prescribed fire (total score)	0.029	2.79	0.005
Use	Landowner experience of using prescribed fire (binary-yes/no)	0.121	10.02	0.000

Hotspot and cold spot mapping identified the areas with a concentration of counties with higher and lower values of corresponding responses at 90, 95, and 99% levels of confidence. Figures 5, 6, and 7 present the results of the hotspot analysis on landowner responses on knowledge (Figure 5a), trust (Figure 5b), perceived risk (Figure 5c), prescribed fire use (Figure 7b), and WTP choice (Figure 7a).

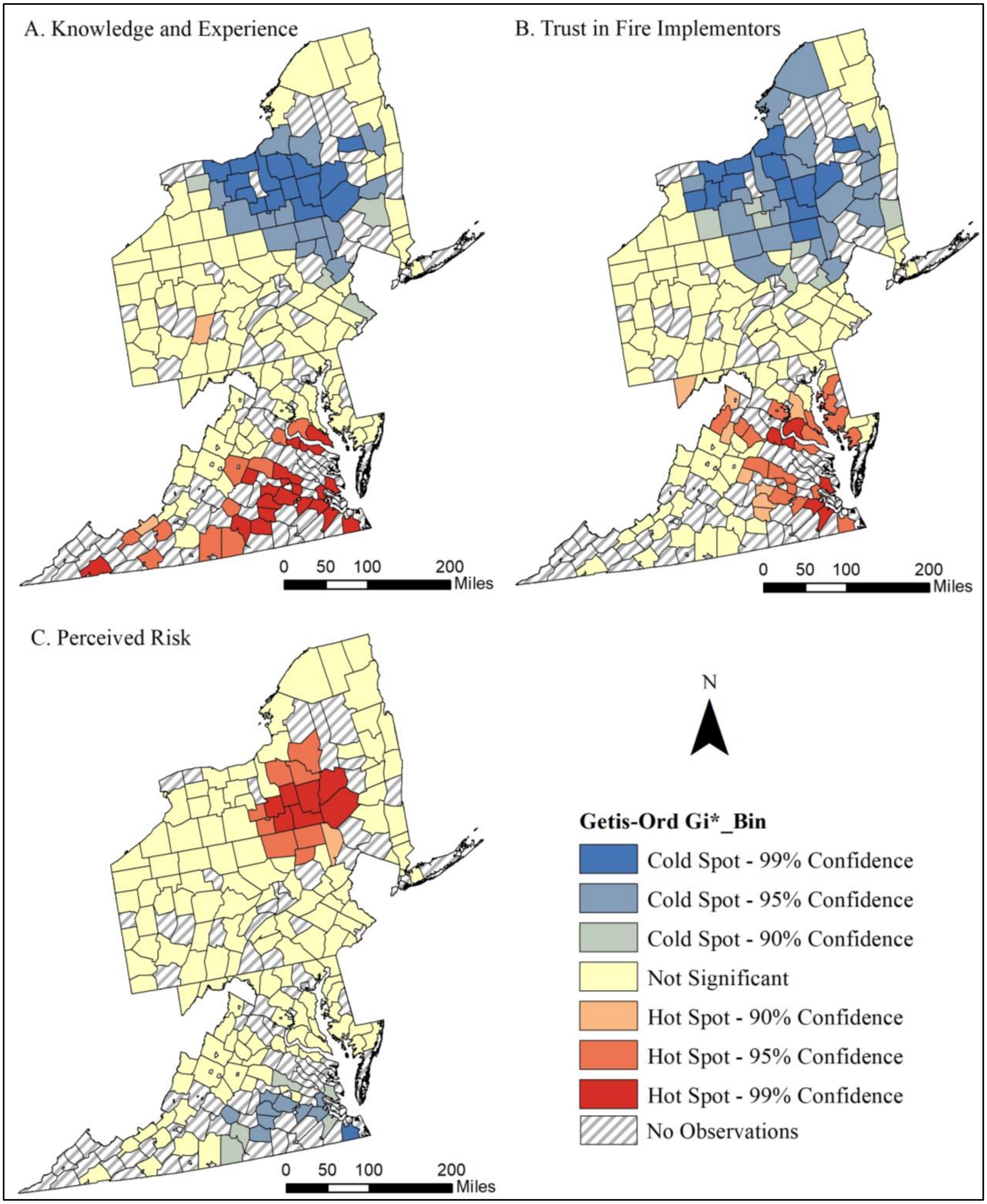

Figure 5 Results of spatial analysis indicating hot spots and cold spots for knowledge scale (A), trust scale (B), and perceived risk scale (C) questions.

Cold spots for knowledge and trust were found around central New York and northeastern Pennsylvania (Figure 5). Conversely, hot spots for knowledge were in southern Virginia and hotspots for trust in both Virginia and Maryland. As expected, hotspots for risk were located around areas with cold spots for knowledge and trust, however, the number of counties was fewer compared to number of counties in knowledge and trust cold spots. Overall, the results suggest that knowledge and attitudes vary within the region and strong opinions about prescribed fire may be concentrated in some counties (Figure 5).

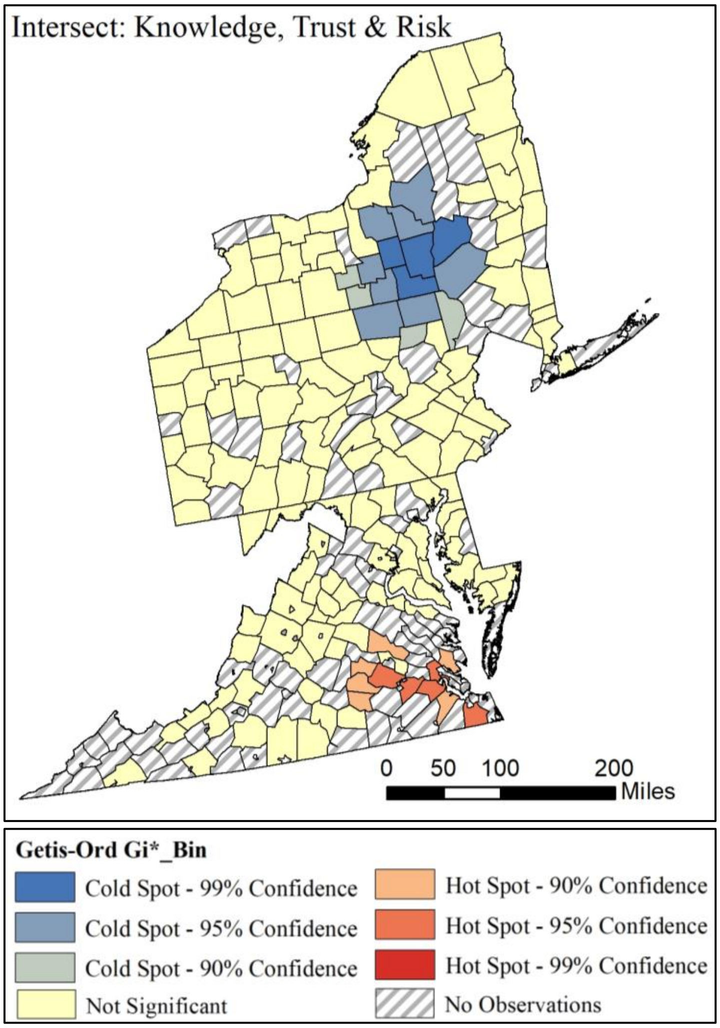

Figure 6 Results of hotspot analysis with knowledge, trust and risk values combined. Note: risk values were reverse coded. Cold spots indicate area with lower knowledge values, lower trust values, and higher perceived risk values.

The map in Figure 6 represents the combined hotspots for knowledge, trust, and perceived risk. The values for risk were reversed to make the interpretation consistent with the knowledge and trust values. Findings indicate that a few counties in central New York have overall strong negative views about prescribed fire and a few countries in southeastern VA have overall strong positive views about prescribed fire. Surrounding counties have more mixed opinions (e.g., high knowledge, low trust). The cold spot in New York also appears to cross the state boundary.

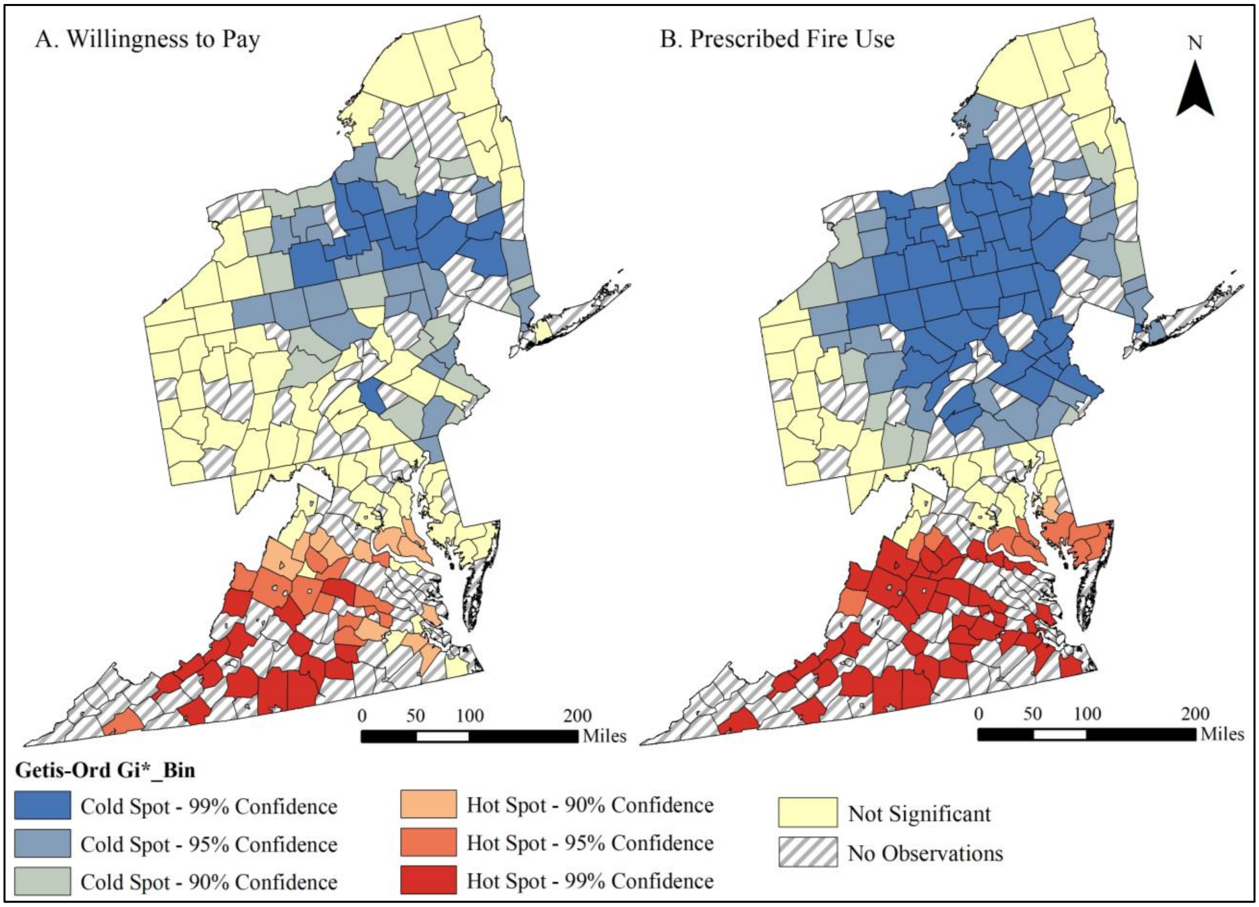

Figure 7 Results of hotspot analysis representing landowner responses to questions: whether they would be willing to pay for burning (WTP choice: yes/no) (A), and whether they have previously used prescribed fire (use: yes/no) (B)

The maps in Figure 7 show results of the hotspot analysis of landowners who have used prescribed burning before and who would be willing to pay some amount for fire (Figure 7a and 7b). Findings show that counties where fire is already used (southeastern VA) were also more likely to contain landowners who are willing to pay for the benefits of prescribed fire. This is in agreement with our assumption that past experiences with prescribed fire play impacts how fire is valued. Where this association did not hold true is in central PA were most counties showed very little use of fire (dark blue), but this did not necessarily create a cold spot for WTP for fire.

Benefit Transfer Results

Based on model 2, a benefit transfer procedure was used to estimate an acceptable mean price for prescribed fire in each county in the study area. Estimated prices (min $34.42 per acre to max $136.30 per acre) for each county are presented in Appendix F. Figure 8 presents the hotspots and cold spots of acceptable prices for each county. Pennsylvania frequently contained counties with higher acceptable prices compared to all other study states. New York and the southern part of Maryland were cold spots indicating that these areas frequently contained counties with lowest acceptable prices for prescribed fire.

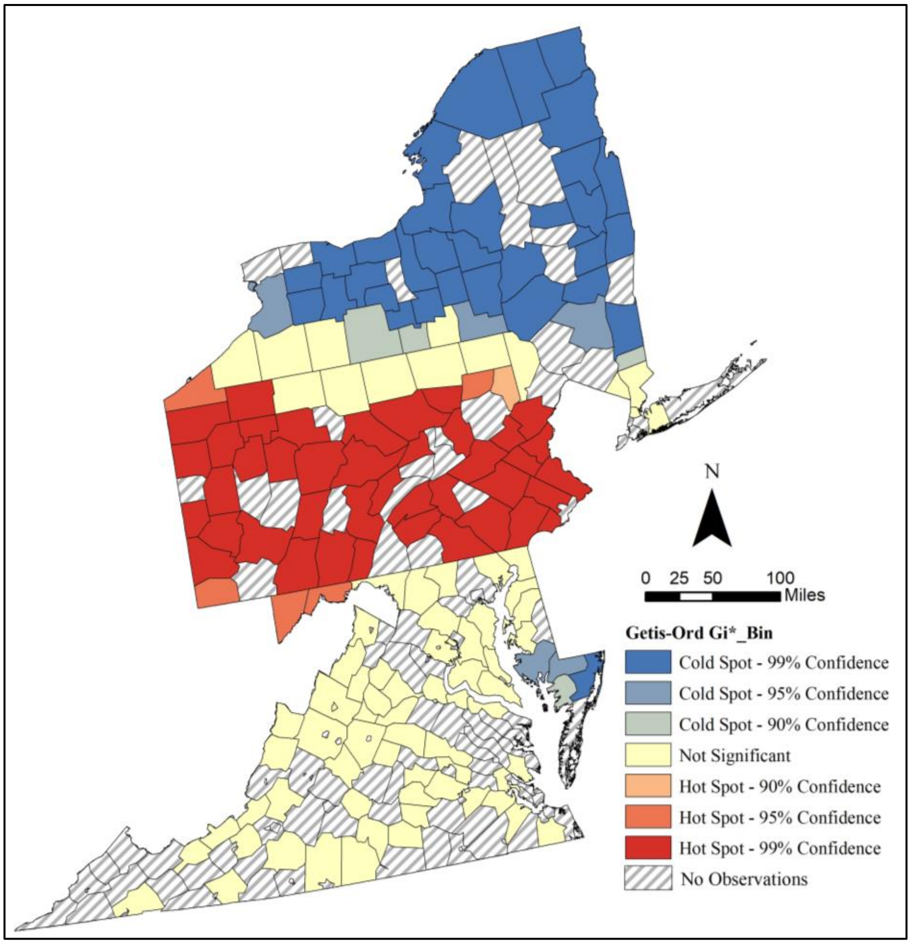

Figure 8 Hotspot analysis of preferred price for each county

Discussion and Conclusions

Prescribed fire is not commonly used by forest landowners in the Mid-Atlantic Region of the US. Only a fraction of survey respondents reported that they actually use fire, many of which lived in Virginia. Despite having little experience with fire, more than half of respondents were interested in adopting prescribed fire as a land management tool, and many were willing to allocate some of their income to help make that happen. Motivations for using prescribed fire were attributed to several key cultural, economic, and governance factors.

Respondents were classified as having generally low level of knowledge about fire due to a lack of foundational experiences using fire. This points to the continuing need for educational interventions that help support the practice of safely using fire and how to include prescribed fire in management plans. Despite having low knowledge, many landowners expressed the belief that the benefits of fire would be greater than potential risks or costs. For example, many believed that prescribed fire would be useful for improving wildlife habitat, controlling invasive species and protecting forest health, and they were willing to pay $10 to $13 more per acre for this benefit. Perceptions of risk in using fire were also generally low. Prescribed fire was rarely seen a threat to public safety, however smoke impacts on human health were a concern.

Cultural values towards prescribed fire did vary significantly across the region with a general north-south gradient. The hotspot analysis revealed a zone in southeastern Virginia where knowledge was relatively very high and risk perceptions very low. Conversely, in central New York the analysis found a zone with very low knowledge and higher risk perceptions. In New York, educational programs may need to focus on more foundational understanding of fire and how it can be safely used. Outside these zones educational programs may need to offer mix of resources for those with different levels of experience and concerns.

Our economic assessment showed good potential for expanding the prescribed fire economy in Virginia and Pennsylvania, but probably not in New York. Mean WTP for prescribed fire across all states was $6 to $14 per acre, however, Virginia and Pennsylvania were willing to pay an additional $50 to $90 per acre respectively. Associated studies that report actual management costs show that prices for implementing prescribed fire are generally lower in the southeastern US (e.g., $30 to $40/acre [Maggard, 2021]) compared to the northeast. Pennsylvania burning costs are highly variable but could be as high as $400 per acre [Regmi et al., 2023]). Even though the cost of using prescribed fire is often high in this region, landowner demand for fire appears to exceed provision of prescribed fire services. For example, 15% of respondents were willing to pay up to $200 per acre. Capturing landowner demand for prescribed fire services can help establish a stronger prescribed fire economy in the Mid-Atlantic Region (i.e., jobs, infrastructure).

Interestingly, findings in Virginia and Pennsylvania suggest that WTP values are not always reflective of knowledge and experience. More specifically, landowners in Virginia were willing to pay less compared to Pennsylvania even though they had more experience with fire. It may be that landowners in Pennsylvania overvalue the benefits of prescribed fire, because of their limited experience using fire, whereas owners in Virginia may be more realistic about using fire. Applying fire could also be challenging in areas where mesophication has already occurred. The long exclusion of fire in some places can also make it difficult to predict long-term outcomes. In these cases, educational programs should help landowners understand the realities of using fire in places where fire has been long excluded. As forest owners become more familiar with prescribed fire, what they may be willing to pay may change.

Governance factors were also key in explaining motivations for using fire. Forest owners were primarily interested in programs that help them coordinate burning activities with state agencies, have better access to consultants, and provide cost-share assistance. All of these activities involve the use of experts and government oversight, which is ideal since many forest owners in this region are inexperienced with using fire. The value of having expert involvement in burning activities ranged between $8 to $17 per acre, which is slightly more than the part-worth values assigned to expected management benefits. In other words, governance factors are critical to helping forest owners move from being just motivated to burn, to actually applying fire. Unlike the southeast, where burning on private lands is often done by the landowners and non-professionals, technical and financial assistance programs in the Mid-Atlantic region should look for ways to support the employment of professionals in applying fire on private lands.

Risk of liability was expressed as a concern among many forest owners, even though the variable for reduced liability was not significant in the models. It may be that how liability protection is conceptualized is different for some forest owners. Some may have differences in perceived risk due to the type of burning they want to do; others may not have a clear understanding of how existing liability protection laws pertain to them. Educational programs should help forest owners understand options for liability protection in their state.

Liability protection for users of prescribed fire is shaped by state laws. All the states in this study have liability protection laws for prescribed fire, but the formulation of these laws and the benefits for landowners are not equal across states. The spatial analysis did not show strong evidence of burn laws (and associated liability protection) influencing forest owner motivations to use prescribed fire. For example, the cold spot in central New York (indicating a strong resistance to using prescribed fire) extended into some counties in Pennsylvania. The hot spot in southern VA (indicating strong support for prescribed fire) was only in the eastern side of the state, even though state laws apply evenly throughout the state. There is evidence, however, that burn laws could interfere with landowners actively putting fire on the ground. For example, economic demand for burning on private lands in Pennsylvania appears high, but more acres are actually burned in Virginia. This difference could be due to a lack of qualified professionals in Pennsylvania that can meet state standards for obtaining liability protection when burning.

Recommendations for Policy

- Pennsylvania is poised to start adopting prescribed fire due to the strong motivations of forest landowners. Education is very much needed to help promote safe use of fire and to help forest owners figure out how prescribed fire can help them achieve their desired management goals. Adaptive management techniques, in particular, may be important to use since ecological outcomes may be difficult to predict. Technical and financial assistance will also be critical for helping landowners to hire professionals to get fire on the ground.
- Landowners in Virginia were more knowledgeable and experienced in using prescribed fire, suggesting that many may be willing to take their management activities to the next level (beyond wildfire hazard reduction) and work with state agencies to achieve landscape level restoration goals. Education programs could support this effort by teaching landowners about prescribed fire as a restoration tool and where restoration activities by the state are currently being conducted.
- Landowners in New York do not appear ready to use prescribed fire. While motivations may vary within the state, there is a strong correlation between low knowledge and high-risk perceptions. Education programs may consider introducing prescribed fire along with other land management tools as a way of increasing knowledge.
- One important constraint to burning on private lands in this region may be a lack of qualified professionals. Burn windows tend to be shorter in northern regions, which means that demand for burning is not year-round. Training more natural resource professionals to conduct burning may be critical for meeting a high volume of demand in a short window of time.

Study Limitations and Future Research

1. Instead of random sampling, this study used a purposive sampling technique to survey landowners who are actively engaged in forest management activities. To ensure this, we collected respondents mailing addresses from landowner associations. In some states, landowner organizations were reluctant to share addresses due to privacy issue. In such cases, we used our website to request interested landowners for survey sign-up which also targeted certain group of landowners. This approach could have increased the risk of non-response bias.
2. To our knowledge, this is the first study evaluating landowners demand for prescribed burning on private lands in the Mid-Atlantic region, and our findings provide a basis for future research. Future research should continue to study what landowners and the public consider to be key factors in prescribed fire implementation such as liability protection and technical resources. Future research should also explore which kinds of education and incentive programs certain categories of landowners may need.

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Appendix B: List of Deliverables

Publications	Status	Title
Extension Article	Completed	Prescribed Fire: Does It Have a Place on My Land?
Extension Article	In process	Social Value of Prescribed Fire in the Mid-Atlantic Region
Research Article	In press	Regmi, A., M. Kreye, J. Kreye (2023) Forest landowner demand for prescribed fire as an ecological management tool in Pennsylvania, USA. *Forest Policy and Economics*. 148 In press
Dissertation	In process	Stakeholder response to emerging natural resource management issues
Research Article	In process	Landowner perspectives of prescribed fire in the Mid-Atlantic region, USA.

Presentations	Status	Title
Presentation	Completed	The Use of Prescribed Burning in the Mid-Atlantic Forests: Forest Owners Perspectives. *Presented at the Society of American Foresters Annual Convention, Baltimore, Maryland. 2022.*
Presentation	Completed	Evaluating demand for prescribed burning through non-market economic valuation. *Presentation at the Association for Fire Ecology and Pau Costa's Fire Across Boundaries: Connecting Science and Management Conference, Florence Italy. 2022.*
Presentation	Completed	The economic value of prescribed burning in northeastern forests. *Presented at the International Society of Forest Resource Economics Conference, Traverse City, Michigan. 2022*
Poster	Completed	Forest Owner Perspectives of Prescribed Fire in the Mid-Atlantic region of the US. *Poster presented at the International Society of Forest Resource Economics Conference, Traverse City, Michigan. 2022*
Poster	Completed	Private Forest Landowner Perspectives of Prescribed Fire across the Northeastern US. *Poster presented at the Natural Areas Conference, Duluth, Minnesota. 2022*
Poster	Completed	Demand for Prescribed Burning on Private Lands in Mid-Atlantic Forests. *Poster presented at the Stone Valley Forest Expo, Shaver's Creek, Pennsylvania. 2022.*
Poster	Completed	The Value of Prescribed Burning in the Northeastern Forests. *Poster presented at the Gamma Sigma Delta, Graduate and Undergraduate Research Expo, Penn State University, Pennsylvania. 2022*
Presentation	Completed	Economic Value of Prescribed Burnings on Private Lands across the Northeastern Forests. *Presented at the 9th International Fire Ecology and Management Congress, Virtual. 2021.*

Appendix C: Metadata

Data was collected using web and mail surveys and recorded digitally using a series of Microsoft Excel database. The survey data includes landowner demographics information (e.g., age, income, etc.), Likert-scale responses, and choice experiment data. The survey data was geocoded using zip code information for the spatial analysis. Spatial data include ArcGIS shapefiles and a set of maps. We are preparing manuscript for the publication. By the time of manuscript publication, we will submit our data and associate metadata to the USDA Forest Service Research Data Archive, following the standards set by the Federal Geographic Data Committee: Content Standard for Digital Geospatial Metadata and the Biological Data Profile. (https://www.fs.usda.gov/rds/archive/metadata).

Appendix D: Survey Instruments

A sample of mail surveys, push-to-web postcards, and online sign-up form

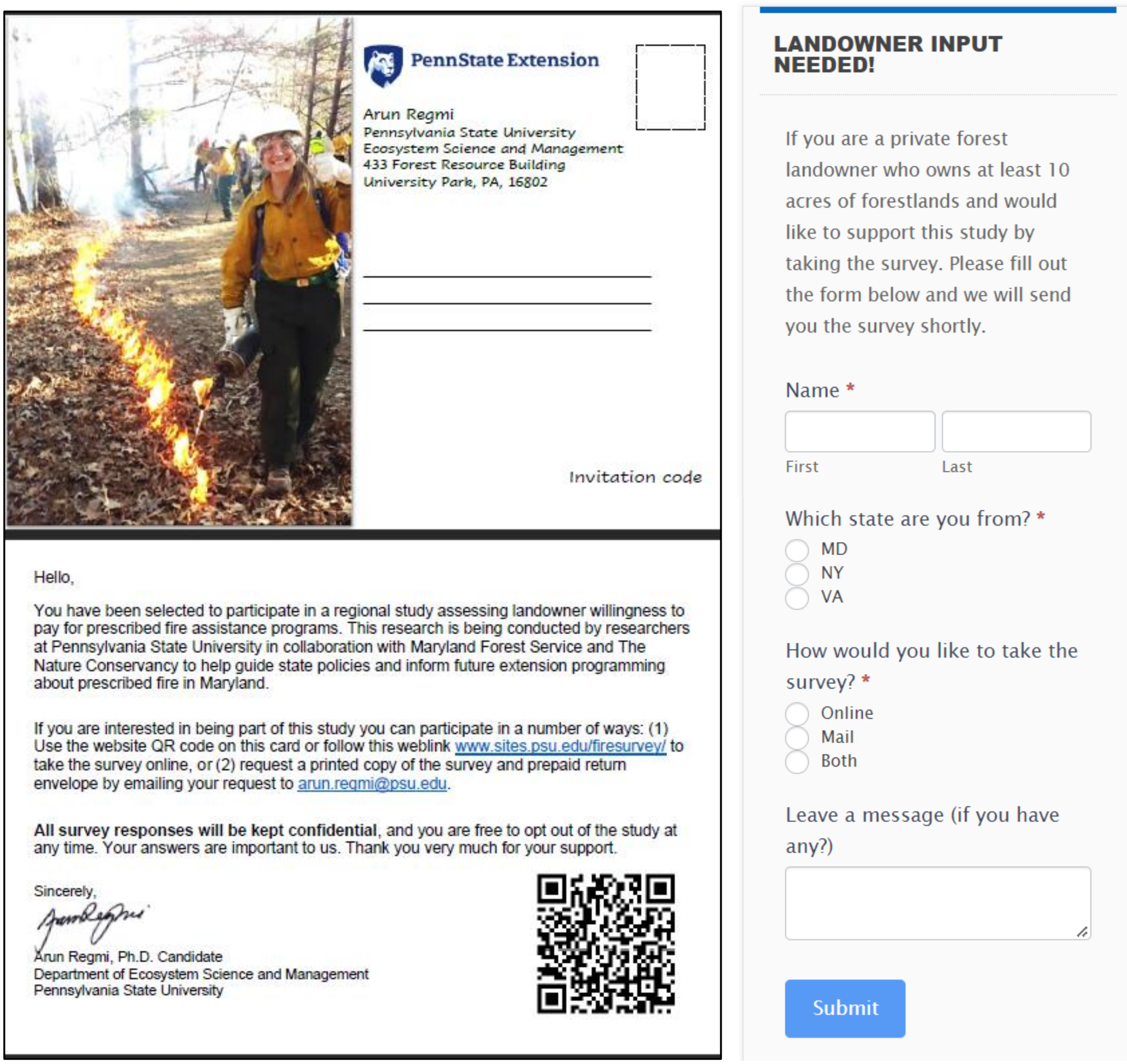

Figure 9 D.1 Sample of a push to web invitation postcard, and the survey sign-up form for the self-opt in method (URL: https://sites.psu.edu/firesurvey/survey/)

Program 1. This program trains managers and landowners how to use prescribed fire as a low-cost management tool to help promote oak regeneration. Participants in this program would have reduced legal liability in the event of an escaped fire. The cost of burning is $20/acre.

Would you enroll in this program?

- ☐ Yes
- ☐ No

Please rate how certain you are of your answer to the question.

	Extremely uncertain 1	2	3	4	5	6	7	8	9	Extremely certain 10
How certain are you?	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Figure 10 D.2 A sample of a discrete choice experiment question with a confidence scale to measure a forest owner's willingness to pay for prescribed fire.

Appendix E: Supplementary Results

Table 9 E.1 Percentage of respondents agreed or disagreed the psychometric statements representing knowledge, trust, and risk of prescribed fire

Statement	N	1	2	3	4	5
Knowledge Statements						
I know people who have used prescribed burning	426	40%	6%	12%	16%	26%
I have taken higher education classes on ecosystem management and prescribed burning	426	67%	8%	9%	9%	8%
I have taken a training course on ecosystem management and prescribed burning	425	70%	6%	7%	10%	7%
I have experience conducting a prescribed burn	426	72%	6%	8%	6%	7%
I have been trained to conduct a prescribed burn	425	75%	5%	7%	5%	7%
I have enough experience and qualifications to be a burn boss	426	82%	6%	8%	2%	3%
Trust Statements						
I trust that trained resource management professionals have the skills needed to conduct a burn safely	430	3%	5%	10%	37%	45%
I trust state agencies will do a good job setting the prescribed fire standards	430	4%	8%	13%	38%	37%
I trust state agencies to run programs that promote the use of prescribed fire on private lands	430	5%	8%	18%	32%	37%
I trust that trained landowners have the skills needed to conduct a burn safely	430	15%	16%	24%	34%	11%
Risk Statements						
Prescribed fire often harms human health (e.g., smoke and air quality)	429	20%	29%	26%	22%	3%
Prescribed fire could harm PA's native plants and trees	429	23%	31%	23%	20%	3%
Prescribed fire can cause soil erosion	428	27%	34%	25%	12%	2%
Animals are usually unable to find safety during prescribed fires	430	27%	45%	16%	10%	3%
Prescribed fire often harms wildlife and destroys their habitat	430	32%	37%	19%	10%	2%
Prescribed fire can reduce water quality	429	33%	33%	27%	6%	1%
Prescribed fire reduces aesthetic/recreational benefits important to me	429	36%	33%	19%	10%	2%
Prescribed fire typically causes damage to private property	429	39%	31%	21%	7%	2%
Prescribed fire and wildfires are equally dangerous to the public's safety	429	47%	28%	12%	10%	3%

Note: Five-point agreement scale was used: 1=Strongly disagree, 2=Disagree, 3=Neither disagree nor agree, 4=Agree, and 5=Strongly disagree.

Table 10 E. 2 Forest Management objectives (n=430)

Rank	Objectives	Mean	Std. Dev.	Freq.	Percent (%)
1	Enhance wildlife populations	0.85	0.36	364	85
2	Recreational hunting	0.73	0.45	313	73
3	Timber production	0.68	0.47	291	68
4	Recreation in general (e.g., hiking, bird watching)	0.66	0.47	283	66
5	Aesthetics, sense of place	0.66	0.48	282	66
6	Preserve or enhance natural heritage	0.65	0.48	279	65
7	Personal privacy, seclusion	0.60	0.49	260	60
8	Carbon sequestration	0.36	0.48	155	36
9	Environmental education/outreach	0.23	0.42	99	23
10	Cultivate and collect non-timber forest products (e.g., maple syrup, mushrooms)	0.20	0.40	86	20

Table 11 E. 3 Forest management activities (n=430)

Rank	Activities	Mean	Std. Dev.	Freq.	Percent (%)
1	Thinning/stand improvement	0.72	0.45	310	72
2	Control invasive plan species	0.70	0.46	299	70
3	Habitat management	0.63	0.48	269	63
4	Harvesting/timber sales	0.62	0.49	268	62
5	Recreation management	0.57	0.50	246	57
6	Planting native species	0.45	0.50	194	45
7	Food plots	0.39	0.49	168	39
8	Erosion/sediment control	0.38	0.49	165	38
9	Control tree regeneration	0.35	0.48	152	35

Appendix F: Benefit transfer value for each county

Table 12 F. 1 Expected preferred price for prescribed fire for each county (adjusted for median household income and state).

State	County	Median Household Income	Income Coeff.	Price Coeff.	State Coeff.	Income Level	WTP ($)
MD	Somerset	47713	0.203	-0.017	0.000	2	23.42
MD	Allegany	54540	0.203	-0.017	0.000	3	35.13
MD	Garrett	55739	0.203	-0.017	0.000	3	35.13
MD	Dorchester	56925	0.203	-0.017	0.000	3	35.13
MD	Wicomico	61181	0.203	-0.017	0.000	3	35.13
MD	Caroline	65409	0.203	-0.017	0.000	3	35.13
MD	Washington	67365	0.203	-0.017	0.000	3	35.13
MD	Worcester	70298	0.203	-0.017	0.000	3	35.13
MD	Kent	71779	0.203	-0.017	0.000	3	35.13
MD	Talbot	72858	0.203	-0.017	0.000	3	35.13
MD	Cecil	77042	0.203	-0.017	0.000	3	35.13
MD	Baltimore	81945	0.203	-0.017	0.000	4	46.84
MD	Prince George's	84835	0.203	-0.017	0.000	4	46.84
MD	Harford	93494	0.203	-0.017	0.000	4	46.84
MD	Frederick	98652	0.203	-0.017	0.000	4	46.84
MD	Queen Anne's	98798	0.203	-0.017	0.000	4	46.84
MD	St. Mary's	99428	0.203	-0.017	0.000	4	46.84
MD	Carroll	101408	0.203	-0.017	0.000	5	58.55
MD	Charles	102668	0.203	-0.017	0.000	5	58.55
MD	Anne Arundel	102793	0.203	-0.017	0.000	5	58.55
MD	Calvert	107308	0.203	-0.017	0.000	5	58.55
MD	Montgomery	117373	0.203	-0.017	0.000	5	58.55
MD	Howard	129474	0.203	-0.017	0.000	5	58.55
VA	Dickenson	29226	0.203	-0.017	0.855	2	72.61
VA	Buchanan	30806	0.203	-0.017	0.855	2	72.61
VA	Lee	32718	0.203	-0.017	0.855	2	72.61
VA	Grayson	33969	0.203	-0.017	0.855	2	72.61
VA	Henry	36683	0.203	-0.017	0.855	2	72.61
VA	Wise	38345	0.203	-0.017	0.855	2	72.61
VA	Scott	39144	0.203	-0.017	0.855	2	72.61
VA	Charlotte	39212	0.203	-0.017	0.855	2	72.61
VA	Russell	39482	0.203	-0.017	0.855	2	72.61
VA	Smyth	40425	0.203	-0.017	0.855	2	72.61
VA	Patrick	40486	0.203	-0.017	0.855	2	72.61
VA	Tazewell	40978	0.203	-0.017	0.855	2	72.61
VA	Lunenburg	41868	0.203	-0.017	0.855	2	72.61
VA	Brunswick	41927	0.203	-0.017	0.855	2	72.61

VA	Mecklenburg	42025	0.203	-0.017	0.855	2	72.61
VA	Halifax	42289	0.203	-0.017	0.855	2	72.61
VA	Nottoway	42869	0.203	-0.017	0.855	2	72.61
VA	Accomack	43210	0.203	-0.017	0.855	2	72.61
VA	Carroll	43532	0.203	-0.017	0.855	2	72.61
VA	Northampton	43553	0.203	-0.017	0.855	2	72.61
VA	Greensville	44534	0.203	-0.017	0.855	2	72.61
VA	Pittsylvania	45382	0.203	-0.017	0.855	2	72.61
VA	Sussex	45801	0.203	-0.017	0.855	2	72.61
VA	Bath	46137	0.203	-0.017	0.855	2	72.61
VA	Highland	46147	0.203	-0.017	0.855	2	72.61
VA	Prince Edward	46189	0.203	-0.017	0.855	2	72.61
VA	Cumberland	46221	0.203	-0.017	0.855	2	72.61
VA	Buckingham	46261	0.203	-0.017	0.855	2	72.61
VA	Washington	46262	0.203	-0.017	0.855	2	72.61
VA	Alleghany	47794	0.203	-0.017	0.855	2	72.61
VA	Page	47951	0.203	-0.017	0.855	2	72.61
VA	Wythe	48043	0.203	-0.017	0.855	2	72.61
VA	Amherst	49170	0.203	-0.017	0.855	2	72.61
VA	Floyd	49729	0.203	-0.017	0.855	2	72.61
VA	Richmond	49831	0.203	-0.017	0.855	2	72.61
VA	Campbell	50258	0.203	-0.017	0.855	3	84.32
VA	Bland	50511	0.203	-0.017	0.855	3	84.32
VA	Lancaster	50739	0.203	-0.017	0.855	3	84.32
VA	Middlesex	51917	0.203	-0.017	0.855	3	84.32
VA	Giles	52478	0.203	-0.017	0.855	3	84.32
VA	Pulaski	52638	0.203	-0.017	0.855	3	84.32
VA	Franklin	52639	0.203	-0.017	0.855	3	84.32
VA	Essex	52681	0.203	-0.017	0.855	3	84.32
VA	Madison	54197	0.203	-0.017	0.855	3	84.32
VA	Westmoreland	54268	0.203	-0.017	0.855	3	84.32
VA	King and Queen	54516	0.203	-0.017	0.855	3	84.32
VA	Southampton	54611	0.203	-0.017	0.855	3	84.32
VA	Montgomery	54641	0.203	-0.017	0.855	3	84.32
VA	Rockbridge	54805	0.203	-0.017	0.855	3	84.32
VA	Surry	54844	0.203	-0.017	0.855	3	84.32
VA	Shenandoah	54921	0.203	-0.017	0.855	3	84.32
VA	Craig	55484	0.203	-0.017	0.855	3	84.32
VA	Dinwiddie	55880	0.203	-0.017	0.855	3	84.32
VA	Appomattox	56176	0.203	-0.017	0.855	3	84.32
VA	Amelia	58526	0.203	-0.017	0.855	3	84.32
VA	Northumberland	58677	0.203	-0.017	0.855	3	84.32
VA	Louisa	59343	0.203	-0.017	0.855	3	84.32

VA	Rockingham	59817	0.203	-0.017	0.855	3	84.32
VA	Augusta	61305	0.203	-0.017	0.855	3	84.32
VA	Bedford	61541	0.203	-0.017	0.855	3	84.32
VA	Nelson	62446	0.203	-0.017	0.855	3	84.32
VA	Caroline	64715	0.203	-0.017	0.855	3	84.32
VA	Greene	64979	0.203	-0.017	0.855	3	84.32
VA	Roanoke	65467	0.203	-0.017	0.855	3	84.32
VA	Gloucester	66701	0.203	-0.017	0.855	3	84.32
VA	Prince George	67001	0.203	-0.017	0.855	3	84.32
VA	Mathews	67009	0.203	-0.017	0.855	3	84.32
VA	Warren	68189	0.203	-0.017	0.855	3	84.32
VA	Botetourt	68410	0.203	-0.017	0.855	3	84.32
VA	Rappahannock	68438	0.203	-0.017	0.855	3	84.32
VA	Orange	68481	0.203	-0.017	0.855	3	84.32
VA	Henrico	68572	0.203	-0.017	0.855	3	84.32
VA	King William	68720	0.203	-0.017	0.855	3	84.32
VA	Isle of Wight	71376	0.203	-0.017	0.855	3	84.32
VA	Culpeper	73116	0.203	-0.017	0.855	3	84.32
VA	Frederick	73250	0.203	-0.017	0.855	3	84.32
VA	Fluvanna	74931	0.203	-0.017	0.855	3	84.32
VA	Albemarle	75394	0.203	-0.017	0.855	3	84.32
VA	Clarke	77936	0.203	-0.017	0.855	3	84.32
VA	New Kent	79698	0.203	-0.017	0.855	3	84.32
VA	Chesterfield	80214	0.203	-0.017	0.855	4	96.02
VA	Powhatan	83914	0.203	-0.017	0.855	4	96.02
VA	Spotsylvania	85330	0.203	-0.017	0.855	4	96.02
VA	King George	87321	0.203	-0.017	0.855	4	96.02
VA	Hanover	88652	0.203	-0.017	0.855	4	96.02
VA	Goochland	89741	0.203	-0.017	0.855	4	96.02
VA	York	90367	0.203	-0.017	0.855	4	96.02
VA	Fauquier	97469	0.203	-0.017	0.855	4	96.02
VA	Prince William	103445	0.203	-0.017	0.855	5	107.73
VA	Stafford	106773	0.203	-0.017	0.855	5	107.73
VA	Arlington	117374	0.203	-0.017	0.855	5	107.73
VA	Fairfax	121133	0.203	-0.017	0.855	5	107.73
VA	Loudoun	136268	0.203	-0.017	0.855	5	107.73
PA	Forest	36594	0.203	-0.017	1.555	2	112.88
PA	Philadelphia	39770	0.203	-0.017	1.555	2	112.88
PA	Cameron	40347	0.203	-0.017	1.555	2	112.88
PA	Fayette	40511	0.203	-0.017	1.555	2	112.88
PA	Potter	40921	0.203	-0.017	1.555	2	112.88
PA	Mifflin	42019	0.203	-0.017	1.555	2	112.88
PA	Clarion	42890	0.203	-0.017	1.555	2	112.88

PA	Cambria	42917	0.203	-0.017	1.555	2	112.88
PA	Clearfield	43361	0.203	-0.017	1.555	2	112.88
PA	Northumberland	43701	0.203	-0.017	1.555	2	112.88
PA	Venango	43885	0.203	-0.017	1.555	2	112.88
PA	Jefferson	43913	0.203	-0.017	1.555	2	112.88
PA	McKean	44023	0.203	-0.017	1.555	2	112.88
PA	Blair	44033	0.203	-0.017	1.555	2	112.88
PA	Sullivan	44926	0.203	-0.017	1.555	2	112.88
PA	Warren	44977	0.203	-0.017	1.555	2	112.88
PA	Indiana	45118	0.203	-0.017	1.555	2	112.88
PA	Huntingdon	45250	0.203	-0.017	1.555	2	112.88
PA	Somerset	45424	0.203	-0.017	1.555	2	112.88
PA	Crawford	45637	0.203	-0.017	1.555	2	112.88
PA	Lawrence	45764	0.203	-0.017	1.555	2	112.88
PA	Mercer	45831	0.203	-0.017	1.555	2	112.88
PA	Armstrong	45879	0.203	-0.017	1.555	2	112.88
PA	Schuylkill	46573	0.203	-0.017	1.555	2	112.88
PA	Luzerne	46577	0.203	-0.017	1.555	2	112.88
PA	Lackawanna	46673	0.203	-0.017	1.555	2	112.88
PA	Bedford	46746	0.203	-0.017	1.555	2	112.88
PA	Columbia	46952	0.203	-0.017	1.555	2	112.88
PA	Erie	47094	0.203	-0.017	1.555	2	112.88
PA	Clinton	47163	0.203	-0.017	1.555	2	112.88
PA	Elk	47917	0.203	-0.017	1.555	2	112.88
PA	Tioga	48449	0.203	-0.017	1.555	2	112.88
PA	Lycoming	48731	0.203	-0.017	1.555	2	112.88
PA	Juniata	49028	0.203	-0.017	1.555	2	112.88
PA	Greene	49116	0.203	-0.017	1.555	2	112.88
PA	Fulton	49420	0.203	-0.017	1.555	2	112.88
PA	Susquehanna	50160	0.203	-0.017	1.555	3	124.59
PA	Wayne	50595	0.203	-0.017	1.555	3	124.59
PA	Carbon	50822	0.203	-0.017	1.555	3	124.59
PA	Bradford	51035	0.203	-0.017	1.555	3	124.59
PA	Snyder	51110	0.203	-0.017	1.555	3	124.59
PA	Union	51349	0.203	-0.017	1.555	3	124.59
PA	Beaver	51887	0.203	-0.017	1.555	3	124.59
PA	Wyoming	53397	0.203	-0.017	1.555	3	124.59
PA	Westmoreland	54142	0.203	-0.017	1.555	3	124.59
PA	Allegheny	54357	0.203	-0.017	1.555	3	124.59
PA	Centre	54407	0.203	-0.017	1.555	3	124.59
PA	Dauphin	54968	0.203	-0.017	1.555	3	124.59
PA	Montour	55233	0.203	-0.017	1.555	3	124.59
PA	Franklin	55751	0.203	-0.017	1.555	3	124.59

PA	Lebanon	56191	0.203	-0.017	1.555	3	124.59
PA	Berks	57068	0.203	-0.017	1.555	3	124.59
PA	Washington	57534	0.203	-0.017	1.555	3	124.59
PA	Lehigh	57685	0.203	-0.017	1.555	3	124.59
PA	Perry	58585	0.203	-0.017	1.555	3	124.59
PA	Monroe	58980	0.203	-0.017	1.555	3	124.59
PA	Lancaster	59237	0.203	-0.017	1.555	3	124.59
PA	York	59853	0.203	-0.017	1.555	3	124.59
PA	Pike	61199	0.203	-0.017	1.555	3	124.59
PA	Cumberland	61640	0.203	-0.017	1.555	3	124.59
PA	Adams	61927	0.203	-0.017	1.555	3	124.59
PA	Northampton	62753	0.203	-0.017	1.555	3	124.59
PA	Butler	63345	0.203	-0.017	1.555	3	124.59
PA	Delaware	66576	0.203	-0.017	1.555	3	124.59
PA	Bucks	79559	0.203	-0.017	1.555	3	124.59
PA	Montgomery	81902	0.203	-0.017	1.555	4	136.30
PA	Chester	88995	0.203	-0.017	1.555	4	136.30
NY	Bronx	34264	0.203	-0.017	0.000	2	23.42
NY	Chautauqua	40639	0.203	-0.017	0.000	2	23.42
NY	Allegany	41305	0.203	-0.017	0.000	2	23.42
NY	Franklin	42050	0.203	-0.017	0.000	2	23.42
NY	St. Lawrence	42303	0.203	-0.017	0.000	2	23.42
NY	Herkimer	42318	0.203	-0.017	0.000	2	23.42
NY	Cattaraugus	42466	0.203	-0.017	0.000	2	23.42
NY	Montgomery	42603	0.203	-0.017	0.000	2	23.42
NY	Lewis	42846	0.203	-0.017	0.000	2	23.42
NY	Delaware	42967	0.203	-0.017	0.000	2	23.42
NY	Fulton	43240	0.203	-0.017	0.000	2	23.42
NY	Jefferson	43410	0.203	-0.017	0.000	2	23.42
NY	Kings	43567	0.203	-0.017	0.000	2	23.42
NY	Steuben	43867	0.203	-0.017	0.000	2	23.42
NY	Chenango	43943	0.203	-0.017	0.000	2	23.42
NY	Broome	44457	0.203	-0.017	0.000	2	23.42
NY	Chemung	44502	0.203	-0.017	0.000	2	23.42
NY	Essex	45216	0.203	-0.017	0.000	2	23.42
NY	Otsego	45268	0.203	-0.017	0.000	2	23.42
NY	Oswego	45333	0.203	-0.017	0.000	2	23.42
NY	Cortland	45338	0.203	-0.017	0.000	2	23.42
NY	Niagara	45964	0.203	-0.017	0.000	2	23.42
NY	Greene	46235	0.203	-0.017	0.000	2	23.42
NY	Seneca	46707	0.203	-0.017	0.000	2	23.42
NY	Oneida	46708	0.203	-0.017	0.000	2	23.42
NY	Yates	46822	0.203	-0.017	0.000	2	23.42

NY	Erie	47372	0.203	-0.017	0.000	2	23.42
NY	Schuyler	47404	0.203	-0.017	0.000	2	23.42
NY	Clinton	47489	0.203	-0.017	0.000	2	23.42
NY	Orleans	48063	0.203	-0.017	0.000	2	23.42
NY	Sullivan	48103	0.203	-0.017	0.000	2	23.42
NY	Washington	48327	0.203	-0.017	0.000	2	23.42
NY	Cayuga	48415	0.203	-0.017	0.000	2	23.42
NY	Tompkins	48655	0.203	-0.017	0.000	2	23.42
NY	Hamilton	49557	0.203	-0.017	0.000	2	23.42
NY	Genesee	49750	0.203	-0.017	0.000	2	23.42
NY	Wyoming	50075	0.203	-0.017	0.000	3	35.13
NY	Onondaga	50676	0.203	-0.017	0.000	3	35.13
NY	Schoharie	50864	0.203	-0.017	0.000	3	35.13
NY	Monroe	51303	0.203	-0.017	0.000	3	35.13
NY	Warren	51619	0.203	-0.017	0.000	3	35.13
NY	Livingston	51690	0.203	-0.017	0.000	3	35.13
NY	United States	51914	0.203	-0.017	0.000	3	35.13
NY	Tioga	51948	0.203	-0.017	0.000	3	35.13
NY	Wayne	52562	0.203	-0.017	0.000	3	35.13
NY	Madison	53345	0.203	-0.017	0.000	3	35.13
NY	Rensselaer	54152	0.203	-0.017	0.000	3	35.13
NY	Schenectady	55188	0.203	-0.017	0.000	3	35.13
NY	Queens	55291	0.203	-0.017	0.000	3	35.13
NY	Columbia	55546	0.203	-0.017	0.000	3	35.13
NY	New York State	55603	0.203	-0.017	0.000	3	35.13
NY	Albany	56090	0.203	-0.017	0.000	3	35.13
NY	Ontario	56468	0.203	-0.017	0.000	3	35.13
NY	Ulster	57584	0.203	-0.017	0.000	3	35.13
NY	New York County	64971	0.203	-0.017	0.000	3	35.13
NY	Saratoga	65100	0.203	-0.017	0.000	3	35.13
NY	Orange	69523	0.203	-0.017	0.000	3	35.13
NY	Dutchess	69838	0.203	-0.017	0.000	3	35.13
NY	Richmond	71084	0.203	-0.017	0.000	3	35.13
NY	Westchester	79619	0.203	-0.017	0.000	3	35.13
NY	Rockland	82534	0.203	-0.017	0.000	4	46.84
NY	Suffolk	84506	0.203	-0.017	0.000	4	46.84
NY	Putnam	89218	0.203	-0.017	0.000	4	46.84
NY	Nassau	93613	0.203	-0.017	0.000	4	46.84