Stated and Revealed Preference Valuation of Forest Ecosystems

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ABSTRACT

Stated preference and revealed preference are two commonly conducted non-market value evaluation methods which can also be applied to make evaluation of forest ecosystem. In the application of these evaluation methodologies, there always exists limitation from the data collection and empirical analysis. In the dissertation here, we extend the traditional evaluation methods with novel design or statistical analysis approaches to solve the practical problem we met in evaluation of forest ecosystem. The first and second chapters are based on stated preference methods. The first chapter employ both the mail survey and on-site survey to investigate the preference for attributes of low-impact timber harvesting programs. In the second chapter, we recruit three interest groups for on-site survey and compare their preference for the low-impact timber harvesting programs. In these first two chapters, choice modeling method is employed to elicit the respondents' preferences, and we also use bootstrap method to get robust estimation results for small sample size data. The last chapter employed revealed preference method to evaluate the economic losses from hemlock damages caused by forest pest. Three different interpolation methods are employed to scale-up the analysis from sites to states. Based on the findings of all three chapters, we can see that these survey design and statistical methods help to overcome the limitations in empirical analysis of forest ecosystem and make more robust inferences for design forest protection policies.

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TABLE OF CONTENTS

CHAPTER I. INTRODUCTION 1

CHAPTER II. THE EFFECT OF ON-SITE EXPERIENCE ON STATED PREFERENCES FOR LOW-IMPACT TIMBER HARVESTING 7

1. Introduction........ 7

2. Previous Literature........ 10

3. Study Application and Design 13

3.1 Stated-Preference Survey 14

3.2 Sample and Survey Administration 15

3.3 Potential Confounding Factors 17

4. Model Specification........ 18

4.1 Econometric Model 18

4.2 Hypothesis Tests 20

5. Results........ 22

5.1 Summary of Estimation Results 23

5.2 Tests of Preference Parameter Equivalency 24

6. Conclusions and Discussion 26

References........ 29

CHAPTER III. ON-SITE EXPERIENCE EFFECT ON THE PREFERENCES OF INTEREST GROUPS FOR FOREST MANAGEMENT 42

1. Introduction........ 42

2. Survey Design........ 45

2.1 Sample Recruitment........ 46

2.2 Survey Administration 47

2.3 Stated-preference Survey 47

3. Model Specifications 48

3.1 Random Utility Model 48

3.2 Hypothesis Test 49

4. Results 50

4.1 Estimation Results for Interest Groups 51

4.2 Tests of Preference Parameter Equivalency 51

5. Conclusion 52

References 53

CHAPTER IV. THE EFFECT OF SPATIAL INTERPOLATION ON PROPERTY VALUE MODELS: A CASE OF FOREST PEST DAMAGE 61

1. Introduction 61

2. Literature Review 63

3. Modeling Framework 66

4. Description of the Study Area 67

5. Spatial Interpolation 69

5.1 Inverse Distance Weighting Interpolation 70

5.2 Spline Interpolation 70

5.3 Kriging Interpolation 71

6. Model Specification 72

6.1 Traditional Hedonic Model 73

6.2 Repeated Sale Model 74

7. Results 74

7.1 Spatial Interpolation 74

7.2 Sampled Data Analysis 76

7.3 Interpolated Data Analysis 77

8. Discussion 78

References 81

CHAPTER V. CONCLUSION 99

LIST OF FIGURES

Figure 2.1 Maine Population Density 39

Figure 2.2 Stated-Preference Question.. 40

Figure 2.3 The Holt Research Forest 41

Figure 3.1 Stated-Preference Question.. 60

Figure 4.1 Locations between Household Properties and Hemlock Stands........................ 94

Figure 4.2 Hemlock Stands in the Study Area 95

Figure 4.3 Semivariogram Model and the Parameters.. 96

Figure 4.4 Interpolated Live Basal Area by Kriging in the Study Area (2007-2011)........ 97

Figure 4.5 Interpolated Vigor by Kriging in the Study Area (2007-2011) 98

LIST OF TABLES

Table 2.1 Forest Management Attributes and Levels 33

Table 2.2 Definitions of Forest Management and Design Variables 34

Table 2.3 Socioeconomic Characteristics of Respondents 35

Table 2.4 Number of Respondents Who Changed Votes for Forest Management Referenda between Pretest Survey and Posttest Survey 36

Table 2.5 Forest Management Preference Parameter Estimates for On-site and Mail Surveys 37

Table 2.6 Forest Management Preference and Scale Parameter Estimates for Pooled Samples 38

Table 3.1 Attributes and Levels 55

Table 3.2 Definitions of Variables 56

Table 3.3 Socioeconomic Characteristics of Respondents 57

Table 3.4 Preference Parameter Estimates for Interest Groups 58

Table 3.5 Hypothesis Test Results for Comparison between Groups and Surveys 59

Table 4.1 Live Basal Area and Vigor for Sampled Hemlock Stands 85

Table 4.2 Descriptive Statistics of Housing Characteristics Variables 86

Table 4.3 Cross Validation results for Live Basal Area and Vigor 87

Table 4.4 Interpolated Live Basal Area and Vigor for all Stands (n=6,126) 88

Table 4.5 Estimation Results Based on Sampled Data (case A and B) 89

Table 4.6 Estimation Results Based on Sampled Data (case A) 90

Table 4.7 Estimation Results Based on Inverse Distance Weighted Method 91

Table 4.8 Estimation Results Based on Spline 92

Table 4.9 Estimation Results Based on Kriging 93

Chapter I. Introduction

Forest ecosystem is an important landscape which can generate great benefit for the society. Forests can not only provide us natural resources like timber, oil and natural gas, but also they provide scenic beauty, recreation places, wildlife habitat, clean water and air for communities. A healthy forest ecosystem play an important role to maintain environmental sustainability, and it is also helpful to mitigate the global climate change. To maintain a healthy forest ecosystem, sustainable forest management strategies should be taken to satisfy all its economic, social and ecological development goals (Kreieger, 2001).

In recent decades, people are beginning to pay more attention to the ecological and social value of forest. Unlike economic value, ecological and social benefits are usually provided to the society as public goods which are not sold in the market and therefore are hard to measure in price. However, as there always exists trade-off between different goals of forest management, the measurement of this non-market value from forest would be helpful to achieve the optimal utilization of forest resource (pearce, 2001). It can be employed into the benefit-cost analysis for state and federal governments to design forest management policies.

Non-market evaluation methods have been conducted for a long time to make evaluation for the forest value (Swanson and Loomis, 1996). However, it has been also recognized by researches that there may still exist limitation and bias for these evaluation methodologies in the real world analysis. Forest ecosystem is a complex system. They serve multiple functions for the society, and they provide different utilities for different people. There exists challenges to get a complete and accurate value for the benefit from forest ecosystem in the design of non-market value evaluation process. How to improve the validity and accuracy of the evaluation results in application of forest ecosystem management deserve conducting further investigation.

Stated preference method and Revealed preference method are two main non-market value evaluation methods. Stated preference approach is based on survey questions to elicit the willingness to pay from the respondents (Mitchell and Carson, 1989; Bateman *et al.*, 2003). In the survey, one hypothetical market is built with designed new environmental conditions. Two main approach are contingent valuation and choice experiment (Hanley et al., 2001). In the contingent valuation research, the respondents compare the current condition with the new condition to make decision of their willingness to pay or willingness to accept. In the choice modeling research, two or more choice conditions are given to the respondents to choose from. A set of attributes, including environmental conditions and choice payments, are clearly described in each choice status for respondents to distinguish with.

Compared with the stated preference method, revealed preference approach is conducted based on the assumption that real market behavior could reflect consumers' choice decision to maximize their welfare utility (Paul Samuelson, 1938). Hedonic price and travel cost methods are two main revealed preference methods. They can be employed to measure the tourism value, recreation value and aesthetic value from the forest ecosystem. Revealed preference approaches primarily allow us to measure the market value while stated preference approaches would also allow us to measure the non-market value of forest resources.

Both of these non-market value evaluation methods have been widely employed to measure the market and non-market value from forest ecosystem, and they are complementary with each other. We could employ these methods to elicit the willingness to pay for the policy designed to improve the forest ecosystem condition or estimate the economic losses from the forest damages. Then these measurements can be put into cost-benefit analysis for decision making.

However, as forest is a complex ecosystem, there still exists challenges to get valid and accurate evaluation results. In the following chapters, we will focus on choice modeling method in stated preference evaluation and hedonic modeling in revealed preference evaluation. And we will try to solve the problems we meet in practice when we apply these methodologies to evaluate forest ecosystem.

Chapter II. Stated Preference Evaluation: on-site experience effect on the survey respondents

An important issue in the design of stated-preference surveys to elicit forest value is whether the information provided to respondents within a survey instrument is adequate to yield valid value estimates. As there may exist bias in the answers to stated preference survey, on-site experience with a resource is one way to provide respondents with first-hand information about complex ecological resources and management plans. Providing respondents with on-site experience about forest ecosystem management alternatives may influence their expectation of the benefits and costs resulting from new policies and programs.

In Chapter II, mail survey and on-site survey are offered to two groups of respondents. The respondents who participated into the on-site survey at the research forest were asked to complete pretest and posttest of the same survey instrument. And they are also same with the mail survey. After completing the pretest, respondents were taken on a guided walk through the research forest, and completed the posttest survey after their walks. In the survey, three sets of different choice questions are listed for the respondents to choose from. The choice attributes are property tax rebate to land owner, percent of land open for timber harvesting, public access and cost. Through this survey design, we investigate whether preference parameters for attributes of low-impact timber harvesting programs differ between respondents to a mail survey versus respondents provided with an on-site forest experience (walk through a research forest).

Chapter III. Stated Preference Evaluation: Comparison of Preferences among Interest Groups

In the design and administration process of the forest management legislations, forest owners and environmental activists are two interest groups who will be mostly affected by the forest management decisions. So they often actively participate and influence the design of forest management policies. However, as interest groups share diverse aspects of forest value, their preference may not represent the preference of the general public. They can have shared and also conflict attitudes with the general public toward the forest management policies. In Chapter III, we extend our analysis to the on-site experience effect on the preferences among stakeholders for forest management practices.

The preferences of interest groups for forest management policies have been investigated for long time, and researches have shown differences in preferences between interest groups. However, there has been no research investigated whether the difference of knowledge level or experience with forest affects the attitude diversity among interest groups. Generally, the forest owners have more real experience and the environmentalists have more knowledge with the forest ecosystem. These differences of knowledge level with forest ecosystem would also induce the attitude diversity among interest groups.

The survey design is similar with Chapter II. We provided an on-site experience to three interest groups: woodlot land owner, environmental activists and the general public. Respondents were asked to complete pretest when they arrived at the research forest. After completing the pretest, respondents were taken on a guided walk through the research forest, and completed the posttest survey after their walks. Through their walk, they could stop at designed sites and read the cards there to get knowledge about the forest management practices.

We would compare the preference differences among the three interest groups for both the pretest and posttest survey. We would also compare the preference difference between the pretest and posttest survey for each interest group. Then we try to investigate how the on-site experience with forest ecosystem affect their attitude and whether the difference of knowledge level is the main factor that causes the preference difference among interest groups.

Chapter IV. Revealed Preference Evaluation: The Economic Loss from Forest Pest Infestation

Previous hedonic studies have shown that healthy trees and forests could provide scenic and recreation value to the residential properties (Anderson and Cordell 1985, Dombrow et al. 2000, Tyrvainen and Miettinen 2000, Netusil et al. 2010). These economic benefits from healthy forests indicate the potential losses from the disturbances to the forests. Forest pest outbreaks are important factors that impose negative effects on forest ecosystem services (Huggett 2008, Holmes et al. 2009, Rosenberger et al. 2012). Mountain pine beetle, spruce budworm, gypsy moth and the hemlock woolly adelgid are all major forest pests that have caused great damages to the forests in U.S. However, only a few studies have evaluated the economic impacts on property values from such forest pest outbreaks.

The hemlock woolly adelgid (HWA) is a non-native forest insect that causes defoliation and mortality of hemlock in the eastern U.S. forests. In Chapter IV, we employ revealed preference method to evaluate the economic impact from the spread of HWA infestation for local communities. As HWA is sensitive to temperature, this can also signal the economic effect from global warming.

One limitation for the analysis is that we could only measure the hemlock damages at specific hemlock stands. A challenging problem is how to scale-up or extrapolate results obtained from site specific studies to other forest regions at risk of HWA.

Inverse distance weighting, spline and kriging are geo-statistical methodologies which help to interpolate the hemlock damage characteristics to all the hemlock stands in the study area. Although these interpolation methods are common used technics in spatial statistics by scientists, there are not many papers tried to introduce the interpolated environmental results from spatial interpolation into the hedonic price models. We use these three techniques to interpolate hemlock health variables from the sampled 142 hemlock stands to the >6000 hemlock stands in the study area.

Then we estimate the economic consequences of the spatial and temporal expansion of HWA infestation based on these three interpolation methods. And we would compare to see whether these spatial interpolation methodologies would give us consistent estimation results in the hedonic models.

The details for each research topic are described in the following chapters.

Chapter II. The Effect of On-site Experience on Stated Preferences for Low-impact Timber Harvesting

1. Introduction

A key consideration in the design of stated-preference surveys is the information provided to respondents describing the ecosystem goods or services being valued and the increment of change to be valued, which occurs in the context of the prior experience or knowledge respondents have with the topic of investigation. In studies estimating use values, respondents typically have specific, first-hand experience with the resource and the researcher focuses on describing changes in the resource that respondents are asked to value. When nonuse values are elicited, respondents may not have specific, first-hand experience. Applications estimating nonuse or total values likely require respondents who lack specific knowledge/experience to base their responses on their general knowledge/experience, which may or may not be directly relevant, and the information provided in the survey instrument.

The breadth and depth of information provided in stated-preference surveys is carefully designed through one-on-one interviews, focus groups and/or field pretests (Boyle, 2003; Champ, 2003; Mitchell and Carson, 1989). A logical question that one might ask is whether the acquired information from a survey can substitute for personal experience. This issue may be especially relevant in applications such as valuing programs to protect ecological resources, like forests, where respondents may have little or no direct experience with the resource change being valued.

Researchers have shown that responses to stated-preference questions vary with respondent experience. For example, Boyle, Welsh and Bishop (1993) found that experienced white-water boaters valued scenarios of white-water trips they had not experienced the same as they valued their actual white-water experiences, but that this was not the case for less experienced boaters. Cameron and Englin (1997) found that value estimates increased and variance estimates decreased with respondent experience. The Boyle study investigated use values for Colorado River rafting where all respondents had taken at least one trip on the river, but some respondents had taken multiple trips on the Colorado River and other rivers. The Cameron study investigated what appears to be a total value for trout fishing in the Northeast U.S. where respondents may have had more or less fishing experience, but the experience need not be specific to trout. Despite these differences in study contexts, both studies indicate that the prior experience respondents bring to their participation in a stated-preference study can influence value estimates. More important, each of these applications involved the estimation of use values where respondents had some type of specific experience with the resources in question. When estimating values for programs to protect ecological resources, respondents may have little or no direct experience with the resources being valued.

We can think of the information that respondents use in answering stated-preference questions as falling into two broad categories, *prior knowledge* and *acquired knowledge*. *Prior knowledge* is the knowledge that individuals possess prior to engaging in the stated-preference study. This can be specific knowledge gained from personal experience with a resource or general knowledge obtained from reading or some other indirect source of information. Survey participants can also augment prior knowledge when responding to surveys administered by mail or internet by talking to others, searching the internet, etc. before or while answering survey questions. *Acquired knowledge* is the information that individuals obtain from participation in a stated-preference study that is provided by the investigator through the survey process.

In the research reported here we investigate a specific type of acquired knowledge - investigator provided on-site experience. A stated-preference survey focusing on low-impact timber harvesting was administered by mail and on-site at the Holt Research Forest, a 120-hectare oak-pine forest located in the state of Maine, USA. Respondents to the traditional mail survey answered stated-preference questions based on their prior knowledge and the acquired knowledge provided in the survey instrument. Respondents who participated on-site at the research forest were asked to complete pretest and posttest administrations of the same survey instrument. After completing the pretest, respondents were taken on a guided walk through the research forest, where they received additional acquired information about natural and managed forests via information cards and direct observation, and completed the posttest survey upon completion of their walks.

The research forest is unique in that half of the forest is left as a natural area with no timber harvesting and the other half is managed for high quality lumber using low-impact timber harvesting practices (Moore and Witham, 1996). This management regime matches the policy question in the survey, which was an incentive program for owners of small forest holdings to set aside some of their forestland from timber harvesting and to use low-impact timber harvesting practices on the remaining land.

In the analyses reported here we investigate two issues. First, we evaluate whether those who agreed to participate on-site have the same preferences as those who agreed to complete the mail survey; a comparison of the mail and pretest results. This step is important to identify whether differences in sample frames confound the comparison of information treatments. Second, we investigate if the mail and posttest results are statistically similar. This is the primary investigation of the effect of on-site acquired information where respondents experienced the forest first-hand. Our results show that there were no differences in preference parameter estimates between the mail and pretest results. Nor did we find differences in preference parameters between the mail and posttest responses to the survey. Thus, at least in this case study, the results indicate that on-site information does not substantially alter the observations of respondents' preferences. However, we find that the forest walks reduced variance estimates, which suggest that study subjects had more confidence in their responses to preference questions after their walks through the forest. We also found that people who agreed to participate on-site hold stronger preferences for low-impact timber harvesting than those who participated remotely through the mail survey. Thus, caution is warranted when people are recruited on-site to participate in a stated-preference study as values might be upwardly biased due to sample selection that is unrelated to observable demographic characteristics of survey respondents.

2. Previous Literature

Researchers have investigated how varying information and respondent experience/knowledge affect answers to stated-preference questions. Studies reveal that value estimates can be sensitive to respondent experience and the level of information provided (Boyle et al., 1993; Cameron and Englin, 1997; Tkac, 1998; Munro and Hanley, 2000; Hoehn and Randall, 2002; Holmes et. al, 2013). Generally, when more detailed information on the resource being valued is provided estimated values increase (Samples et al, 1986; Bergstrom et al., 1990; Bergstrom and Dorfman, 1994; Cameron and Englin, 1997) or the variance of the value estimate is reduced (Boyle, 1989; Cameron and Englin, 1997). Providing information specific to respondents can enhance the validity of value estimates (Ajzen et al., 1996; Poe and Bishop, 1999).

Kenyon and Edward-Jones (1998) showed that providing acquired information consisting of photographic, textual and ecological data resulted in respondents making the same responses as ecological experts. Boyle et al. (1995) found white-water boaters rank river flows for rafting the same as expert rafting guides. These studies suggest that the "public" can have preferences over valuation scenarios that are consistent with "expert" opinion, but this does not answer the question of how personal experience specific to a resource affects responses to stated-preference questions.

When stated-preference questions address trade-offs among complex ecological services, such as manifest in policy alternatives regarding the management of forest ecosystems, respondents with limited prior knowledge or experience may choose among policy alternatives using their intuition or heuristic rules that may or may not be consistent with the nuances of the specific ecosystem policy, being valued (Urama and Hodge, 2006; Fror, 2008; Vista et al., 2009). Evidence shows that after deliberating and discussing survey information respondents can change their stated preferences (Kenyon et al., 2001; Spash, 2002; MacMillan et al., 2006).1

Without personal resource experience, respondents may answer valuation questions according to their expectations of the utility they will receive from the new resource conditions proposed in the valuation scenario. These ex ante predictions can induce bias if responses to

[1] Whittington and colleagues gave respondents time to think before providing a final answer to a stated-preference question (Whittington et al., 1992; Cook et al., 2012). While the investigators did not provide additional information during the time to think period, it is possible that survey respondents may have sought additional information when thinking about how they would answer the stated-preference question.

stated-preference questions would differ given personal on-site experience that helps to resolve uncertainty regarding the ultimate change in utility that will be experienced (Kahneman and Sugden, 2005; Ladenburg, 2009). For example, Tinch et al. (2010) employed a workshop approach to compare respondents' preferences for changes in moorland and farmland intensity before, during and after a visit to a location within the Peak District National Park in England. They found that preference estimates were not statistically different before and after the visit. Carlsson et al. (2011) compared households' WTP for avoiding power outages before and after a storm, and found a significant increase in the proportion of respondents stating $0 willingness to pay after the experience of power outage; perhaps the outcome of the power outage was not a severe as anticipated ex ante.

Several studies have investigated the effect of exposure to specific environmental goods on stated-preference estimates, but the results differ. Tisdell and Wilson (2001 and 2005) conducted a study that gave participants an opportunity to view sea turtles when visiting a park; the participants who saw turtles had higher values than those who did not observe turtles. In another study, participants who saw mahogany gliders (an endangered possum in Australia) in the natural setting did not have values that were statistically different from before they saw the gliders (Tisdell and Wilson, 2008). The first result suggest that people had a higher quality experience when they observed the turtles, but this increase in quality of the experience was not fully anticipated by those who did not see the turtles. The second study suggests that, ex ante, study participants did correctly anticipate the effect on the quality of their experiences from seeing the gliders.

These seemingly contradictory results (Tinch et al. vs. Carlsson; Tisdell and Wilson (2001 and 2005) vs. Tisdell and Wilson (2008)) may be artifacts of differing levels of prior knowledge between the park and power outage applications, and the turtle and glider applications, which affected anticipated ex post conditions in the power outage and turtle applications. If it is the case that the accuracy of ex ante expectations are application specific, research is required to identify applications where experience is necessary to estimate credible stated-preference values. We contribute to this body of research by employing an approach similar to Tinch et al. (2010) and ask how on-site experience with specific low-impact forest management affects preferences for this program of forest management. If the low-impact forest management program proposed in our study were implemented, respondents would not have known which land owners would choose to participate and if the participating land owners would be near where study subjects live, work or recreate. Thus, the values we estimate are dominated by nonuse (or passive-use) values, whereas the Tinch et al. (2010) study estimated total values of people who live near the park and preference responses likely contained a large use-value component.

3. Study Application and Design

The valuation application is a state-wide program to incentivize owners of small, private forest holdings in Maine, USA to manage their forestlands using low-impact timber harvesting methods and to set some of their forestlands aside from timber harvesting. At the turn of the 20th century about 30% of Maine was farmland and the remainder was forestland (Ahn et al., 2002). Today the state is nearly 90% forested and timber harvesting is a major industry in the state.[2] Land along the coast of Maine was cleared by early settlers for farming and then abandoned due to the movement of agriculture to more fertile lands in the Midwest. As farmland was abandoned, the land returned to the naturally occurring forestland (see Irland, 1982). These

[2] http://www.umaine.edu/mial/products/maine_cd.htm, accessed June 21, 2012.

forests are maturing and are being harvested for the first time in generations, and this is occurring in the areas with the highest population density in Maine (Figure 2.1). In response to the ecological, aesthetic and social concerns associated with the harvesting of small forest parcels, forest researchers have proposed alternative timber harvesting practices to maximize the production of high quality timber, enhance wildlife diversity and abundance, protect water quality and to maintain forest aesthetics (Witham *et al*., 1999).

The research reported here uses a stated-preference survey to elicit public preferences for a program that would provide an incentive, through property tax rebates, to owners of forestlands who agree to use low-impact timber harvesting practices and/or set a portion of their forestland aside from timber harvesting. This is a complex issue because it asks the public to weigh low-impact timber harvesting practices and the implications of setting forestland aside from timber harvesting versus standard timber harvesting practices where all forestland is available for harvest. The public may have limited prior knowledge of the ecological implications of both types of forest management.

To provide on-site experience with a forest where low-impact timber harvesting is practiced and some forestland is set aside from timber harvesting, we recruited subjects to come to the Holt Forest to participate in the study and complete the stated-preference survey. The forest has two sections; one half of the forest is managed for low impact timber harvesting (harvest section) and the other half of the forest is set aside from timber harvesting (no-harvest section).

3.1 Stated-Preference Survey

The mail survey was designed and implemented following guidelines proposed by

Dillman (2000 and 2007). An identical survey was administered on-site at the Holt Forest.

Stated-preference questions were developed that asked respondents to vote on three alternative forestry referenda where the referenda were differentiated by program attributes (Figure 2.2). Status-quo conditions were described to respondents so that they would know what continuing forest management conditions would be if they voted “no”. Four attributes were included in the experiment and levels for each attribute are listed in Table 2.1. Three levels were included for the “percent of land open for timber harvesting” attribute - 100%, 50% and 0%. When the percent of land open for timber harvesting is non-zero (50% or 100%), low-impact timber harvesting methods are required. To compensate private forest owners that enroll in the program for the opportunity costs of foregone timber revenue, three property tax rebate levels were evaluated (30%, 70% and100%). Further, preferences for public access to private forest land enrolled in the program were evaluated with a public access (voluntary or required) attribute. The cost levels used in this study are based on a prior stated-preference study of forest policy in Maine (Boyle et al., 2001).

3.2 Sample and Survey Administration

The sample for the mail survey (n=1,000) was obtained from the Maine Department of Motor Vehicles and was a random sample of adults with a driver’s license or state ID card, which covers over 95 percent of the adults in the State of Maine. A total of 390 completed surveys were returned and after excluding the undeliverable surveys the effective response rate was 48%.

The on-site sample was recruited using random digit dialing of households with phone prefixes within a 40 mile radius of the Holt Forest (Figure 2.3). It was not practical to recruit subjects for the on-site treatment from all over the state to participate in the survey as some people live as much as 4-6 hours away from the Holt Forest. It took approximately 11 completed phone calls to get 1 person to participate, and 31 people were recruited to participate in the on-site survey. The size of the on-site sample was limited somewhat by the available budget, but mostly due to the logistics of on-site administration and the desire of the forest researchers that our experiment have minimal impact on the forest and on-going research.

In addition, subjects for the on-site survey were limited to individuals age 65 or younger due to the potential rigor of the walk through the forest. Individuals in the on-site treatment were paid a $40 incentive to compensate them for their travel time to the study site. Participants in the mail survey were not limited by age and were not paid to participate in the study.

The subjects in the off-site sample received the survey in the mail and were requested to return their completed surveys in an enclosed postage-paid envelope. The participants in the on-site sample were recruited to travel to the research forest and participate in the survey. On-site participants completed a pretest administration of the survey when they arrived, which was identical to the instrument used for the mail survey. Participants were then taken on a walk through the forest, which took about 45 minutes. At the end of the walk, the posttest surveys were administered, which were identical to the pretest surveys.

One half of the on-site sample was taken through the harvest section first and then the no-harvest section. The other half of this sample followed the same route through the forest, but in the reverse direction. The walks followed transect lines that divided the forest into research plots and it was necessary to have someone lead subjects through the forest so both groups would follow the same routes and not walk across research plots.[3] Two graduate students led the groups and stopped at designated sites in the forest for participants to observe the forest conditions and to read information cards that described ecological aspects of each location. Stops included a harvest opening in the harvest section and a natural clearing in the non-harvest area of the forest, a skidder path across an ephemeral stream in the harvest section and an uninterrupted ephemeral stream in the no-harvest section, and wildlife habitat in the harvest section (slash – piles of brush and limbs left from harvesting) and no-harvest section (snags – standing dead or dying trees).

3.3 Potential Confounding Factors

Bringing people on-site to participate in the survey introduced a number of factors that could confound a comparison of results with those obtained from the mail survey. These factors include potential differences in sample frames (state wide v. 40-mile radius of Holt forest), respondent recruitment procedures (mail vs. telephone), and survey modes (mail vs. on-site).

These concerns are handled in two ways in the study design. First, we compare socioeconomic characteristics of respondents to the mail and on-site samples to see if there are any significant differences between those who responded. Second, the on-site participants were asked to complete pretest and posttest surveys. The pre/posttest design allows for isolation of sample frame/recruitment/mode effects and the effects of on-site *acquired information*. Respondents to the mail and pretest surveys answered the forest policy survey questions based on their *prior knowledge*. If there are no differences in socioeconomic characteristics and no differences in survey responses between the mail and pretest applications, this suggests that sample frame/recruitment/mode effects do not confound the investigation of the effect of

[3] There were no visible signs of ongoing research that participants could observe during their walks through the forest. Transects were selected that avoided any flagging or other identification of research activities.

acquired information from respondents' walks through the forest.

A finding of "no difference" between the mail and posttest results suggests procedural invariance over survey modes, which is supportive of using a traditional mail survey to estimate non-market values. That is, differences due to sample frames, survey recruitment and those who responded, and survey mode all would serve to create differences in estimated preference parameters between the mail and pretest applications. Thus, if procedural invariance holds between the mail and pretest applications and between the mail and posttest applications, this suggests that potentially confounding factors are not issues of concern and on-site experience is not necessary for this forest application. If differences are identified between the mail and pretest survey results, then confounding factors inhibit identification of the effects of on-site acquired information. If only differences are identified between the mail and posttest survey results, then this is evidence that *acquired information* influenced how people answered the forest policy questions and use of mail survey results should be interpreted with caution.

4. Model Specification

4.1 Econometric Model

Respondents are assumed to have a utility function U_i such that V_i is the observable component of utility and ε_i is the random error (McFadden, 1973; Louviere et al., 2001):

$$U_i = V_i(x, I) + \varepsilon_i \tag{1}$$

where x is a vector of attributes from the forest management program and all other utility arguments are assumed to be orthogonal to x and are suppressed for notational convenience and I

is income. Assuming that the utility function is linear in parameters and ε has an iid extreme value distribution, a logistic model results describing the utility difference (program vs. no program). Of course, income (I) cancels out of the utility difference (program vs. no program/status quo) and does not appear in the econometric estimation:

$$\Delta U_i = \beta \Delta x_i + \Delta\varepsilon_i \tag{2}$$

where $\Delta x_i = x_i^l - x_i^s$, and l and s denote low-impact harvesting and status-quo management conditions, respectively.

Each respondent answered three stated-preference questions and these choices may be correlated. We can generalize the model to allow utility parameters to vary randomly over individuals and allow for correlated responses using a mixed-logit model (Revelt & Train, 1998; Train, 1998; Train, 2003). Specifically, the utility difference of individual (i) in equation (2) is transformed as follows:

$$\Delta U_{ij} = \beta_i \Delta x_{ij} + \Delta\varepsilon_{ij} \tag{3}$$

where parameter estimates (β_i) vary over respondents (i) and ε_{ij} allows for correlated choices over alternatives.

The attribute variables (x) used in estimated equations are defined in Table 2.2. The omitted levels for each of the attributes are “0% of land available for harvesting”, “30% property tax rebate to landowner”, and “voluntary access”.

Two equations were estimated. First, the response data for the mail and on-site surveys were analyzed using a conditional logit model:

$$\Delta U_i = \alpha Asc + \beta \Delta x_i + \Delta \varepsilon_i \tag{4}$$

where *Asc* (alternative specific constant) equals 1 if the alternative represents the condition of one of the referendum programs and 0 if it represents the status quo (no program, thereby maintaining current conditions). If the mean estimate of α is positive, this indicates that respondents derive positive utility from a low-impact timber harvesting program independent of the specified attribute levels. This equation was used to test for differences between preference parameters obtained from the mail and on-site survey results.

Second, the mail survey data were further analyzed with a mixed logit model to consider potential preference heterogeneity across respondents:

$$\Delta U_{ij} = \alpha_i Asc_{ij} + \beta_i \Delta x_{ij} + \Delta \varepsilon_{ij} \tag{5}$$

We assume that α_i and β_i have normal densities with parameter vector θ that include the mean and variance of each distributed parameter. The mixed-logit estimation was not applied to the on-site data due to the limited number of observations.

4.2 Hypothesis Tests

To investigate if on-site and mail respondents have different preferences for the referendum attributes we test the null hypothesis that the on-site, pretest (posttest) parameter estimates are statistically indistinguishable from the mail parameter estimates. Note here we only test whether the respondents have the same preferences toward specific attributes while allow the preference for alternative specific choice to be different between groups.

$$H_0\text{: } \beta_{\text{g}} = \beta_{mail} \qquad \text{vs.} \qquad H_a\text{: not } H_0 \tag{H1}$$

where g denotes estimation results from the pretest or posttest data. The test is complicated by the fact that observed logistic parameter estimates ($\hat{\rho}$) confound the true parameter estimates (β) with the standard error of ε_i ; the scale parameter that is typically normalized to 1 when a single data set is used for estimation. That is, $\rho = \mu\beta$, where μ is the scale parameter, $\mu = 1/\sigma$ and σ is the standard error. Because the true preference parameter vector is β, but we observe $\hat{\rho}$, we must remove the effect of μ to perform the hypothesis test.

Here we apply the method described by Swait and Louviere (1993) to calculate the scale parameter and test whether the scale parameter and preferences are the same across groups. First, we calculate the likelihood ratio test statistics $\lambda_1 = -2[L_\mu - (L_m + L_g)]$ to check whether the preferences for all the attributes are equal between groups. L_μ is the log-likelihood value from the pooled sample (mail plus pretest or posttest data) after adjusting for the relative differences in scale parameters. L_m is the log likelihood value for estimation with the mail data and L_g are the log likelihood values from the on-site data (pretest or posttest).

If we cannot reject the null hypothesis of equal coefficients, we test the hypothesis that the scale parameters are equivalent:

$$H_0: \mu_g = \mu_{mail} \qquad \text{vs.} \qquad H_a: \text{ not } H_0. \qquad \text{(H2)}$$

These hypothesis tests are conducted using the likelihood ratio test statistics $\lambda_2 = -2\left[L_p - L_\mu\right]$. L_p is the log likelihood value from the pooled sample regression with the scale parameter restricted to be equal.

In conducting the tests of the pooled data, it was necessary to allow for potential differences in the alternative specific constant across the mail and on-site samples. This was accomplished by including an interaction variable and the following equation was estimated using the pooled data to conduct the hypothesis tests:

$$\Delta U_{ij} = \alpha_i Asc_{ij} + \beta_i \Delta x_{ij} + \gamma_i Asc_{ij} * Onsite_i + \Delta\varepsilon_{ij} \quad (6)$$

where the additional term $Asc_{ij} * Onsite_i$ allows people who participated on-site to derive higher or lower utility from the low-impact forest management program than those who responded by mail, but still evaluate the attributes similarly. Thus, L_p and L_μ are based on estimation of equation (6).

Both likelihood ratio statistics λ_1 and λ_2 are asymptotically chi-squared distributions with k degrees of freedom, the number of restrictions imposed by the test. As the sample size for the on-site survey is relatively small, the asymptotic properties of the chi-squared distribution may not be valid. Therefore, we also employ the parametric bootstrap method to test the likelihood ratio statistic λ_1[4](Bollen and Stine, 1992; Efron and Tibshirani, 1993; Langeheine et al., 1996). The probability of choosing the new referendum are first estimated under the null hypothesis. Replication samples (n=1000) are generated based on this fitted probability of Bernoulli distribution. Then the likelihood ratio statistic λ_1 is calculated for every sample to obtain the sampling distribution for λ_1. The bootstrap p-value is the proportion of bootstrap samples with a larger value of λ_1 than the original sample.

5. Results

Summary statistics of respondents' socioeconomic characteristics are reported in Table 2.3. For all descriptive statistics, except age, we cannot reject the null hypotheses that the mail

[4] For assessing latent class model fit, the asymptotic distribution generated from naively sampling has an expected value which is twice as large as it should be (Bollen and Stine, 1992).

and on-site respondent characteristics are the same. The one exception is not surprising because the on-site survey recruitment was limited to individuals age 65 or younger due to the potential rigor of the walk through the forest. These results suggest that the individuals who chose to respond to the mail survey are statistically similar to those who chose to participate in the on-site administration of the survey.

In Table 2.4, we summarize patterns of responses to the forestry program referendum questions for the on-site pretest and posttest survey administrations. For the first referendum, three of 30 respondents changed their votes from the pretest to posttest, while one of 30 and six of 31 respondents changed their votes for the second and third referenda, respectively.[5] In total, 9 of 31 respondents changed their answers from "Yes" to "No" or from "No" to "Yes" in at least one forestry program referendum question; one respondent changed their responses to two questions and eight respondents changed their answers to one of the three stated-preference questions. These patterns of responses suggest the walk through the forest did influence survey participants, about a third changed responses to at least one question, but the *acquired information* from the walk did not have a dramatic effect that changed responses to most of the sated-preference questions.

5.1 Summary of Estimation Results

Estimation results of the conditional-logit and mixed-logit models are summarized in Table 2.5. We used the conditional-logit estimation for comparisons of the mail and on-site data. As noted above, the limited number of on-site observations did not support the estimation of

[5] One respondent only answered the third stated preference question in the pretest, but answered all three questions in the posttest. We include only the responses to the third question that this person answered in the pretest and posttest in the data analyses.

mixed-logit models. We analyzed the mail data with a mixed-logit model to consider preference heterogeneity.

BID, public access (ACCESS) and 50% of land available for timber harvesting (H50) are significant for all three data groups, 100% of land available for timber harvesting (H100) is only significant for the mail survey, and the magnitude of landowner rebates (R70 and R100) is only significant, at the 10 % level, in the posttest sample. Requiring public access to private land reduced the probability of an affirmative vote and splitting the land evenly with 50% available for timber harvesting and 50% set aside from timber harvesting increases the probability of an affirmative vote. For the mail survey sample, permitting 100% of the land to be available for timber harvesting also increases the probability of an affirmative vote, but with a smaller effect than a 50:50 split. The null hypothesis that the parameters of variables H50 and H100 are equal is rejected at the 10% level.

The conditional-logit and mixed-logit estimation results are remarkably similar for the mail-survey data; the same parameters are significant and they are of comparable magnitudes. For the mixed-logit model, we report only statistically significant estimates of the standard deviations of the associated preference parameters; those associated with the "amount of land available for timber harvesting" attribute. The results indicate preference heterogeneity regarding the percentage of land available for timber harvesting and 100% of land available for timber harvesting has a smaller standard deviation than a 50: 50 split. The null hypothesis that the parameters and variances of H50 and H100 are equal is rejected at 5% level.

5.2 Tests of Preference Parameter Equivalency

Estimation for the pooled samples (pretest & mail; posttest & mail), with and without the scale parameters restricted to be equal, are summarized in Table 2.6. Comparing the pretest, on-site survey result with the mail survey result, the values of the chi-square statistics are $\lambda_1 = 8.32$ and $\lambda_2 = 0.97$. The critical values for these test statistics at the 10% level are 10.64 (df=6) and 2.71 (df=1), which indicates that we cannot reject either null hypothesis. The p-value of λ_1 based on the bootstrap results is 0.18, which also indicates that the null hypothesis cannot be rejected. Thus, the results indicate that we cannot reject the null hypothesis of no difference in preference parameter estimates between the on-site, pretest results and the mail results. Nor can we reject the null hypothesis of no difference in the scale parameters between these samples of respondents.

Comparing the posttest, on-site survey results with the mail survey results, $\lambda_1 = 5.52$ and $\lambda_2 = 6.15$. Here again, the critical values for the test statistics at the 10% level are 10.64 (df=6) and 2.71 (df=1), which indicates that we cannot reject the null hypothesis for λ_1. Further, the bootstrap p-value is 0.42 and supports that the null hypothesis cannot be rejected. Thus, we cannot reject the null hypothesis that the preferences for the forest management attributes are the same. However, these results indicate that the scale parameters are significantly different at the 5% level. The relative scale of the posttest sample with respect to the mail sample is 1.949. Because the scale factor is inversely related to the variance of the error term, and because the variance of the error term reflects the degree of uncertainty in choosing between alternatives, the informational walk apparently helped respondents become more certain about their forest management preferences.

The hypothesis test results reported above are conditional on inclusion of *OS*Asc* in the estimated equations. Inclusion of this variable allows on-site respondents to have a preference for the low-impact forest management program, independent of the attribute levels, that differs from those on the off-site (mail) sample; *OS*Asc* is positive and significant. The fixed-effect shift is approximately the same magnitude for both the pretest and posttest data. This result indicates that people participating in the on-site administration of the survey are more likely to vote affirmatively for a low-impact timber harvesting referendum than those who responded by mail, indicating that they hold higher values for the program. This result suggests that people who care more about forest issues were more likely to participate in the on-site survey and hold a higher value for the forest protection program than those who did not participate on-site, but they do not hold different preferences for program attributes. Note, the preference for low-impact forest management is not due to differences in demographic characteristics such as those reported in Table 2.3. Thus, other personal characteristics than common demographics appear to drive preferences for low-impact forest management.

6. Conclusions and Discussion

The results of our study indicate that stated preferences for low-impact timber management attributes do not vary between mail and on-site applications of the survey, and this result is robust to the pretest and posttest applications. However, the variance term did differ between the pretest and posttest results, inducting that the on-site walk reduced uncertainty in subjects' responses to the stated-preference questions. Further, participants in the on-site treatment had a stronger preference for low-impact timber management than did respondents to the mail survey.

The most important finding is that the informational walks through the forest did not statistically affect preference parameter estimates relative to the mail-survey results. This is good news as survey respondents could comparably evaluate the stated-preference questions for a complex ecological application and suggests that the traditional approach of conducting surveys remotely by mail can reliably estimate stated preferences for an environmental program without respondents having direct, on-site experience.

In contrast, we cannot conclude that studies that recruit people to participate on-site can provide reliable information to estimate the benefits of an environmental program. There is an efficiency-bias tradeoff here. On-site experience reduces variance, which can affect the outcome of statistical tests and confidence intervals on welfare estimates; thereby, enhancing estimation efficiency. Those who have stronger preferences for forest resources appear to be more likely to participate on-site, which could lead to overestimation of willingness to pay and therefore overestimation of aggregate benefits or costs.

Our conclusion of procedural invariance for stated-preference estimates of program attributes should be interpreted with caution. We might not observe differences between the mail and on-site results for a number of reasons such as: respondents possessed sufficient prior experience such that the acquired knowledge on-site was not necessary, on-site respondents recalled their pretest responses and their posttest responses were anchored on their prior answers, or we could not detect differences because of the limited size of the on-site sample.

To counter the first caution, our results do show differences in scale parameters after the forest walk so there is an effect of on-site experience. In addition, we note that our results are similar to Tinch et al. (2010) who also conducted pretest and posttest surveys in an application where participants received acquired information on-site, and they failed to reject the null hypothesis that pretest and posttest preferences were the same.

As about one third of the participants changed at least one of their responses after the forest walk, it seems unlikely that their responses to posttest questions are anchored on responses to pretest questions.

The small sample argument is of concern, but for our specific application, due to budget constraints and concerns about too many people walking through the experimental forest, we could not obtain a larger on-site sample.

We recommend that future research investigate the replicability of our (and the Tinch et al. 2010) findings in other ecological settings (e.g., wetland, marine protected areas, etc.), with treatments where some on-site participants respond to pretest and posttest administrations of the survey and other on-site participants respond only to the posttest administration. This type of design can investigate the effect of anchoring between the pretest and posttest administrations of the survey while also investigating differences between remote and on-site respondents. Future studies should also include larger on-site samples as budgets and study site conditions permit.

From a policy perspective, in our specific application, there is a benefit to the public from encouraging private landowners to use more benign timber management practices. However, requiring public access to private land as a condition of receiving a public subsidy was not supported. In addition, allowing some timber harvesting is preferred to precluding timber harvesting entirely, but there is heterogeneity in preferences regarding the share of land open for timber harvesting. The public was not concerned with the magnitude of subsidy that landowners received, which gives decision makers latitude in the amount of property tax rebates that are used to incentivize participation in the program. The results indicate an economic benefit to implementing timber management practices that protect forest ecosystems, protect water quality and that may help to mitigate global warming.

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Table 2.1 Forest Management Attributes and Levels

Attributes	Levels
Property tax rebate to participating landowners	30% 70% 100%
Percentage of land available (set aside) for timber harvesting	0% (All set aside) 50% 100% (None set aside)
Public access to land of participating landowners	Voluntary Required
Cost per household	\$1, \$20, \$40, \$60, \$80, \$100, \$120, \$160, \$180, \$200, \$400, \$800, \$1600

Table 2.2 Definitions of Forest Management and Design Variables

Variables	Definitions
Bid	cost per household
Access	1 if public access is required and 0 otherwise
H50	1 if 50% of "land available for harvesting" and 0 otherwise
H100	1 if 100% of "land available for harvesting" and 0 otherwise
R70	1 if 70% "property tax rebate to landowner" and 0 otherwise
R100	1 if 100% "property tax rebate to landowner" and 0 otherwise
Asc	1 if the alternative represents referendum conditions and 0 if current condition
OS	1 if responses from on-site (pretest or posttest) survey and 0 if mail survey

Table 2.3 Socioeconomic Characteristics of Respondents[a]

	Samples		
	Mail	On-site	Test Statistics
Gender (male=1)	53% (3)[b]	42% (9)	z = 1.13
Average Age	48 (1)	42 (2)	t = 3.11***[c]
Average Household Income	$46,021 (1,515)	$43,448 (4,459)	t = 0.55
Education:			
Eight years or less	2%	0%	χ^2= 5.64
Some high school	5%	0%	
High school graduate or equivalent	26%	18%	
Some college, A.S degree or technical	30%	29%	
school	25%	39%	
B.A. degree or equivalent	9%	7%	
M.A. degree or equivalent	3%	7%	
Advanced degree			
Land Owner	18% (2)	13% (6)	z= 0.76
Member of Environmental Group	15% (2)	14% (7)	z= 0.04
Voting Participation	82% (2)	81% (7)	z = 0.24
N	355	31	

[a] Sample statistics reported are for respondents who answered at least one of the three stated-preference questions.
[b] Standard deviations in parentheses.
[c]*** denotes significant at the 1% level.

Table 2.4 Number of Respondents Who Changed Votes for Forest Management Referenda between Pretest Survey and Posttest Survey

Pretest→Posttest	Question 1	Question 2	Question 3	Count
Yes→No	1	1	3	5
No→Yes	2	0	3	5
Total	3	1	6	9

Note: Yes=approve the new referendum; No=reject the new referendum.

Table 2.5 Forest Management Preference Parameter Estimates for On-site and Mail Surveys

Variables	Conditional Logit			Mixed Logit[a] Mail	
	Pretest	Posttest	Mail	Mean	Standard Deviation
Asc	-0.320	-0.248	0.018	0.095	
	(0.761)[c]	(0.820)	(0.176)	(0.188)	
Bid	-0.002**[d]	-0.003**	-0.001***	-0.002***	
	(0.001)	(0.001)	(0.000)	(0.000)	
Access	-1.533***	-1.106*	-0.536***	-0.622***	
	(0.543)	(0.574)	(0.143)	(0.163)	
H50	1.976***	2.862***	1.371***	1.554***	1.019*
	(0.600)	(0.687)	(0.183)	(0.270)	(0.534)
H100	-0.069	1.124	1.072***	1.257***	0.697**
	(0.707)	(0.723)	(0.186)	(0.250)	(0.331)
R70	0.498	0.962	-0.069	-0.032	
	(0.652)	(0.727)	(0.177)	(0.196)	
R100	0.645	1.373*	-0.037	-0.065	
	(0.663)	(0.751)	(0.172)	(0.191)	
Log-likelihood	-46.253	-40.609	-586.080	-583.227	
N	91	93	1056	1056	

[a] The mixed-logit model was not applied to the on-site data due to the limited number of observations.

[b] Only significant variances are reported for the mixed-logit estimation.

[c] Standard deviations in parentheses.

[d] *** denotes 1% level of significance, ** denotes 5% level of significance, * denotes 10% level of significance.

Table 2.6 Forest Management Preference and Scale Parameter Estimates for Pooled Samples

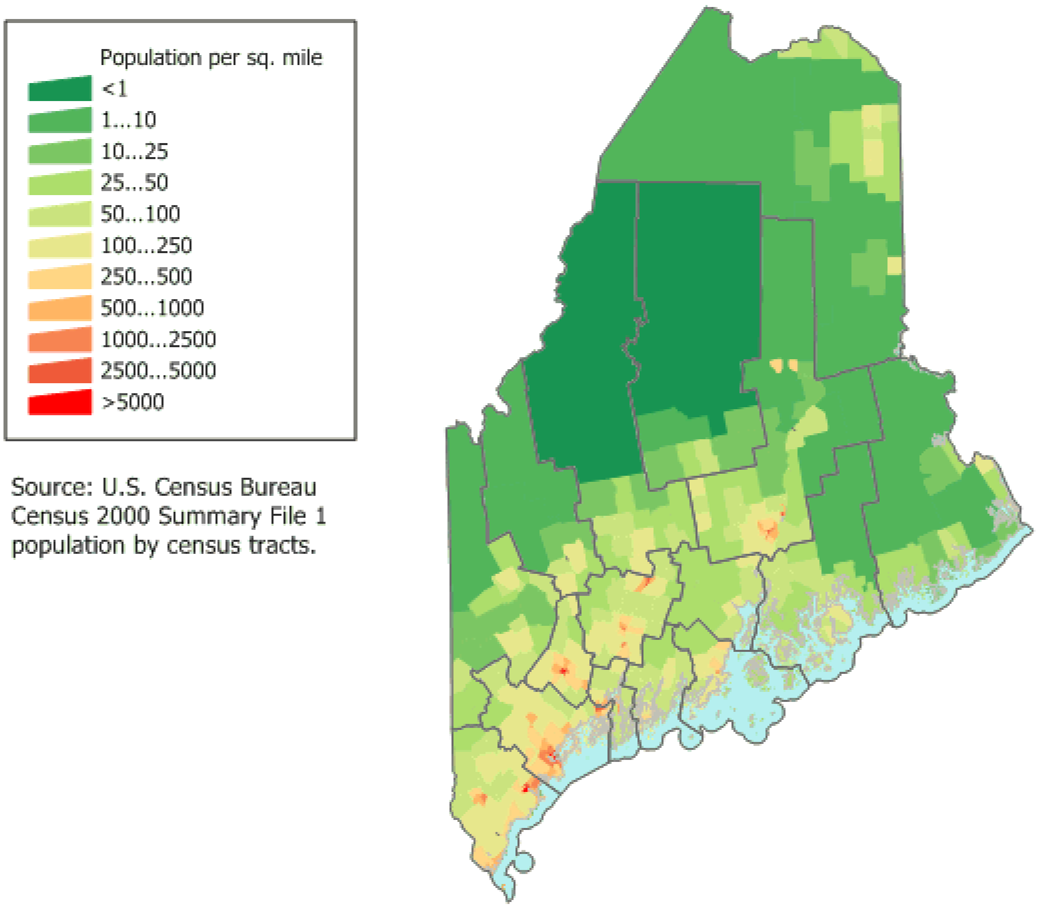
Variables	Pretest & Mail		Posttest &Mail	
	Restricted	Unrestricted	Restricted	Unrestricted
Asc	-0.023	-0.056	-0.021	-0.113
	(0.171)[a]	(0.168)	(0.171)	(0.163)
Bid	-0.001***[b]	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Access	-0.595***	-0.591***	-0.566***	-0.525***
	(0.137)	(0.133)	(0.138)	(0.127)
H50	1.416***	1.370***	1.491***	1.374***
	(0.173)	(0.167)	(0.175)	(0.160)
H100	1.020***	0.962***	1.109***	0.984***
	(0.177)	(0.172)	(0.179)	(0.164)
R70	-0.051	-0.055	-0.007	0.007
	(0.169)	(0.164)	(0.170)	(0.157)
R100	0.002	0.011	0.044	0.091
	(0.166)	(0.162)	(0.167)	(0.155)
$\mathrm{OS} * \mathrm{Asc}$	0.611**	0.658***	0.599	0.674***
	(0.245)	(0.197)	(0.245)**	(0.156)
μ[c]		1.335		1.949
Log-Likelihood	-636.979	-636.493	-632.524	-629.451
N	1147	1147	1149	1149

[a] Standard deviations in parentheses.

[b] *** denotes 1% level of significance, ** denotes 5% level of significance, * denotes 10% level of significance.

[c] μ represents the relative scale parameter of on-site pretest (or posttest) with respect to the mail sample with the scale parameter for the mail sample normalized to 1.

Figure 2.1 Maine Population Density



Source: http://www.worldofmaps.net/en/north-america/maine-usa/map-population-density-maine.htm

Figure 2.2 Stated-Preference Question

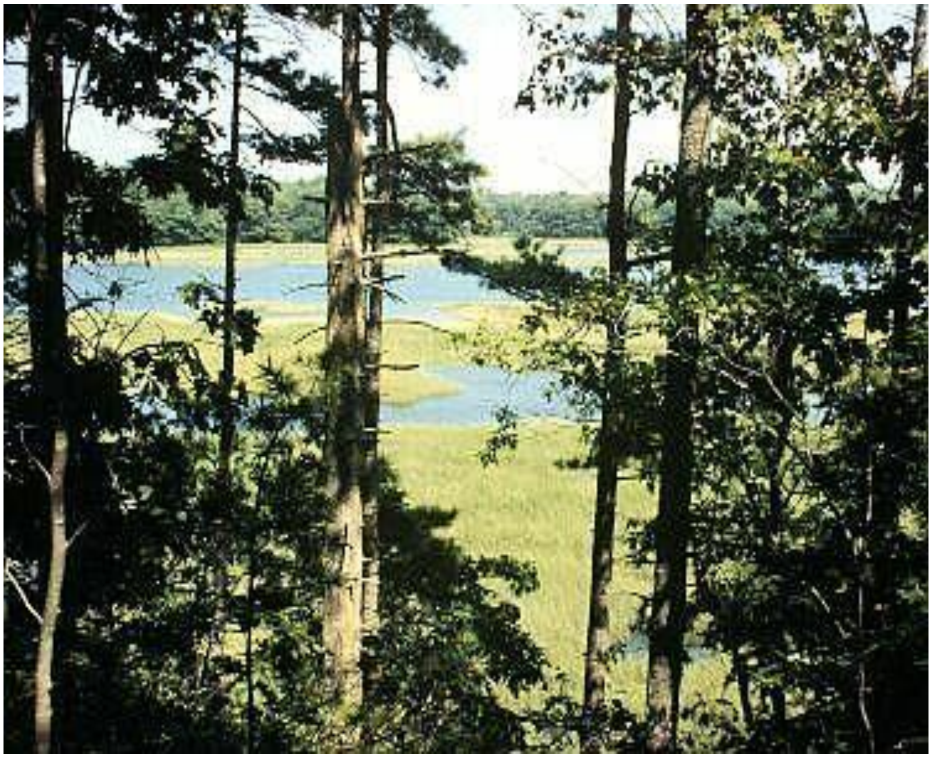
Now we would like to know how you would vote on each of the referendum options if they were put on the Maine election ballot next year. Please tell us if you would vote YES to approve or NO to reject each option. You can vote YES for more than one option. (CIRCLE YES OR NO FOR EACH OPTION).

How would you vote?

Referendum Options	Percent of land open for timber harvesting	Timber harvesting practices	Public access	Percent of property tax rebate to landowners	Cost to your family per year	(Circle YES or NO)
Current Condition in Maine	100	Forest Practices Act	Voluntary access	0	$0	
Referendum option 1						YES NO
Referendum option 2						YES NO
Referendum option 3						YES NO

Note: "percent of land available for timber harvesting" and "timber harvesting practices" are perfectly co linear. If 50% or 100% of the land is available for timber harvesting in one of the referendums, then "timber harvesting practices" would be low-impact forest practices.

Figure 2.3 The Holt Research Forest



Source: http://www.umaine.edu/holtforest/

Chapter III. On-site Experience Effect on the Preferences of Interest Groups for Forest Management

1. Introduction

There is a growing concern about the health of forest ecosystem, and the demand for forest management to promote forest health is increasing. Forest professionals propose alternative harvesting practices which are designed to simultaneously provide consistent timber production and protect the forest ecosystem. According to alternative harvesting practices, the landowners are required to harvest timber from their forests at regular intervals and set part of their land away from harvesting each time. These alternative harvesting practices could maximize the production of high quality timber, enhance wildlife diversity and abundance, and maintain the forests aesthetic qualities (Witham et al. 1993). Legislation and referendum could be imposed to regulate timber harvesting and incentive forest owners to undertake these alternative harvesting practices.

An understanding of the public attitudes and value toward forest management legislations would be helpful in the design and administration process. Forest owners and environmental activists are two interest groups that will be affected by the forest management decisions, they often actively participate and influence the design of forest management policies. The attitudes and perceptions of these stakeholders should also be jointly considered in the forest use strategies. However, as interest groups have diverse opinions on forest values, their preferences may not represent the preferences of the general public. They can have shared and also conflicting attitudes with the general public toward forest management policies.

The preferences of interest groups for forest management policies have been investigated for a long time (Bliss et al. 1994; Rantala and Primmer 2003; Watson and McFarlane 2004; Kant and Lee 2004). Researches have shown differences in preferences between interest groups (Kumar and Kant 2007; Berninger et al. 2009; Berninger et al. 2010). Foresters have a stronger preference for the economic use of the forest than Aboriginal groups, Environmental Non-government Organizations, and Ministry of Natural Resources (Kumar and Kant 2007), and they consider the current forest policies and stakeholders' power status more acceptable than the other citizens (Valkeapaa and Karppinen, 2013). The specialist forest users like cyclists, horse riders are more bio-oriented and exhibit higher values for improvements of recreation facilities in forests than the general users (Christie et al. 2007).

There are also studies that show the common attitudes among stakeholders. The attitudes of the general public are not significantly different from the non-industry private forestland owners for timber harvesting (Bliss 1994; Bliss 1997; Schaaf et al. 2006). In another study, campers and the public were found to share common bio-centric attitudes toward forest values (Watson and McFarlane 2004). And the values of open access right and forest ownership are broadly shared among stakeholders (Rantala and Primmer 2003).

This diversity of attitudes toward forest management policies are influenced by a lot of social and culture factors. Age, gender, education, income, religon and ethnicity are all factors which may affect environmental preference (Tarrant et al. 2003; Schaaf et al. 2006; Kumar and Kant 2007). In addition, the preferences among different interest groups can also change across time and region with different forest use conditions and history (Torgler and Garcia-Valinas 2007; Berninger et al. 2009; Berninger et al. 2010).

Knowledge and Experience with forest management has been shown to be important to obtain accurate valuation of environmental resources (Boyle et al. 1993; Cameron and Englin 1997; Hoehna and Randall 2002). For forest practices, research has shown that increased knowledge can raises public's acceptability of clear cutting (Bliss et al. 1997). Broussard et al. (2001) provided a series of educational experiences to American urban youth, and found that the participants changed their attitudes with timber harvesting and agreed that it could be beneficial. However, in another study McFarlane and Boxall (2003) used the number of correct responses to forest-related facts as an index for knowledge, and found that it is not correlated with campers' and hunters' attitudes about forest management.

There has been no research that investigated whether the difference of knowledge level affects attitude diversity among interest groups. Woodlot owners and environmental activists are more familiar with the functioning of forest ecosystems. The owners of forestlands have substantial experience with timber harvesting and are familiar with the effect of alternative forest management practices. On the other hand, environmental activists are more aware of the environmental consequences of timber harvesting, and the benefits from appropriate forest management. The public can also obtain their knowledge of forest ecosystem from social media and recreation activities. The differences in their knowledge level may influence their standpoints toward forest management policies.

In this study, we compare the preferences of different groups of individuals in a choice study of forest management practices. We randomly recruited study participants from three groups of individuals, an organization of small woodlot owners, an environmental group actively attempting to influence forest management policy and the general public. We provide an on-site treatment during the survey which ensures that all the groups share the same information about forest ecosystem and forest management for evaluation. Study participants were recruited to the research forest where half of the land is managed using low-impact timber harvesting procedures and the other half of the land is left as a natural area. Subjects completed a stated-preference survey on forest management practices when they arrived at the site (pretest), were led on walks through both sections of the forest, and then were re-administered the survey (posttest).

By providing an actual experience with the forest, the study intends to: (1) compare the perceptions of different groups for forest management policies, and (2) investigate whether the onsite experience affects the preferences among different individuals for forest management practices. The results show that there exists preference heterogeneity among interest groups and these differences still exists after the on-site experience. The on-site experience has not significantly changed the preferences towards forest management for each group. So the knowledge with forest management has little effect on the preference diversity among interest groups.

2. Survey Design

The on-site survey took place at Holt Research Forest, which is managed by the University of Maine. The forest has two sections; one half of the forest is managed for low impact timber harvesting (harvest section) and the other half of the forest is set aside from timber harvesting (no-harvest section). The trees in Holt Research Forest had arrived at maturity for timber harvesting, and the low impact harvest had been conducted for five years. Therefore, the visit to this forest could provide suitable information to the on-site participants of the effects on ecosystems from low impact timber harvesting.

2.1 Sample Recruitment

The recruitment of the on-site sample was conducted through phone calls. The sample of the small landowner group was drawn from the members of Small Woodlot Owners of Maine (SWOM) or from the landowners who had their land registered in the Maine's Tree Growth program. All of them needed to own more than 10 acres of land. The environment activists sample was drawn from the members of Maine Audubon's activist (MAA) who did not belong to the small landowner group. The general public sample was collected from Maine citizens via random digit dialing, and they did not belong to the two groups above.

The sample of small land owners and the general public were identified from the communities within one hour drive distance from the Holt Research Forest, and the environment activists lived in the town within one hour and half drive distance, since there were fewer samples available. In addition, subjects for the on-site survey were limited to individuals age 65 or younger due to the potential rigor of the walk through the forest. Individuals were paid a $40 incentive to compensate them for their travel time to the study site.

A total of 100 people participated in the study; 35 were owners of small forest holdings and members of SWOM, 34 were members of the Maine Audubon, and 31 were from the general public. The on-site sample was limited due to available budget, but mostly due to the logistics of on-site administration and the desire of the forest researchers that our experiment has minimal impact on the forest and on-going research.

2.2 Survey Administration

The subjects in the on-site sample were recruited to travel to the research forest and participate in the survey. All three groups responded to the same survey instrument, but the survey was administered to each group on a different day over three weekends. These on-site subjects completed a pretest administration of the survey when they arrived at the forest. They were then led by two graduate students to walk through the forest which took about 45 minutes. After the walk, all the participants got together, and answered the posttest surveys which were identical to the pretest surveys.

The walks followed transect lines that divided the forest into research plots and it was necessary to have someone lead subjects through the forest so both groups would follow the same routes and not walk across research plots.6 Two graduate students led the groups and stopped at designated sites in the forest for participants to observe the forest conditions. There are also cards to read which described the characteristics of the forest, so the participants could gain knowledge about different characteristics of the forest and the effect of harvesting. Stops included a harvest opening in the harvest section and a natural clearing in the no-harvest area of the forest, a skidder path across an ephemeral stream in the harvest section and an uninterrupted ephemeral stream in the no-harvest section, and wildlife habitat in the harvest section (slash – piles of brush and limbs left from harvesting) and no-harvest section (snags – standing dead or dying trees) of the forest.

2.3 Stated-preference Survey

The survey was designed and implemented following guidelines proposed by Dillman

[6] There were no visible signs of ongoing research that participants could observe during their walks through the forest. Transects were selected that avoided any flagging or other identification of research activities.

(2000 and 2007). A stated-preference question was employed where respondent were asked to vote on three alternative forestry referendums and each referendum was differentiated by program attributes (Figure 3.1). Respondents were informed about current conditions so that they would know what continuing forest management conditions would be if they voted “no”. The levels for each attribute are listed in Table 3.1. There are three levels for the “percent of land open for timber harvesting”, 100%, 50% and 0%. The attribute of “Timber harvesting practices” is low-impact harvesting when any of the referendums allow timber harvesting (100% or 50%). The “cost” amounts are based on a prior stated-preference study of forest policy in Maine (Boyle et al. 2001). A random design was used to assign the attribute levels to each choice situation, and there were at least one different attributes between each of the three alternative choice situations.

3. Model Specifications

3.1 Random Utility Model

Respondents are assumed to have a utility function U_i such that V_i is the observable component of utility and ε_i is the random error (McFadden 1973; Louviere et al. 2001):

$$U_i = V_i(x) + \varepsilon_i \tag{1}$$

where *x* is a vector of attributes from the forest management program. Assuming that the utility function is linear in parameters and ε has iid extreme value distribution, we obtain the conditional logit model.

$$\Delta U_i = \beta \Delta x_i + \Delta\varepsilon_i \tag{2}$$

The attribute variables (x) are defined in Table 3.2. The omitted levels for each of the attributes are “0% of land available for harvesting”, “30% property tax rebate to landowner”, and “voluntary access”. We employed the conditional logit model to estimate the preferences for all three interests groups seperately in the pretest survey and the posttest survey.

3.2 Hypothesis Test

To investigate if pretest and posttest respondents have different preferences for the referendum attributes we test the null hypothesis that their parameter estimates are statistically indistinguishable from each other.

$$H_0\!: \ \beta_{\text{before}} = \ \beta_{after} \text{ vs. } \ H_a\!: \ \text{not } H_0 \qquad \text{(H1)}$$

Unlike linear regression parameters, in the estimation of logistic models ε_i is standardized to have a variance of 1, so estimated parameter estimates ($\hat{\rho}$) are confounded with the variance ($\rho = \mu\beta$), where μ is the scale parameter, $\mu = 1/\sigma$ and σ is the standard error. Thus, the true preference parameter vector is β, but we observe $\hat{\rho}$.

We apply the method described by Swait and Louviere (1993) to calculate the relative scale parameter and test whether the scale parameter and preferences are the same between pretest and posttest surveys. First, we calculate the likelihood ratio test statistics $\lambda_1 = -2[L_\mu - (L_{before} + L_{after})]$ to check whether the preferences for all the attributes are equal. L_μ is the log likelihood value from the pooled sample after adjusting for the relative differences in scale parameters. L_{before} is the log likelihood value for the estimation with the pretest data and L_{after} is the log likelihood value from the posttest data.

If we cannot reject the null hypothesis, we test the hypothesis that the scale parameters are equivalent:

$$H_0: \mu_{before} = \mu_{after} \quad \text{vs.} \quad H_a: \text{ not } H_0. \tag{H2}$$

These hypothesis tests are conducted using the likelihood ratio test statistics, $\lambda_2 = -2(L_p - L_\mu)$. L_p is the log likelihood value from the pooled sample regression with the scale parameter restricted to be equal. Both test statistics λ_1 and λ_2 are asymptotically chi-squared distributions with *k* degrees of freedom, the number of restrictions imposed by the test.

We follow the above steps to test the preference differences between pretest survey and posttest survey separately for all three interest groups. We also follow the same procedure to test the preference differences of interest groups between each other in the pretest survey or the posttest survey.

4. Results

Summary statistics of respondents' socioeconomic characteristics are reported in Table 3.3. We use t test, z test and chi-square test to identify whether these groups of respondents have the same socioeconomic characteristics. The environment activists and the public have the same proportion of gender and mean of age, while the woodlot owners have more males and are much older. The woodlot owners and the environment activists have higher household income and education levels than the general public. Moreover, woodlot owners and environmental activists are more actively involved in forest management than the general public. These differences of socioeconomic characteristics may also affect the perception and attitudes toward forest management. However, here we will not include these effects into our analysis. We would focus on the preference differences in these sample frames.

4.1 Estimation Results for Interest Groups

Estimation results of the conditional logit models for every interest group are summarized in Table 3.4. The preferences of woodlot owners are significantly influenced by the choice attributes of public access and 100% of land available for timber harvesting in both the pretest and posttest. Requiring public access to private land reduces the probability of an affirmative vote and 100% of land available for timber harvesting increases the probability of an affirmative vote. For environmental activists and the general public, the cost to households (*Bid*) has a significantly negative effect on their choice decisions. Splitting the land evenly with 50% available for timber harvesting and 50% set aside from timber harvesting increases the probability of an affirmative vote. For the general public, requiring public access to private land also has a significant negative effect on their choice decision.

4.2 Tests of Preference Parameter Equivalency

The results for the comparison of preference parameters between groups and surveys are shown in Table 3.5. For all interest groups, we cannot reject the null hypothesis that the preference parameters and the scale parameters are the same between pretest and posttest survey.

The comparisons among interest groups in the pretest survey shows that there exist preference differences between each pair of interest groups. The null hypothesis that the preferences of woodlot owners and environmental activists (general public) are the same is rejected at 1% level. The null hypothesis that the preferences of environmental activists and general public are the same is rejected at 10% level. The preference difference between environmental activists and the general public is relatively smaller than the difference between woodlot owners and the general public. We cannot test the null hypothesis of no difference in the scale parameters between the interest groups as we reject the null hypothesis of no difference in preference parameter estimates in the first step.

5. Conclusion

The results indicate that stated preferences for forest attributes do not vary between the pretest and posttest of surveys for all three interest groups. However, preference differences exist among the three interest groups both in the pretest and posttest survey. This suggests that the preference of interest groups (woodlot owners and environmental activists) do not represent the preference of the general public for proposed forestry programs. Furthermore, this preference heterogeneity does not just come from a lack of knowledge or experience with forest management. These results indicate that the lobbying on forest policy by SWOM and Maine Audubon, which satisfies the preferences of their respective members, may not be representative of the preferences of the general public. Thus, policy makers must seek information on the preferences of the general public when making forest policy and not assume that the input of interest groups is sufficient to design policies that maximize public benefits.

The sample sizes are small due to the logistics of administering the study on-site at the experimental forest. Future research should include larger on-site samples as budgets and study site conditions permit. Then the sample would make a better representation of the preferences for forest attributes and provide more reliable hypothesis testing. We should offer more attribute levels of choices in the stated-preference questions which would be helpful to identify the preferences for any individual.

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Table 3.1 Attributes and Levels

Attributes	Levels
Property tax rebate to participating landowners	30% 70% 100%
Percentage of land available (set aside) for timber harvesting	0% (All set aside) 50% 100% (None set aside)
Public Access to land of participating landowners	Voluntary Required
Cost per household	$1, $20, $40, $60, $80, $100, $120, $160, $180, $200, $400, $800, $1600

Table 3.2 Definitions of Variables

Variables	Definitions
Bid	Negative value of cost per household
Access	1 if public access is required and 0 otherwise
H50	1 if 50% of "land available for harvesting" and 0 otherwise
H100	1 if 100% of "land available for harvesting" and 0 otherwise
R70	1 if 70% "Property tax rebate to landowner" and 0 otherwise
R100	1 if 100% "Property tax rebate to landowner" and 0 otherwise
Asc	1 if the alternative represents referendum conditions and 0 if current condition

Table 3.3 Socioeconomic Characteristics of Respondents

	Woodlot Owner (W)	Environmental Activist (E)	General Public (G)	Test Statistics
Gender	79%	34%	42%	W&E: z=3.62***[a]
(male=1)	(7)[b]	(8)	(9)	W&G: z=3.02***
				E&G: z=0.62
Average Age	50	44	42	W&E: t=2.72***
	(2)	(2)	(2)	W&G: t=3.49***
				E&G: t=0.86
Average Household Income	\$64,833	\$58,485	\$43,448	W&E: t=0.93
	(5,060)	(4,542)	(4,459)	W&G: t=3.17***
				E&G: t=2.36**
Education				
High school graduate or equivalent	0%	0%	18%	W&E: x^2=2.37
Some college, A.S degree or technical school	21%	9%	29%	W&G: x^2=11.63**
B.A. degree or equivalent	33%	30%	39%	E&G: x^2=18.26***
M.A degree or equivalent	33%	45%	7%	
Advanced degree	12%	15%	7%	
Voting Participation	94%	97%	81%	W&E: z=0.56
	(4)	(3)	(7)	W&G: z=1.61
				E&G: z=2.05**
Observations	35	34	31	

[a] *** denotes 1% level of significance, ** denotes 5% level of significance, * denotes 10% level of significance. Standard deviations in parentheses.
[b] Standard deviations in parentheses.

Table 3.4 Preference Parameter Estimates for Interest Groups

	Woodlot Owner	Environmental Activist	General Public
Pretest Survey			
Asc	0.260	0.815	-0.320
	(0.721)	(0.569)	(0.761)
Bid	-0.0003	-0.0009*	-0.0016**
	(0.0006)	(0.0005)	(0.0007)
Access	-1.647***	-0.530	-1.533***
	(0.529)	(0.462)	(0.543)
H50	0.549	2.348***	1.976***
	(0.89)	(0.643)	(0.600)
H100	1.501**	0.633	-0.069
	(0.644)	(0.531)	(0.707)
R70	1.692***	-0.0394	0.498
	(0.652)	(0.594)	(0.652)
R100	0.506	-0.534	0.645
	(0.636)	(0.575)	(0.663)
Log-likelihood	-50.889	-58.396	-46.253
N	102	102	91
Posttest Survey			
Asc	0.223	0.525	-0.248
	(0.912)	(0.581)	(0.820)
Bid	-0.0007	-0.0020***	-0.00290**
	(-0.0008)	(0.0007)	(0.0013)
Access	-1.801***	-0.113	-1.106*
	(0.674)	(0.475)	(0.574)
H50	1.183	2.290***	2.862***
	(0.821)	(0.707)	(0.687)
H100	2.707***	-0.054	1.124
	(0.871)	(0.536)	(0.723)
R70	1.309	-0.435	0.962
	(0.825)	(0.608)	(0.727)
R100	1.046	-0.247	1.373*
	(0.815)	(0.594)	(0.751)
Log-likelihood	-36.388	-55.378	-40.609
N	93	102	93

Table 3.5 Hypothesis Test Results for Comparison between Groups and Surveys

	H1	H2
Comparison between pretest and posttest surveys		
Woodlot Owner	0.867	0.154
Environmental Activist	0.808	0.598
General Public	0.908	0.347
Comparison between groups for pretest survey		
Woodlot Owner & Environmental Activist	0.002	
Woodlot Owner & General Public	0.008	
Environmental Activist & General Public	0.098	
Comparison between groups for posttest survey		
Woodlot Owner & Environmental Activist	0.000	
Woodlot Owner & General Public	0.001	
Environmental Activist & General Public	0.077	

Note: H1 represents the null hypothesis test for the equivalency of preference coefficients; H2 represents the null hypothesis test for the equivalency of scale parameter.

Figure 3.1 Stated-Preference Question

Now we would like to know how you would vote on each of the referendum options if they were put on the Maine election ballot next year. Please tell us if you would vote YES to approve or NO to reject each option. You can vote YES for more than one option. (CIRCLE YES OR NO FOR EACH OPTION).

How would you vote ?

Referendum Options	Percent of land open for timber harvesting	Timber harvesting practices	Public access	Percent of property tax rebate to landowners	Cost to your family per year	(Circle YES or NO)
Current Condition in Maine	100	Forest Practices Act	Voluntary access	0	$0	
Referendum option 1						YES NO
Referendum option 2						YES NO
Referendum option 3						YES NO

Note: "percent of land available for timber harvesting" and "timber harvesting practices" are perfectly co linear. If 50% or 100% of the land is available for timber harvesting in one of the referendums, then "timber harvesting practices" would be low-impact forest practices.

Chapter IV. The Effect of Spatial Interpolation on Property Value Models: a Case of Forest Pest Damage

1. Introduction

Property value modeling is a commonly employed method to value changes in environmental assets based on the idea that the prices of properties represents the sum of values associated with property attributes (Palmquist 1991). Recent years have seen important developments and refinements in the property value method, which include natural experiments to identify price effects, access to large-scale electronic data on property sale prices and characteristics, and the use of GIS (geographic information system) data to incorporate spatial dimensions of property attributes (Calhoun 2001, Parmeter and Pope 2009, Paterson and Boyle 2002).

When an investigator wishes to merge property sale data with spatial data on an environmental amenity, one problem encountered in the matching process is that the environmental data may be limited (Palmquist and Smith 2001). Although environmental data varies across broad geographical area, these data are usually measured at certain sample sites. For example, if one is interested in how air quality affects property prices, the property data may include all sales in a given area for a specified period of time while the air-quality data is collected at fixed monitoring sites[7]. The air quality data is measured continually doe discrete, but small increments in time, e.g., hourly. For other environmental media, in addition to being spatially discrete, the data may only be reported for specific points in time and the timing of

[7] http://www.epa.gov/airquality/airdata/, accessed December 12, 2013.

measurements may vary across sites, e.g., volunteer lake water quality monitoring[8]. A challenging task is how to scale or extrapolate site and or time specific environmental data to all property sales within a defined geographical area.

Some investigators have explored this challenge in the context of air pollution using spatial extrapolation procedures such as Kriging (Beron et al. 2001). Ara et al. (2006) interpolated beach water quality data over space and time. Both air and water quality, within a specific area, such as an air quality basin or coastal bay might be consider ubiquitous, in that pollutants disperse out from emission sites and perhaps experience some rate of decay over distance and/or time.

In this chapter, we explore a different, yet important, type of data. Here we investigate the effect of spatial data extrapolation on the estimation of hedonic model and repeated sale model in the context of an invasive forest pest, the hemlock wooly adelgid (Brush, 1979, McClure 1991, Orwig et al., 2002). Here the data on the infestation are measure at discrete spatial locations and points in time like for the water and air quality data, but the host (hemlock trees) does not provide for continuous dispersal through space. Hemlock trees are clustered in discrete stands and, thus, the infestation must jump from stand to stand as the infestation spreads spatially through time. We investigate the effect of different methods of spatial data interpolation on the estimation of a hedonic property value model and a repeated sale model.

We investigate the use of three spatial data interpolation methods:

- inverse distance weighting (IDW),
- splines and

[8] http://water.epa.gov/type/watersheds/monitoring/vol.cfm, accessed December 12, 2013

- Kriging.

We also consider data interpolation error across approaches and the effects on the estimated property value models.

It is thought that changes in climate may increase the frequency and severity of forest fires, insect and disease outbreaks, droughts and storms that can affect trees (Dale et al., 2001; Bentz, 2008; Frankel, 2008). The subsequent losses of trees can impact property values via reductions in shading to reduce heat impacts, reductions in the scenic aesthetics of an area and other consequences. Dying and dead trees can pose risks to residents and their homes. The hemlock wooly adelgid, as an example case study, causes death of affected trees within about five years. Forward-looking communities can adapt their tree planting and protection efforts to lessen these climate-induced impacts and information on the economic value of tree canopy cover can be used to help justify such efforts. Thus, exploring the impacts of data extrapolation to investigate the economic effects of forest impacts is important to support forest and climate policy.

Our results indicate that the invasion of HWA has caused dramatic losses of healthy hemlock stands in the study area. Both the hedonic model and repeated sale model show that there exist substantial accompanying losses in property value for the households nearby. Spatial interpolation methods provides us useful tools to scale up our economic analysis.

2. Literature Review

Spatial interpolation is one well developed methodology in environmental science (Burrough and McDonnell 1998, Webster and Oliver 2001). Inverse distance weighting (IDW), splines and Kriging techniques have all been widely used to predict spatial variables in a forestry context (Biondi et al. 1994; Köhl and Gertner 1997; Gunnarsson et al. 1998; Jansen et al. 2002). For example, Figueiredo-Filho et al. (1996) employed spline technique to evaluate stem diameters and volumes of trees in southern Brazil. Wulff et al. (2006) also conducted Kriging to estimate geographical distribution and dispersal of forest damage from the outbreak of Gremmeniella based on the National Forest Inventory dataset. Malhi et al. (2006) employs three techniques, inverse distance weighting spline and Kriging to interpolate the biomass in old-growth Amazonian forests. Their cross-validation results showed IDW is the most appropriate method although its algorithm is least sophisticated.

These spatial interpolation methods has not commonly employed in economic research except for the evaluation analysis of air pollution. The reason is that the air pollution is only measured at several monitoring stations, while the households are located across the space. Previous researches employed spatial statistical method to interpolate the air condition measurements across study area and then match them with the household sales value based on their locations (Kim et al. 2003, Beron et al. 2004, Anselin and Lozano-Gracia 2008, Fernandez-Aviles et al. 2012).

Ara et al. (2006) has also met the same challenge when they try to evaluate the economic impact from water quality. The water quality along 18 beaches was originally measured at different place and at different time. They also employed geo-statistical method to interpolate the water quality and matched the household properties with the interpolated water quality of the nearest beach.

However, there are seldom studies which investigate how spatial interpolation will affect our hedonic economic analysis when we use prediction results rather than the true measurements in the property vale models. Anselin and Le Gallo (2006) have compared different spatial interpolation techniques (Thiessen polygons, inverse distance weighting, Kriging and splines) when their prediction results are used as the measurement of air quality in the hedonic models. Their results showed that Kriging provides the best results for interpretation.

In our case, we try to investigate the economic losses from hemlock mortality caused by HWA infestation. Holmes et al. (2010a) found that severely-defoliated hemlocks in northern New Jersey reduced the values of residential parcels with the stricken trees and reduced the value of nearby (up to 0.5km) properties. In our study, we employ the interpolation approach (inverse distance weighting, Kriging and splines) to scale up the analysis from specific area (e.g., county) to state level. We also investigate how different spatial interpolation methodologies would affect the hedonic model and repeated sale model analysis.

Different with Anselin and Le Gallo (2006), we first employed cross-validation methods to compare the prediction accuracy among interpolation methods before making property value analysis. Because of our data structure, we can also compare the property value analysis results based only on sampled hemlock damage data (true measurements) with the results based on interpolated data (prediction results). As the hemlock stands are spread discrete over space, and the outbreak of HWA infestation may not always happen continuous through space. There are much more variation of the sampled HWA damage data compared to the measurement of air pollution. And here we will check how the spatial interpolation methods would affect the inference from property value models in this data structure.

3. Modeling Framework

In the property value model analysis, when we value changes in environmental assets, the property value are assumed to be influenced by different attributes, like house-specific characteristics, land cover characteristics, and environmental characteristics.

In the empirical analysis, we would need to match the environmental attributes with household sales. However, the measurements of environmental attributes would be limited which are usually measured at specific sites. Even if they are representative of the environmental characteristics over study area, the property sales data at these sampled sites may not be representative of all the property values. When we only consider the impact at these specific sites, we would lose the information from property sales data over large spatial area.

For instance, in this study we assume only when the hemlock stands locate within certain distance of households, they will affect the property value. Then, there are four types of locations between household properties and hemlock stands (Figure 4.1). In case A, the buffer only intersects with sampled hemlock stands. In case B, the buffer intersects with both the sampled and non-sampled hemlock stands. In case C, the buffer intersects only with the non-sampled hemlock stands; we do not have the hemlock damage information. In case D, the buffer does not intersect with any hemlock stands; these properties are assumed to not be affected by the HWA infestation.

Based on the sampled data, we only have the full hemlock damage information for case A. However, as the number of household properties which are only influenced by sampled hemlock stands is small, it may not be representative of the whole study area. We can also employ sampled hemlock damage information to check the impact of HWA infestation on properties in case B. However, we would miss the information of non-sampled stands which could bias our estimates.

To make the maximum use of household sale data, we would want to interpolate the environmental damage to the whole study area and match them with the sales data. In our case, using interpolated hemlock damage data, we would be able to enlarge our economic analysis to all the household sales which are influenced by HWA infestation (case A, B and C in Figure 4.1). However, as we employ prediction results rather than the true measurements in the property value model, the prediction error induced by different spatial interpolation methods can also affect the validation of our property value model. Here we would conduct our model analysis in case A & B, case A and case A, B & C. Comparison of these estimation results in all these cases would show the most reliable method to analyze the economic losses caused by HWA.

4. Description of the Study Area

In the research here, our application is to estimate the economic consequences of the spatial and temporal expansion of HWA through central Connecticut and Massachusetts. The HWA was first introduced into Virginia from Japan in the early 1950s; in the past half-century, it has spread to hemlock forests along the east coast of the U.S and became a threat to the eastern hemlock forests of New England (McClure 1991). The population growth of HWA is sensitive to temperature and precipitation, and climate change is expected to favor the spread of HWA (Orwig et al., 2002).

In an effort to understand and characterize hemlock stands at the local and landscape levels in New England, ecologists at the Harvard Forest identified, mapped, and characterized hemlock stands within a 7,500 km^2 area covers central portions of Connecticut and

Massachusetts (see Figure 4.2). In both states, all stands of eastern hemlock >1.3 ha in area were identified using high-resolution aerial photographs that were then scanned and digitally transferred into a GIS overlay. A total of 6,126 hemlock stands were identified in the study area using this method.

The field surveys were conducted at 142 hemlock stands (red dots in Figure 4.2), and hemlock health characteristics were documented in these sampled stands. The sampled stands were distributed as evenly as possible over the study area. Hemlock vigor and live basal area are two key hemlock damage characteristics recorded in 2007, 2009, and 2011. Live basal area (m^2/ha) is the area of a given section of land that is occupied by the cross-section of tree trunks and stems at their basal. Vigor was measured on the basis of the amount of retained foliage in each stand. There are four vigor categories; 1 = 0 – 25% foliar loss, 2= 26-50% foliar loss, 3 = 51-75% foliar loss and 4 = 76 – 99% foliar loss.

Table 4.1 shows the summary descriptive statistics of live basal area and frequency distribution of hemlock vigor for the sampled hemlock stands. Both the mean and maximum value of hemlock live basal area decreased between 2007 and 2011. Except for the severely damaged hemlock stands (vigor=4), the number of damaged hemlock stands (vigor=2 or vigor=3) is increasing through time while the number of healthy hemlock stands (vigor=1) is decreasing. It is likely that the number of severely damaged hemlock stands dropped in 2011 because dead trees either fell over or were removed, and were no longer included in the survey.

To investigate the effect of HWA infestation on residential property, we select three groups of household properties which are located around the hemlock stands within a distance of 0.1km, 0.5km or 1km. DataQuick provides the dataset which contains all the house attributes and sales price during the study years (2007-2011). Lot size, living area, number of bath rooms, house age and distance to highway are included as housing characteristics. We also introduce dummy variable *AC* and *fireplace* to indicate whether the house has air conditioning and fireplace.

Land cover in the neighborhood can also influence the household property value (Irwin 2002; Patterson and Boyle 2002). We constructed land cover variables based on National Land Cover Data (2006) using raster of $30m^2$ pixels. The six different types of land cover variables constructed are water, open space, high developed district, forest, agricultural land and wetland. They are calculated as the percentage of the buffer area around household property which is covered by the each land type, while the size of the buffer is respectively 0.1km, 0.5km, or 1km corresponding for each group.

In Table 4.2, we list the summary statistics of housing characteristic variables for properties of group <1km. We calculate summary statistics separately for the group of properties located near the sampled stands and in the sampled years, and for the group of properties located near all the hemlock stands which were saled out from 2007 through 2011. Comparing the summary statistics, we can see the housing characteristics and land cover characteristics are similar between the two groups.

5. Spatial Interpolation

We first employ the geo-statistic interpolation methodologies to scale up our hedonic analysis and predict the spatial distribution of forest damage data; they are based on the assumption that the values should be more similar when the points are near to each other. Inverse distance weighting (IDW), Spline and kriging are three interpolation methodologies commonly applied in the forestry studies; they are readily available in the geo-statistical wizard of Geostatistical Analyst Tool in ARCGIS 10.1.

5.1 Inverse Distance Weighting Interpolation

Inverse distance weighting (IDW) assigns values of hemlock damages to unknown points with a weighted average of the values observed at the locations in the neighbor. It gives greater weights to points closest to the prediction location, and the weights diminish as a function of distance (Shepard 1968). An interpolated value u at non-sampled point x using IDW is:

$$u(x) = \frac{\sum_i w_i(x) u_i}{\sum_i w_i(x)} \quad (1)$$

Here u_i denotes the hemlock damages at sampled point x_i, $i = 0,1,\cdots N$. $w_i = \frac{1}{{d_i}^p}$ while d_i is a given distance from the known point x_i to the unknown point x. p is the power parameter which is set equal to 1 here for all the following cases.

5.2 Spline Interpolation

The Spline tool estimates values of non-sampled points using a mathematical function that minimizes overall surface curvature, resulting in a smooth surface that passes exactly through the input points (Franke 1982; Mitas and Mitasova 1988). We applied a Tension spline here as it provides the best fit based on the cross validation results. The algorithm is as following:

$$u(x) = \alpha + \sum_{i-1}^{N} \frac{\lambda_i}{2\pi\varphi^2} [\ln\left(\frac{d_i\varphi}{2}\right) + c + K_0(d_i\varphi)] \quad (2)$$

Here α and λ_i are coefficients found by the solution of a system of linear equations; c is a constant number. K_0 is the modified Bessel function. d_i is a given distance from the known point x_i to the unknown point x. φ^2 is the weight parameter which determines the smoothness of the surface. The Kernel Parameter here is calculated by minimizing the root mean square error during cross validation.

5.3 Kriging Interpolation

Kriging predicts the value at a non-sampled location using the weighted average of the known values of its neighbors while the weights are determined by a semivariogram model of spatial autocorrelation (Isaaks and Srivastava 1989; Cressie 1993; Goovaerts 1997; Schabenberger and Gotway 2005). The semivariogram model follows the pattern described in Figure 4.3 (Stein 1999). The semivariance is

$$\rho(h) = \frac{1}{2n}\sum_{i=1}^{n}(u(x_i) - u(x_i + h))^2 \qquad (3)$$

where x_i represents any sampled hemlock stand, $(x_i + h)$ is a sampled stand distance h from x_i, $u(\cdot)$ is the observational value at the sampled location.

The parameters of function form, range, nugget effect and sill are estimated which define the empirical semivariogram model (Cressie 1985; Chilès and Delfiner 1999). Nugget is the semivariance at distance 0 which is defined as measurement errors. Range is the distance at which the semivariance levels off, while sill is the semivariance at the distance of range.

Here the spatial correlation is assumed as isotropic over the study area, i.e. that the spatial correlation is only depending on the distance between two points but not the direction of their separation. As the infestation of HWA has the potential to move from southwest to northeast, we make trend analysis at first. A second-order polynomial trend is removed at first if there exists significant trend over space, while the kriging analysis is performed on the residuals. After kriging over the surface, this trend will be added back to the predicted values and create the final prediction results. Both the simple kriging and ordinary kriging interpolation methods are applied. It depends on which method provides the best fit based on the cross validation results.

Cross validation is used to evaluate which model provides the best predictions. Cross validation is performed by removing one point from data set and then predicting its value using the data at the rest locations. Comparing the predicted value to the observed value across all the points, we can obtain the measurements for evaluation. To have a good fit of the model, the mean standardized prediction error (MSE) should be close to 0, root mean square error (RMSE) should be small, and the root mean squared standardized error (RMSS) should be close to 1.

$$MSE = \frac{\sum_{i=1}^{n}(\widehat{u_i} - u_i)/\hat{\sigma}_i}{n} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{u_i} - u_i)^2}{n}} \tag{5}$$

$$RMSS = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{u_i} - u_i)^2/\hat{\sigma}_i}{n}} \tag{6}$$

6. Model Specification

Live basal area and vigor are two key hemlock damage variables that have the potential to induce economic losses for the residential property nearby. Based on the interpolation methodologies described above (IDW, Spline and Kriging), we interpolated both hemlock live basal area and vigor separately for each year over the whole study area. Both the live basal area and vigor are interpolated directly as continuous variables.

The value of live basal area and vigor for the 6,126 hemlock stands are then extracted from the interpolated space based on 200m ×200m grid. They are calculated as the mean of interpolated value for covered spatial area. Then for each household property, the measurements for live basal area and vigor are calculated by the mean of the hemlock stands which intersects with the buffers (0.1km, 0.5km, or 1km) around the household properties. For 2008 and 2010, they are calculated as the mean value of the previous year and following year. Live basal area (lba_{it}) and the interaction between live basal area and vigor ($lba_{it} * vigor_{it}$) are included in the model as the measurements for environmental attributes.

6.1 Traditional Hedonic Model

For the traditional hedonic model, the household property value would be affected by different attributes, house-specific characteristics Z_i, land cover characteristics L_i, and environmental characteristics E_{it} (lba_{it} and $lba_{it} * vigor_{it}$). The fixed effect panel models are commonly used to handle the problem with other spatially correlated omitted variables as Equation (7).

$$\ln P_{it} = Z_i\alpha + +L_i\beta + lba_{it}\gamma + lba_{it} * vigor_{it}\theta + \tau_t + \omega_j + \varepsilon_{it} \tag{7}$$

Here P_{it} is the sale price for property i at time t in the semi-logarithmic function form. τ_t is the time effect, and ω_j is the spatial effect.

The house-specific characteristics Z_i include lot size, living area, number of bath rooms, house age, air conditioning, fireplace and distance to highway. The land cover characteristics L_i include the percentage of buffer area covered by water, open space, high developed district, forest, agricultural land and wetland. The time effect is set as dummy variables from 2007 to 2011, while the spatial fixed effect is set based on zip code.

According the hedonic estimation result in equation (7), the marginal effect of hemlock damage on property value is

$$\frac{\partial lnp}{\partial vigor} = lba_{it}\theta \quad (8)$$

$$\frac{\partial lnp}{\partial lba} = \gamma + vigor_{it}\theta \quad (9)$$

6.2 Repeated Sale Model

One concern with the traditional hedonic model is that the property value is affected by lots of characteristics. When the missing attributes in the error term are correlated with the attribute variables in the model, the coefficients could be biased. One way to deal with this problem is to employ repeated sale model. The repeated sale method starts with the assumption that the change of price value is only introduced by the change of household characteristics. Then by taking difference between two sales from one property, the effects from fixed attributes would be can cancelled out. Then the model turns to be

$$\ln P_{it} - \ln P_{it-1} = (lba_{it} - lba_{it-1})\gamma + (lba_{it} * vigor_{it} - lba_{it-1} * vigor_{it-1})\theta + \tau_t + \omega_j + \varepsilon_{it} \quad (10)$$

Here τ_t and ω_j are employed to capture the time effect and spatial effect. τ_t is the year of the most recent sale.

7. Results

7.1 Spatial Interpolation

Live basal area and vigor are separately interpolated over space for the sample years of 2007, 2009 and 2011. Cross validation results for interpolation methods of IDW, spline, and Kriging are listed in Table 4.3 which indicates relatively accurate predictions of our models.

Mean prediction error (ME) and root mean square error (RMSE) are available for all three interpolation methods, while mean standardized prediction error (MSE) and root mean square standardized error (RMSS) are only available for kriging. The cross validation results of ME and RMSE are similar across interpolation methods, while different interpolation methods provide best predictions in different years. Thus, it is hard to tell which method provides better interpolation results only based on cross-validation results.

The summary descriptive statistics of interpolated live basal area and vigor for hemlock stands (n=6,126) are shown in Table 4.4. The data in Table 4.4 shows the large decrease in the size and health level of hemlocks in the study area from year 2007 to year 2011. Comparing three interpolation methods, we can see the differences of predicted values among three interpolation methods. The mean predicted values from three interpolation methods are generally similar, while the standard deviation of the predicted values exist differences. Especially, kriging provides the smallest standard deviation for live basal area and vigor in 2011 with highest minimum value and lowest maximum value.

The interpolated live basal area over the study area for each year based on kriging is shown in Figure 4.4. Through time we see the live basal area has declined (blue areas disappear and purple areas increase substantially). In year 2007, the maximum of interpolated live basal area is about 77 m2/ha. In year 2011, the interpolated live basal area over all the study area is not larger than 20 m2/ha.

The interpolated probability of healthy hemlock stands (2007-2011) based on kriging is shown in Figure 4.5. The change of the hemlock vigor follows the same pattern as live basal area; the purple area decreases substantially. Overall, the data reveals the HWA infestation in

2007 was primarily in southern Connecticut and the hemlocks in Massachusetts were generally healthy. By 2011, a period of four years, the HWA infestation had spread substantially into Massachusetts.

7.2 Sampled Data Analysis

First, we estimate the hedonic model only based on sampled stand data. The estimation results including household properties of case A and B in Figure 4.1 are listed in Table 4.5, while the estimation results only including household properties of case A are listed in Table 4.6. Both tables include estimation results based on three different estimation models. The first estimation model is based on hedonic model including all the sale observations from 2007 to 2011. The second estimation model is also based on hedonic model which only include the most recent sale observation for each property. The last estimation model is based on repeated sale model which only include the last two sale observations for each property.

From the estimation results, we can see that the coefficients of live basal area and its interaction with vigor is insignificant in buffer 0.1km, however, their signs are consistent with intuition. But these coefficients are significant with incorrect sign for buffer 0.5km and 1km. The sample size is too small to conduct repeated sale analysis. We only employ the repeated sale model in buffer 1km for case A&B. The result shows that the effects from live basal area and vigor are insignificant.

As the sample size is quite small for the sampled stand data, they may not be representative of the impact in the whole study area. Especially for buffer 0.1 km, the standard error may be too large to get any significant results. The incorrect signs of coefficients in buffer 0.5 km and 1 km may be caused by the missing variables in the error term are correlated with the variable of live basal area or vigor. Then the estimation results can be biased. These results incentive us to investigate the hemlock damage effect in larger spatial scale.

7.3 Interpolated Data Analysis

We estimate the property sale models based on interpolated data of hemlock damage from all three interpolation methods. The estimation results based on these three interpolation methods (IDW, Spline and kriging) are separately listed in Table 4.7, Table 4.8 and Table 4.9. From the estimation results base on IDW interpolation method, we can see that live basal area has significant positive effect at 10% level for both hedonic models at all three buffer sizes. The interaction between live basal area and vigor has significant negative effect at 10% level for buffer sizes of 0.1km and 0.5 km. From the estimation results base on spline and kriging interpolation method, the coefficients for both live basal area and its interaction with vigor are significant at 10% level for hedonic models with all buffer sizes.

However, in the repeated sale model, the coefficients for live basal area and vigor are only significant at 10% level for 0.1km buffer based on the interpolated methods of IDW and spline. In the estimation model based on kriging interpolation method, they are significant at 5% level for 0.1km buffer, and live basal area is also significant at 10% level for 0.5km.

Comparing the magnitude of coefficients for live basal area and its interaction with vigor, they are decreasing with the increase of buffer size. Comparing through different interpolation methods, the magnitude of coefficients for live basal area and its interaction with vigor are relatively similar between spline and IDW interpolation methods, while they are relatively higher for the kriging interpolation method. The reason may be that the ranges of interpolated value are relatively smaller for kriging method.

Based on the repeated sale model estimation results of buffer <0.1km after kriging, we calculate the marginal effects of lba and $lba * vigor$. At the mean of live basal area in 2011 which is 16.5 m^2/ha, when the stand vigor increases by one unit, the residential property value will decrease by 29.5%. When the hemlock stand is healthy ($vigor = 1$), that the hemlock live basal area increases by 1 m^2/ha, will cause the sale price to increase by 0.45%. When the hemlock stand is seriously damaged ($vigor = 4$), that the live basal area increases by 1 m^2/ha, will cause the sale price to decrease by 4.9%.

Holmes et al. (2010b) estimated that hemlock defoliation and mortality resulted in a 1-1.6% decrease in residential property values of parcels that had hemlocks on the property. The estimated marginal effect for vigor is relatively large here compared with Holmes et al. (2010b). One reason could be that we employed different formation of hemlock damage measurements here. As the interaction of vigor and live basal area is introduced into the model, their effects on the property price are interdependent. Another reason could be that the property markets in Connecticut and Massachusetts were still in adjustments to the hemlock damage while the property market of New Jersey was in different market equilibrium.

8. Discussion

The results of this study indicate that HWA has caused dramatic damages to hemlock stands in central Connecticut and central Massachusetts during the period 2007-2011. This landscape change causes the decrease of the sales price for properties residing in the study area.

All three spatial interpolation methods give relatively consistent estimation results that the hemlock damage caused by HWA infestation will decrease the value of residential properties which locate inside 0.1km buffer area. Compared with the repeated sale estimation results, the significances in the hedonic model with buffer 0.5km and 1km may be caused by the correlation with the missing variable in the error term.

According to the impact of HWA on residential property values, the aggregate economic losses have likely rapidly accelerated in the study area during the past several years. It can cause even larger damages when the infestation of HWA moves further into northern area where there are more hemlock forests. Although forest management tools are not currently available to either slow the spread or to protect naturally regenerated hemlock forests from HWA, the economic benefits of developing such tools could be substantial. Slowing the advance of HWA into residential forests could convey substantial benefits to homeowners, and may substantially exceed the cost of such programs. Protecting or delaying the onset of HWA in such areas may be a smart investment of public and private funds.

From the sampled data estimation results, we can see that the inference based only on the sampled stands may lose property sale information. We could not correctly estimate the effect of hemlock damage based on the small sampled size. Spatial interpolation methods provide us useful tools to enlarge the scale of our analysis and lead to consistent inference. However, there will still be measurement errors when we used the prediction results rather than the true value in hedonic model analysis. When we compare predicted value with actual values for live basal area, for example, we can see there are relatively large prediction errors for stands with large live basal area, especially in 2011. That is because the distribution of sampled values is skewed with most observations for smaller live basal areas and less frequent observations for large live basal areas. This prediction error may exacerbate the computation of HWA damages in terms of maximum live basal area. Similarly for vigor, with the small frequency of observing severely damaged stands, there are relatively large prediction errors for stands with low vigor. So we should be cautious in investigating the HWA effect on property values based on these interpolated hemlock damage indicators. Here we just employed the mean of interpolation values for non-sampled hemlock stands in our hedonic estimation. We would also consider about introducing the distributions of interpolation values and measurement errors of predictions into the hedonic analysis for further investigation.

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Table 4.1 Live Basal Area and Vigor for Sampled Hemlock Stands

	Year	2007	2009	2011
Live Basal Area	Mean	38.23	27.83	15.31
(m^2/ha)	SD	27.59	16.29	11.89
	Min	0	0	0
	Max	125.45	73.34	54.04
	N[a]	140	138	122
Vigor Class[b]	1	8	11	9
(stand count)	2	18	19	23
	3	33	37	44
	4	82	71	47
	N	141	138	123

[a] The sample size decreased over years as some hemlock stands disappeared or were not allowed for access again.
[b] For vigor classes: 1 = 0 – 25% foliar loss, 2= 26-50% foliar loss, 3 = 51-75% foliar loss and 4 = 76 – 99% foliar loss.

Table 4.2 Descriptive Statistics of Housing Characteristics Variables

	Mean	SD	Min	Max
Households Sampled (N=1,680)				
House price ($2003)	336,415	253,001	38,543	5,337,336
Living area (ft^2)	2,060	913	420	12,872
Lot size (ft^2)	63,692	129,927	0	2,400,174
Baths	1.81	0.82	0	8
Age	1957	46	1680	2011
Air conditioning (%)	0.30	0.46	0	1
Fireplace (%)	0.50	0.50	0	1
Distance to highway (m)	883	910	0.06	6,654
Water (%)	1.95	4.37	0	31.33
Open space (%)	12.38	8.21	1.26	46.84
Developed area (%)	0.93	2.11	0	15.16
Forest (%)	39.62	27.87	0	96.06
Agricultural (%)	5.69	8.12	0	56.18
Wetland (%)	4.19	4.98	0	35.48
Interpolated (N=24,731)				
House price ($2003)	277,616	189,890	7,517	12,364,360
Living area (ft^2)	1,746	767	0	12,872
Lot size (ft^2)	51,204	135,630	0	7,122,060
Baths	1.63	0.72	0	9
Age	1960	39	1680	2011
Air conditioning (%)	0.27	0.44	0	1
Fireplace (%)	0.45	0.50	0	1
Distance to highway (m)	843	849	0	7,102
Water (%)	2.05	4.86	0	40.88
Open space (%)	13.88	8.83	0	56.78
Developed area (%)	1.46	2.72	0	31.43
Forest (%)	40.82	24.81	0.22	97.39
Agricultural (%)	5.95	8.16	0	73.58
Wetland (%)	6.08	7.18	0	54.65

Table 4.3 Cross Validation of Interpolation Results for Live Basal Area and Vigor

		Year	ME[a]	RMSE[b]	MSE[c]	RMSS[d]
Inverse Distance Weighted	Live Basal Area	2007	0.447	23.525		
		2009	-0.177	15.678		
		2011	-0.126	11.961		
	Vigor	2007	-0.002	0.692		
		2009	0.006	0.666		
		2011	0.005	0.834		
Spline	Live Basal Area	2007	-0.079	23.411		
		2009	0.069	15.816		
		2011	0.029	12.046		
	Vigor	2007	-0.003	0.701		
		2009	-0.011	0.662		
		2011	-0.005	0.806		
Kriging	Live Basal Area	2007	-0.288	22.855	-0.012	0.950
		2009	-0.230	14.686	-0.015	1.024
		2011	-0.002	11.955	-0.000	1.043
	Vigor	2007	-0.002	0.690	-0.003	0.879
		2009	0.002	0.657	0.003	0.864
		2011	-0.001	0.849	-0.001	0.908

[a] ME represents mean prediction error.
[b] RMSE represents root mean square error.
[c] MSE represents mean standardized prediction error.
[d] RMSS represents root mean square standardized error.

Table 4.4 Interpolated Live Basal Area and Vigor for all Stands (n=6,126)

		Year	Mean	SD	Min	Max
Inverse Distance Weighted	Live Basal Area (m^2/ha)	2007	48.6	13.7	4.6	114.0
		2009	32.0	5.8	2.1	62.0
		2011	16.3	4.5	1.6	47.3
	Vigor	2007	1.2	0.4	1.0	3.6
		2009	1.3	0.4	1.0	3.8
		2011	1.9	0.3	1.1	3.7
Spline	Live Basal Area (m^2/ha)	2007	50.3	15.2	4.0	110.4
		2009	31.5	6.2	6.4	52.2
		2011	16.6	5.1	2.4	43.6
	Vigor	2007	1.2	0.4	1.0	3.6
		2009	1.3	0.4	1.0	3.8
		2011	1.9	0.4	0.8	4.0
Kriging	Live Basal Area (m^2/ha)	2007	48.7	11.3	8.4	76.7
		2009	32.6	4.5	10.8	42.8
		2011	16.5	1.8	9.5	19.6
	Vigor	2007	1.2	0.4	0.5	2.9
		2009	1.3	0.4	0.9	3.7
		2011	1.9	0.2	1.4	3.1

Table 4.5 Estimation Results Based on Sampled Data (case A and B)

	<0.1km	<0.5km	<1km
Hedonic Model (Full)			
lba ($\times 10^{-3}$)	0.231	-3.367***	-1.877***
	(2.880)	(1.026)	(0.868)
lba *vigor ($\times 10^{-3}$)	-0.174	1.326***	0.732**
	(1.136)	(0.468)	(0.400)
N	151	725	1725
Hedonic Model (Recent)			
lba ($\times 10^{-3}$)	1.218	-3.311***	-1.836***
	(3.010)	(1.080)	(0.713)
lba*vigor ($\times 10^{-3}$)	-0.499	1.328***	0.725***
	(1.169)	(0.496)	(0.335)
N	148	725	1682
Repeated Sale Model			
lba ($\times 10^{-3}$)	--	--	-0.316
			(4.138)
lba*vigor ($\times 10^{-3}$)	--	--	0.404
			(1.704)
N	3	20	43

Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; * denotes significant at the 10% level.

Table 4.6 Estimation Results Based on Sampled Data (case A)

	<0.1km	<0.5km	<1km
Hedonic Model (Full)			
lba ($\times 10^{-3}$)	1.186	-3.376***	-2.963***
	(3.074)	(1.307)	(0.942)
lba *vigor ($\times 10^{-3}$)	-0.682	1.422**	1.235***
	(1.207)	(0.558)	(0.409)
N	133	505	1084
Hedonic Model (Recent)			
lba ($\times 10^{-3}$)	1.457	-2.987**	-3.006***
	(3.148)	(1.334)	(0.948)
lba*vigor ($\times 10^{-3}$)	-0.709	1.339**	1.256***
	(1.218)	(0.564)	(0.410)
N	131	491	1056
Repeated Sale Model			
lba ($\times 10^{-3}$)	--	--	--
lba*vigor ($\times 10^{-3}$)	--	--	--
N	3	20	25

Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; * denotes significant at the 10% level.

Table 4.7 Estimation Results Based on Inverse Distance Weighted Method

	<0.1km	<0.5km	<1km
Hedonic Model (Full)			
lba ($\times 10^{-3}$)	2.085*	1.598***	0.988**
	(1.097)	(0.498)	(0.384)
lba *vigor ($\times 10^{-3}$)	-1.017	-0.609*	-0.244
	(0.697)	(0.319)	(0.249)
N	2,948	13,925	24,731
Hedonic Model (Recent)			
lba ($\times 10^{-3}$)	2.295**	1.962***	1.206***
	(1.119)	(0.510)	(0.392)
lba*vigor ($\times 10^{-3}$)	-1.384**	-0.814**	-0.316
	(0.704)	(0.323)	(0.252)
N	2,762	13,087	23,267
Repeated Sale Model			
lba ($\times 10^{-3}$)	13.491*	3.743	1.964
	(8.063)	(2.709)	(2.282)
lba*vigor ($\times 10^{-3}$)	-9.854*	-1.086	-0.150
	(5.738)	(1.725)	(1.359)
N	360	1,636	2,850

Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; * denotes significant at the 10% level.

Table 4.8 Estimation Results Based on Spline

	<0.1km	<0.5km	<1km
Hedonic Model (Full)			
lba ($\times 10^{-3}$)	1.969*	1.501***	0.944**
	(1.039)	(0.475)	(0.369)
lba *vigor ($\times 10^{-3}$)	-1.344*	-0.861***	-0.588**
	(0.701)	(0.329)	(0.256)
N	2,948	13,925	24,731
Hedonic Model (Recent)			
lba ($\times 10^{-3}$)	2.091**	1.838***	1.116***
	(1.060)	(0.488)	(0.377)
lba*vigor ($\times 10^{-3}$)	-1.684**	-1.060***	-0.666**
	(0.709)	(0.334)	(0.260)
N	2,762	13,087	23,267
Repeated Sale Model			
lba ($\times 10^{-3}$)	13.189*	3.914	1.592
	(7.301)	(2.567)	(2.159)
lba*vigor ($\times 10^{-3}$)	-10.080*	-1.393	1.017
	(5.141)	(1.963)	(1.547)
N	360	1,636	2,850

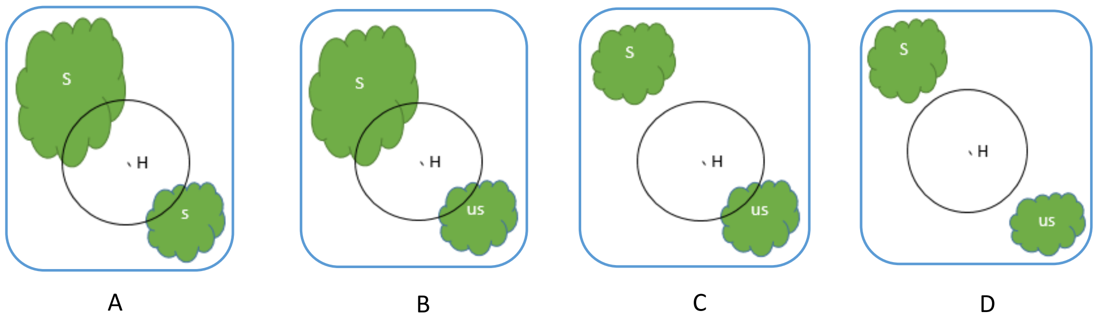
Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; * denotes significant at the 10% level.

Table 4.9 Estimation Results Based on Kriging

	<0.1km	<0.5km	<1km
Hedonic Model (Full)			
lba ($\times 10^{-3}$)	1.951*	2.811***	2.155***
	(1.003)	(0.574)	(0.451)
lba *vigor ($\times 10^{-3}$)	-2.527***	-2.790***	-2.227***
	(0.809)	(0.426)	(-0.337)
N	2,948	13,925	24,731
Hedonic Model (Recent)			
lba ($\times 10^{-3}$)	3.633***	3.119***	2.394***
	(1.249)	(0.587)	(0.459)
lba*vigor ($\times 10^{-3}$)	-3.488***	-2.904***	-2.282***
	(0.856)	(0.433)	(0.341)
N	2,762	13,087	23,267
Repeated Sale Model			
lba ($\times 10^{-3}$)	22.372**	6.314*	3.630
	(10.303)	(3.418)	(2.841)
lba*vigor ($\times 10^{-3}$)	-17.864***	-3.468	0.856
	(6.589)	(2.321)	(1.879)
N	360	1,636	2,850

Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; * denotes significant at the 10% level.

Figure 4.1 Locations between Household Properties and Hemlock Stands



Note: H represents household property; S represents sampled hemlock stand; US represents non-sampled hemlock stand.

Figure 4.2 Hemlock Stands in the Study Area

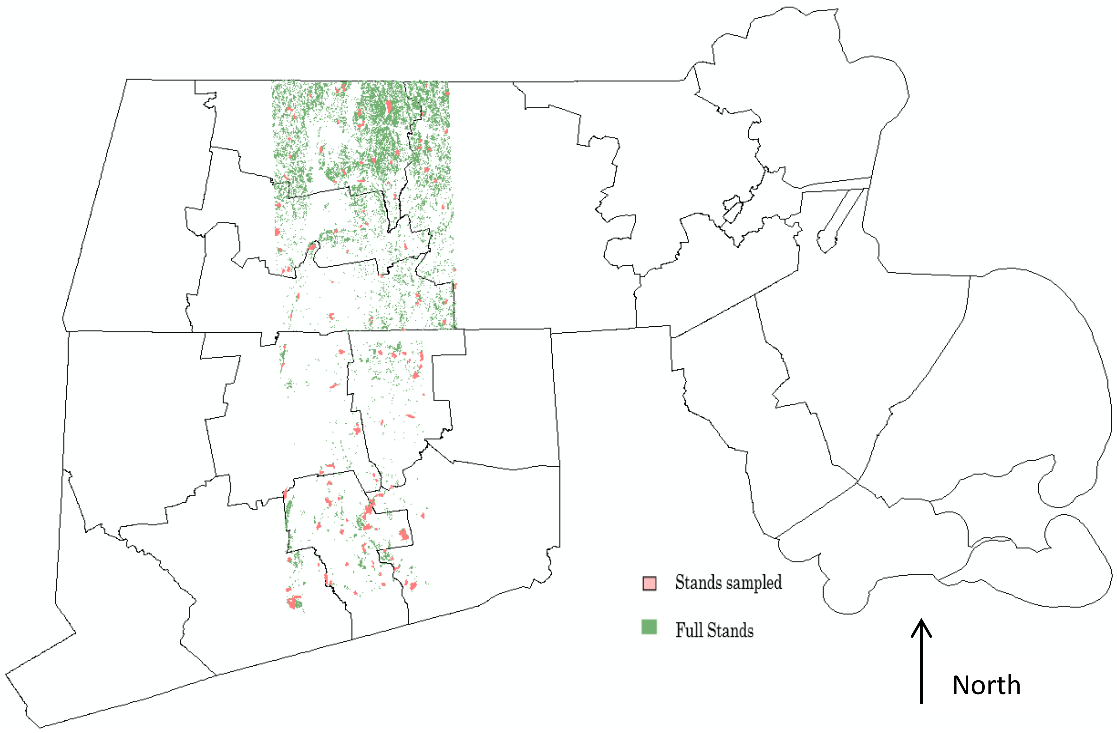


Figure 4.3 Semivariogram Model and the Parameters

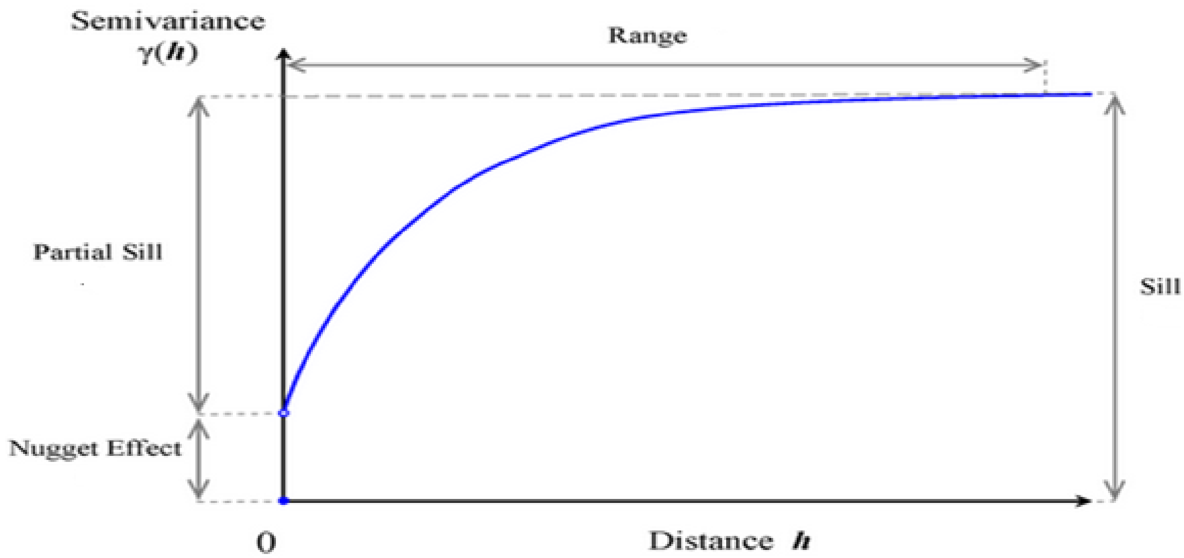


Figure 4.4 Interpolated Live Basal Area (m^2/ha) by Kriging in the Study Area (2007-2011)

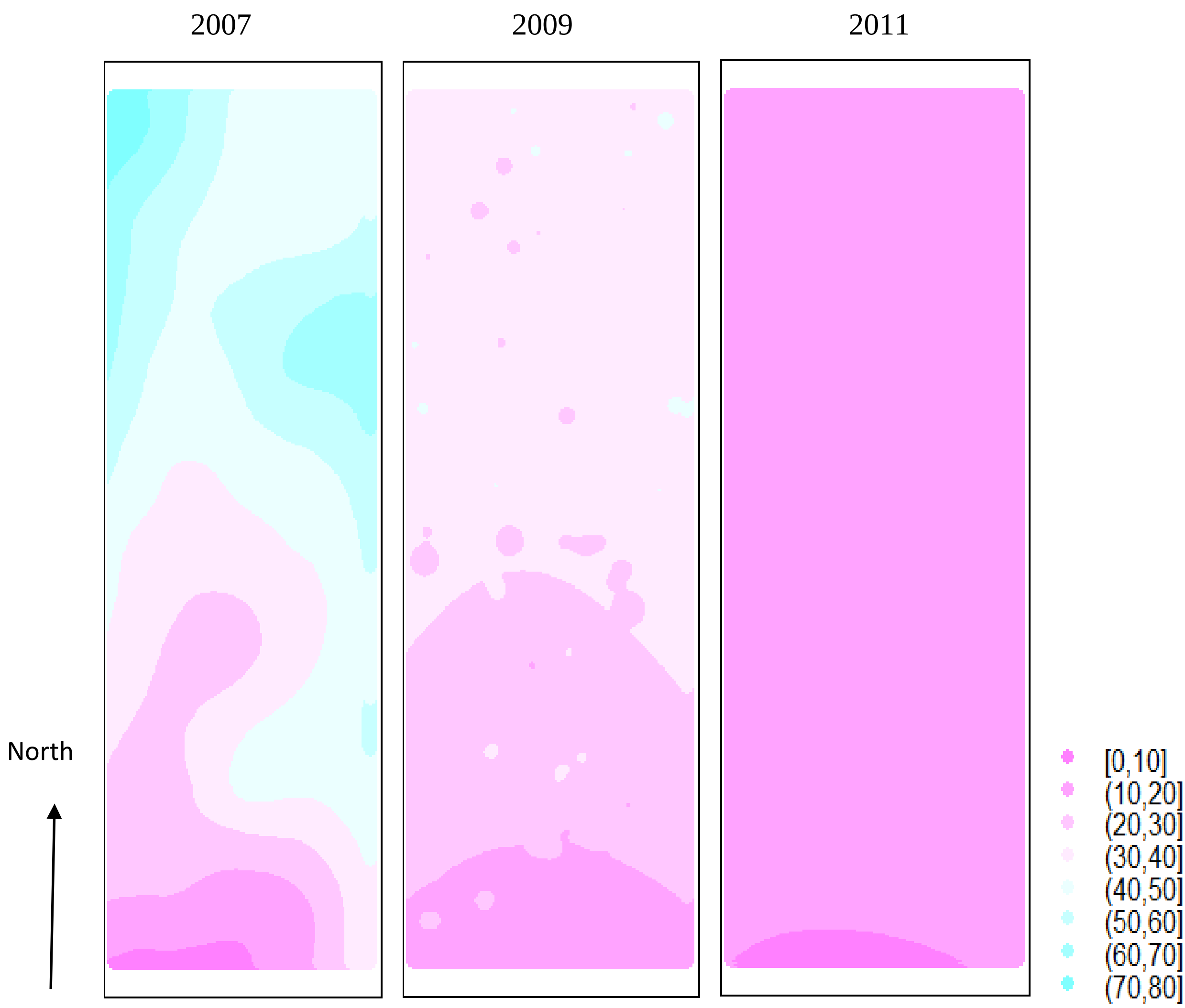
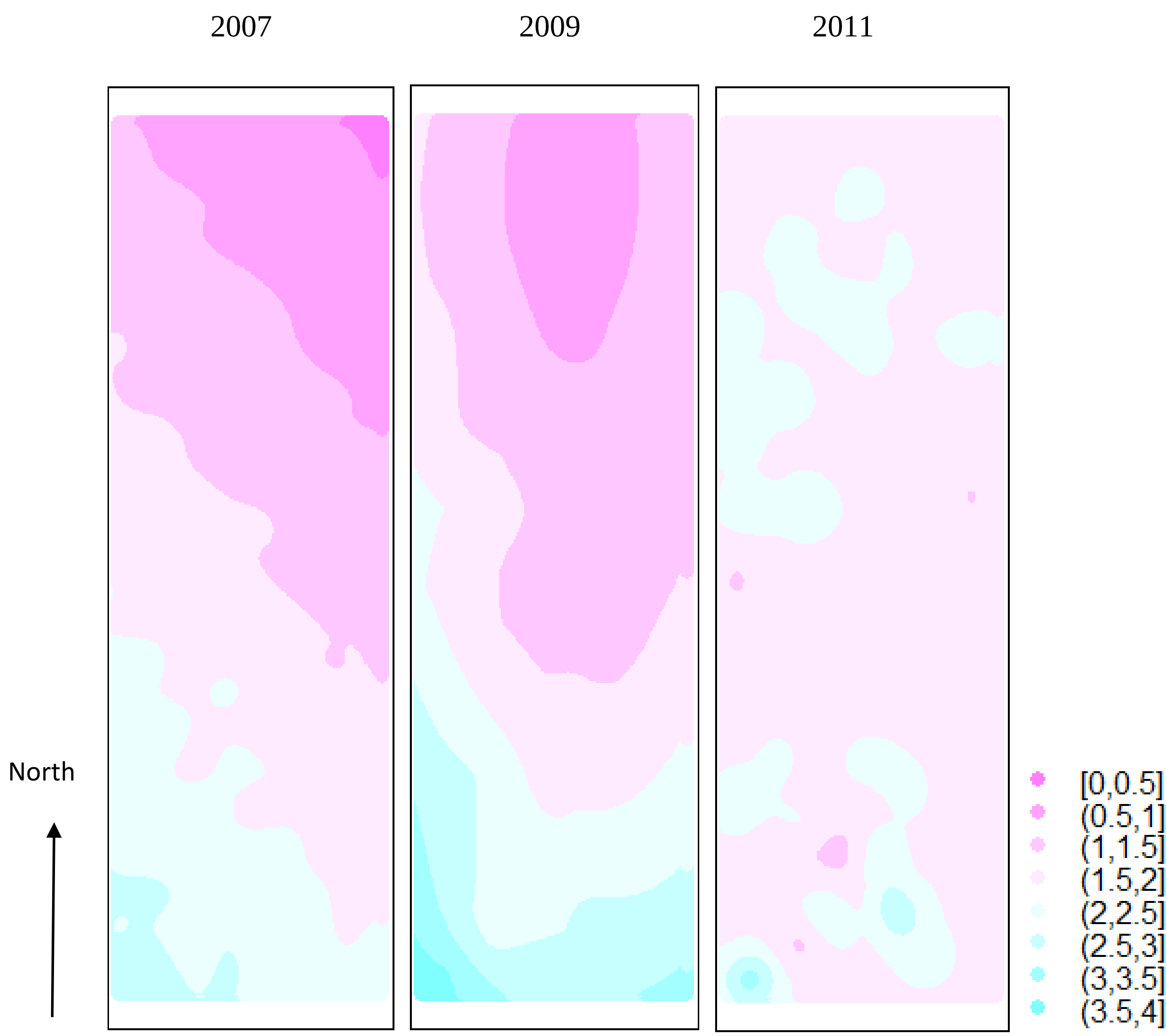


Figure 4.5 Interpolated Vigor by Kriging in the Study Area (2007-2011)



Chapter V. Conclusion

In the three chapters above, we separately employed stated preference method and revealed preference method to evaluate the forest ecosystem. In the first two chapters, we employed stated preference method to elicited respondents' preference for low impact timber harvesting practices. In the third chapter, we employed revealed preference method to estimate the economic losses from forest damages caused by HWA infestation.

In Chapter II, the empirical analysis shows that stated preferences for timber harvesting attributes are not statistically different between the mail and on-site applications of the survey, and this result is robust to pretest (before experience) and posttest (post experience) applications. However, the on-site treatment reduced the variance of the error term, indicating that on-site participants made clearer distinctions between alternatives after their walks through the forest. Finally, we found that on-site subjects had a stronger preference for low-impact timber harvesting after controlling for program attributes, which suggests an over-estimation bias in welfare estimates that might occur with on-site recruitment of study subjects.

In Chapter III, comparing the preferences of interest groups before and after the on-site experience, we found that none of the interest groups significantly changed their preference. On-site experience does reduce their preference heterogeneity for specific forest management attributes, however it would not change their attitude diversity toward the forest management practices. So the knowledge with forest management has little effect on the preference diversity among interest groups. The standpoints of each interest group is the most influential factor which effect their preference for forest management.

In Chapter IV, our results indicate dramatic loss of healthy hemlock stands in the study area over time and space, with the infestation moving in a northeasterly direction. We also considered the impacts of this infestation on residential property values based both on sampled hemlock data and interpolated result. Our analysis shows that healthy hemlock trees will impose positive effect on the residential properties located within the distance of 0.1km from the hemlock stands while the damaged hemlock trees will impose negative effect on the residential properties. All three spatial interpolation technics provide consistent estimation results. So the spatial interpolation methodologies provide us a useful tool to enlarge the scale of economic impact analysis and give robust estimation results.

From all three chapters above, we can see that in practical analysis about forest ecosystem, the application of stated preference and reveal preference methods would meet challenges and have their shortcoming to get valid evaluation results. Appropriate survey design would help to avoid the bias in the stated preference research, while statistical methods could help to overcome the shortage of limited sample data set. Improvement in the traditional stated preference and reveal preference methods would make more robust inferences for designed forest protection policies. They would be helpful to ensure the effectiveness of forest policy conduction and achieve successful forest managements.