DEMAND FOR INFORMATION BY U.S. SOUTHWEST WILDLAND FIRE MANAGERS

by

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Abstract

This thesis investigates the demand for information among wildland fire managers in the U.S. Southwest, focusing on their use of data products and information sources. Utilizing data from a comprehensive, internet survey, targeting a well-defined and small population of Southwest wildland fire managers, the study explores how fire managers use information to make decisions. The findings reveal that information use is significantly influenced by the number of decisions managers make and whether decisions are made before or during season. Information use is affected by manager characteristics such as their education, age, experience, and job type. It is also affected by the agencies they work for as well as the dispatch centers where they work. Finally, information use depends on the characteristics of the information sources. The study employs least squares, negative binomial, logistic, and linear probability regression models to analyze these factors. Results indicate that tailored fire-specific information sources are more likely to be used than general ones, while use of decision support tools are less likely to be used. The study provides valuable insights for improving the design and delivery of information products, thereby enhancing decision-making efficiency in wildfire management.

Keywords: Wildland fire management, information demand, random utility model

Chapter 1. Introduction

Wildland fires are non-structure fires that occur in the wildland (as opposed to developed or urban areas). (National Wildfire Coordinating Group, 2006). There are three kinds of wildland fire.

- Prescribed fire: A fire ignited by fire managers on purpose to achieve a specific objective. This may be to reduce fuel levels to lower the risk of future fires. These are also referred to as “controlled burns.”
- Wildland use fire: A fire that has ignited naturally (e.g., via lightning) that fire managers allow to burn over a designated area in order to achieve a management object (e.g., to reduce fuel loads).
- Wildfire: An unplanned, unwanted wildland fire including unauthorized human-caused fires, as well as wildland fire use fires and prescribed fires that escape intended areas of control. For wildfires, the fire management objective is to put the fire out (suppression).

Over the past decade, an average of 62,000 wildland fires have started per year in the United States, burning an average of 7 million acres per year. Over this same period, federal wildland fire suppression costs have averaged more than 2.5 million per year (NIFC, 2024). The economic burden from wildland fire are estimated to be much larger. Economic burden combines the costs of fire prevention and suppression with economic losses from fire, including destruction of property and loss of human life. The National Institute of Standards and Technology has estimated the economic burden of wildland fire to range from $71.1 billion to $347.8 billion ($2016 US) annually (Thomas et al., 2017).

Given these costs, it is not surprising that multiple federal agencies have developed data products and decision support systems to help wildfire managers make better-informed fire management decisions. Along with data products and information sources specially tailored to wildland fire management, managers also rely on other weather, climate, and drought data products.

While significant resources have been devoted to the supply of information for fire management, less attention has been paid to the demand side. Recent empirical work relying on qualitative research methods suggests that fire managers are not using decision support systems or data products developed for fire management (or at least, not using them as intended) and that existing information may not meet fire manager needs (Colavito, 2017, 2021; Fillmore and Paveglio, 2023; Hunter et al., 2020; Noble and Paveglio, 2020; Rapp et al., 2020; Ryan and Cerveny, 2011; Schultz, et al. 2021). Currently, there is a research gap in assessing the demand for fire management information. A better understanding of what information fire managers use, how they use it, and what is *not* used will help in developing, not just more data products, but ones that are actually useful to wildland fire managers.

Aims and Scope

This thesis assesses the demand for fire management information by professional wildland fire managers in federal, state, and tribal agencies in the U.S. Southwest. It builds on three strands of literature. One is a series of articles on the demand for economic information by decision makers at different points along the food and agriculture supply chain (Just, et al., 2002; Wolf et al., 2001a; Wolf et al., 2001b; Just et al., 2006). In this framework, decision makers can use information to make decisions with better outcomes, but acquiring and analyzing information can have monetary, time, or other resource costs. In this framework, key variables driving decision-maker demand for information include:

- the decision maker's occupation or role within a system,
- characteristics of the system in which the individual or firm participates,
- the firm's or individual's level of human capital, and
- the characteristics of the information sources that affect the costs and benefits of using them.

Differences in information use are explained by differences of these four factors. While these papers focus on use of economic information by individuals in private agribusiness firms, the basic structure of the models they developed can be applied to fire managers working in public agencies.

Another relevant literature deals directly about the value of weather and climate information (Freebairn and Zillman, 2002; Frisvold and Deva, 2011; Frisvold and Murugesan, 2013; Johnson and Holt, 1997; Stewart, 1997; Wilks, 1997). Some of this literature attempts to estimate how information use increases profits, utility, or other benefits to users. In other cases, the net benefits of information to the user is treated as a latent variable, which is used to predict use or non-use of information.

A third type of literature has relied on structured interviews and qualitative research methods of small numbers of wildland fire managers to understand how they use information and to identify barriers to and facilitators of information use (Colavito, 2017, 2021; Fillmore and Paveglio, 2023; Hunter et al., 2020; Noble and Paveglio, 2020; Rapp et al., 2020; Ryan and Cerveny, 2011; Schultz, et al. 2021). Fire manager responses can be interpreted in terms of a "demand for information" and "value of information" models. This literature also informed the design and the choice of variables for a survey whose data is used extensively in this thesis.

The plan of this thesis is as follows. Chapter 2 discusses an internet survey of Southwest fire managers and the data derived from it that is used for statistical analysis. It discusses survey design, results of checks on the representativeness of the sample population to the total, target population, and basic respondent characteristics. Chapter 3 introduces a simple model of demand for information use by fire managers. It attempts to explain the wide differences in the total number of information sources that wildland fire managers use. This approach is based on the demand or economic information framework of Just, Wolf, Wu, and Zilberman (Just et al., 2002) and related papers. We refer to this as the JWWZ framework. The JWWZ framework is used to develop and test hypotheses about the demand for fire manager information use.

Chapter 4 introduces a more complex, random utility model of fire manager information use. The model attempts to explain use or non-use of an information source *i*, by fire manager *j* as a discrete choice problem. Whether a particular source is used by a particular manager is specified as a function of the manager's personal characteristics, the characteristics of their job or agency, and the characteristics of the information source itself. Chapter 5 concludes with an overall summary of findings, discussion of policy implications, and discussion of direction for future research.

Chapter 2. Survey Methods and Data

Quantitative data were collected through an internet survey instrument developed in Qualtrics. The survey population was drawn from the Southwest Area Interagency Fire, Aviation and Dispatch Directory. The Dispatch Directory which includes personnel from the twelve interagency dispatch centers covering the Southwest Area, plus the Southwest Coordination Center (SWCC). The population covers a wide range of operational fire management personnel (regional, state, and unit level), including higher-level firefighters, aviators and aviation program managers, incident commanders and incident command staff, fire planners, fire ecologists, fire prevention specialists, fire environment decision support specialists, and miscellaneous support staff. National Weather Service (NWS) forecasters and incident meteorologists from NWS offices serving the Southwest Area were also included. Most of the population is involved in making or supporting strategic and/or tactical wildland fire management decisions. The Dispatch Directory that was used to build our population includes names, positions, locations, organizations, and contact information for Southwest fire management professions from federal agencies (Bureau of Indian Affairs, Bureau of Land Management, Fish & Wildlife Service, Forest Service, National Oceanic and Atmospheric Administration, and National Park Service), state agencies (Arizona Department of Environmental Quality, Arizona Department of Forestry and Fire Management, New Mexico Energy, Minerals and Natural Resources Department (EMNRD) Forestry Division, and individual tribal fire management and forestry agencies. To better define our target population, we removed positions listed in the directory from our target population that were not directly related to fire management decisions (e.g., accountants, budget analysts, and clerical staff). This left an email list of 485 potential respondents as our target population of Southwest wildland fire management professionals.

A draft survey instrument was pre-tested by colleagues in University of Arizona Cooperative Extension and the Climate Assessment for the Southwest (CLIMAS) and revised in response to comments and suggestions. Potential respondents were sent an introductory email informing them of the purpose of the survey followed by a second email with a survey link in the second week of October 2021. Eight subsequent reminders were sent. The survey was open for five weeks, ending after the third week of November.

From the original 485 people contacted, four responded that they did not use weather and climate information as part of their jobs and four responded that they were no longer in a position where that was the case. These eight were therefore not part of our intended population, reducing the pertinent population to 477 respondents. Of these, 206 provided responses about use of climate and weather information, for an overall response rate of 206/477 = 43.2%. This compares favorably to response rates from previous surveys of wildland fire managers: Calkin et al. (2013), 28%; Ryan and Cerveny (2011), 17%; Wilson et al. (2011), 34%; Christensen (2015), 24%.

Our target population is well-defined and small. However, as population size falls, the response rate needs to increase to avoid imprecision and to safeguard against non-response bias (Draugalis and Plaza 2009; Krejcie and Morgan 1970; Verma and Verma 2020). A concern with non-responses is that the sample population may not be representative of the target population. Information about the target population, however, can be used to evaluate the representativeness of the sample. The Dispatch Directory provides information about the agencies where both respondents and the entire target population work. The distribution of respondents by agency in the sample was quite close to the distribution for the target population as a whole (Table 2.1). Response rates were higher from agencies with fewer people, but absolute differences were small. The sample appears quite representative of the target population, at least with respect to the agencies where respondents work.

Table 2.1. Distribution of the sample population and total population with respect to agency where the wildland fire manager works

Agency	**Total Population**	**Sample Population**
Forest Service	49.5%	47.6%
Bureau of Land Management	15.9%	13.1%
Bureau of Indian Affairs	12.2%	10.7%
AZ Department of Forestry & Fire Management	7.8%	9.7%
National Park Service	5.0%	5.3%
NM Forestry Division	2.9%	3.9%
Fish & Wildlife Service	2.7%	4.4%
Tribal Agencies	1.9%	1.5%
NOAA	1.5%	2.4%
AZ Department of Environmental Quality	0.6%	1.5%

Table 2.2 provides basic information about the survey population. Virtually all respondents were based in either Arizona or New Mexico. Most operated in one or both of these states, while 11% -19% also operated in other western states. Nearly 63% of respondents had 20 years of experience or more. More than 80% had 15 or more years of experience. The most common age category was 40-49 years (45% of respondents). Few

respondents were younger than 30 or had less than five years of experience. Nearly 15% of respondents had masters, professional or PhD degrees, while 45% had bachelor's degrees. Another third of respondents had some college, but no bachelor's degree, while less than 7% had high school degrees. Only 3.4% of respondents were administrators, while 41.5% stated their role as fuels and fire management (prevention), 27.3% stated their role was fire suppression, and 27.8% listed other as their primary role in fire management.

Table 2.2 Survey respondent characteristics

State where respondent operates (can be >1)	Percentage of respondents	Experience (years)	Percentage of respondents
Arizona	67.0%	0 – 4	2.9%
New Mexico	58.0%	5-9	5.7%
California	16.0%	10-14	10.9%
Nevada	14.0%	15 - 19	17.7%
Utah	14.0%	20 - 29	48.6%
Colorado	14.0%	>30	14.3%
Texas	19.0%		
Other	11.0%		
Age		Job within Agency	
Less than 30	0.6%	Agency Administrator	3.4%
30 – 39	17.1%	Fire Manager, fuels and fire	41.5%
40 – 49	44.9%	Fire Manager, suppression	27.3%
50 – 59	27.3%	Other	27.8%
>60	10.2%		
Education Level			
High School Graduate	6.8%	Masters / Professional Degree	13.1%
Some College	33.5%	Doctoral Degree	1.7%
College Graduate	44.9%		

Chapter 3. A Simple Model of Demand for Fire Management Information

One may express the value of information V_i to an individual fire manager making a particular decision *i* as

(1) $V_i \{b_i [k, \rho, \alpha, \delta, x (s_i)] - b_{i0} (k, \rho, a, x_{i0})\} A - c_i (s_i, k, A, \rho, \alpha, \delta)$

where

A = land area managed

$b [x (s_i)]$ = benefits per unit land area given information

$b_0 (x_0)$ = benefits per unit land area when information is not accessed

x_{i0} = decision made or action taken when information is not accessed (for decisions $i = 1, \ldots, n$)

$x_i (s_i)$ = decision made or action taken given new information (for decisions i = 1, …n)

s_i = amount of information sources accessed or the intensity of use from a given source to make decision *i*

c_i = costs of processing information for decision *i*, include time costs and costs of delay

k = index of knowledge or technical capacity

ρ = individual's job or role within the fire management system

α = agency that the individual works for

δ = dispatch center where the individual works

In the optimization problem, the fire manager may make multiple decisions. This can be written as

(2) $\max \Sigma V_i \{b_i [k, \rho, \alpha, \delta, x (s_i)] - b_i (k, \rho, a, x_{i0})\} A - \Sigma c_i (s_i, k, A, \rho, \alpha, \delta)$

with respect to s_i for $i = 1, \ldots n$ decisions, and subject to $t_i (s_i) < \underline{t}_i$

where $\underline{t}_i$ is some constraint on the decision maker. This could be a resource constraint, or it could be a time cost. Decision makers must take action over some fixed time interval. They only have so much time to collect information.

The Lagrangian for the fire manager's constrained optimization problem is

(3) $\max L = \Sigma V_i \{b_i [k, \rho, \alpha, \delta, x_i (s_i)] - b_{0i} (k, \rho, a, x_{i0})\} A - \Sigma c_i (s_i, k, A, \rho, \alpha, \delta)$
$+ \Sigma \lambda_i (\underline{t}_i - t_i (s_i))$

where the λ_i terms represent the shadow costs of the decision maker's time constraints.

The first order conditions for optimal information acquisition for each decision is

(4) $(\partial V_i / \partial b_i) (\partial b_i / \partial x_i) (\partial x_i / \partial s_i) = \partial c_i / \partial s_i + \lambda_i (\partial t_i / \partial s_i)$

The decision maker will acquire information up to the point where the marginal benefit meets the marginal cost of acquiring more information, including the shadow cost of the time constraint. If the time constraint is binding ($\lambda_i > 0$), it means the decision maker has used up all their allotted time and must decide / take action with information gathered at that point.

The value of information to the fire manager is the increase in benefits from using information to make decisions minus any costs entailed in accessing and processing the information. This model is similar to those Johnson and Holt (1997), Parker and Zilberman (1996), Frisvold and Deva (2011), Simon et al. (2022). Benefits might be measured in terms of damages avoided. Costs need not be strictly monetary costs. They could be costs of the manager's time to access information and apply it to decisions. With a time dimension, there could also be costs of delays in implementing a decision. A prompt decision with limited information could be better than a more-informed decision that is made "too late." We do not observe the actual and benefits and costs to the fire manager of accessing information. Following Frisvold and Murugesan (2013), we assume that manager will only access an information source if the expected benefits outweigh the costs.

Just et al. (2002) posit that the value of information will depend on the decision maker's occupation or role within the system where they operate (specified as ρ). They also posit that the value of information will depend on the overall system where they operate. This is captured in our study by two variables: α, the agency that the individual works for, and δ, dispatch center where they work.

One can solve the optimization problem in equation (2) for the optimal level of total information use $S = \Sigma s_{ij}$ for each individual, j, as a function of a fire manager's personal and employment characteristics: $S = S(k, A, \rho, \alpha, \delta)$. This suggests some testable hypotheses about fire manager use of information.

H1: Managers who make more decisions will access more information. With n decisions, each decision has the potential to be improved upon by collecting information.

H2: Managers have incentives to use more information sources during fire season than before it, as more resources will be at immediate risk (and more damage to potentially reduce). During fire season, however, time constraints on using information could be more pressing. Managers may not have time to seek more information. The overall effect on information use will depend on which of these two effects (potential damages vs. time constraints) are stronger.

H3: Managers operating at a regional scale will access more information than those at a more local scale, as the benefits of information can be applied over a wider area.

H4: More formal education encourages information use as it increases knowledge or technical capacity, lowering costs of processing and utilizing information.

H5: Age and experience may have countervailing effects. Managers may acquire "on-the-job" knowledge via years of experience, reducing the costs of information use. Conversely, younger (and less-experienced) managers may have been exposed to newer forms of information technology and be better able to interact with newer data sources. Age and experience may signal more on-the-job knowledge, but also signal less familiarity with newer forms of information technology.

H6: Following Just et al (2002), a decision maker's *occupation or role* within the system where they operate (in this case, the fire management system) will affect their demand for information.

H7: The agency and dispatch center will affect an individual manager's use of information. Following Just et al (2002), the attributes of the *system where a decision maker works* affects demand for information. The environment of an agency or dispatch center may influence the information that the managers use and share among themselves.

These hypotheses will be tested via linear regression analysis of factors affecting the total number of information sources used by fire managers in the survey.

Figure 3.1 Effects of changes in the marginal benefits of information use

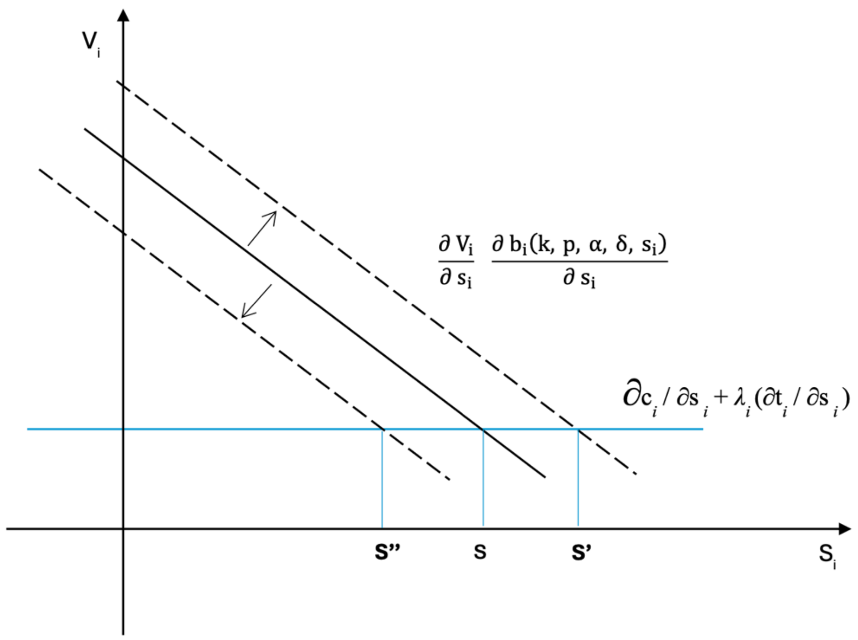
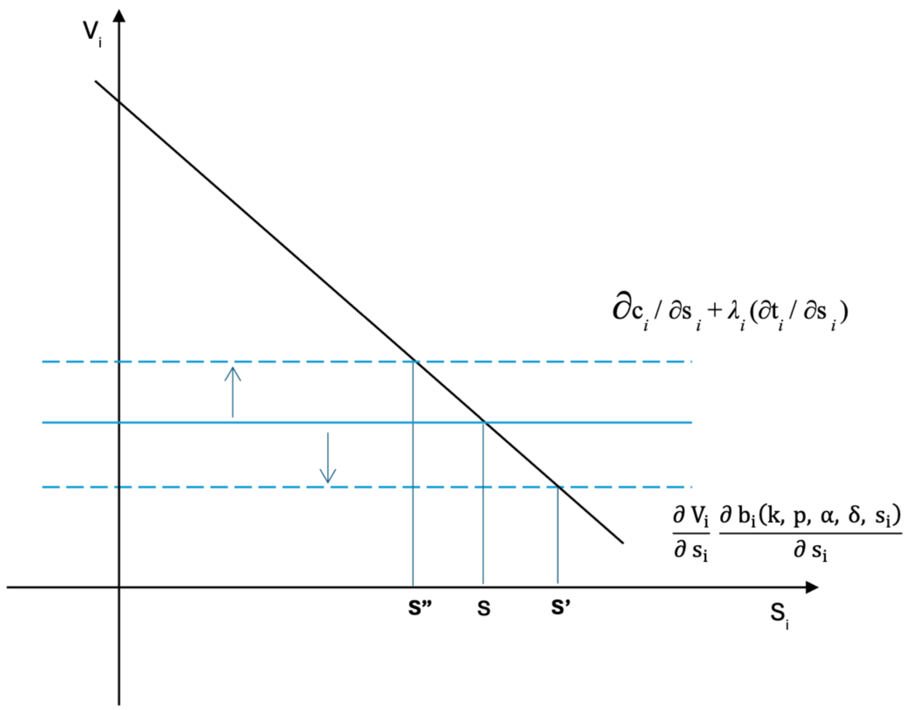


Figure 3.1 shows how shifts in the marginal benefits of information affect the optimal level of information use. It is a graphical presentation of the first order conditions (4).

Hypothesis H3 suggests that managers operating at a regional scale will access more information than those at a more local scale, as the benefits of information can be applied over a wider area. In Figure 3.1, increasing the scale that information can be applied over shifts the marginal benefit curve out, increasing optimal information use. Hypothesis H2 suggests that during fire season, there are more resources at risk, so that the value of information would also increase (shifting the marginal benefit curve out). The marginal benefits are significantly higher in the larger region-wide dispatch center (the SWCC) compared to smaller ones. This is because it can deploy sources over extensive areas, resulting the marginal benefit curve shifts to right, to S'. If the areas they operate are smaller, the marginal benefits experience a leftward shift, intersecting at point S''.

Figure 3.2 illustrates effects of shifts in the marginal cost of information use. Hypothesis H4 suggests that more formal education while reduce manager costs of analyzing information. This would shift the marginal cost curve down and increase optimal information use. As mentioned above, managers may face severe time constraints. If these are very binding then the shadow cost λ_i terms may increase. This will cause the marginal cost curve to shift up, limiting information use. Hypothesis H5 suggests that age and experience can act in complex ways that either shift the marginal cost curve up or down.

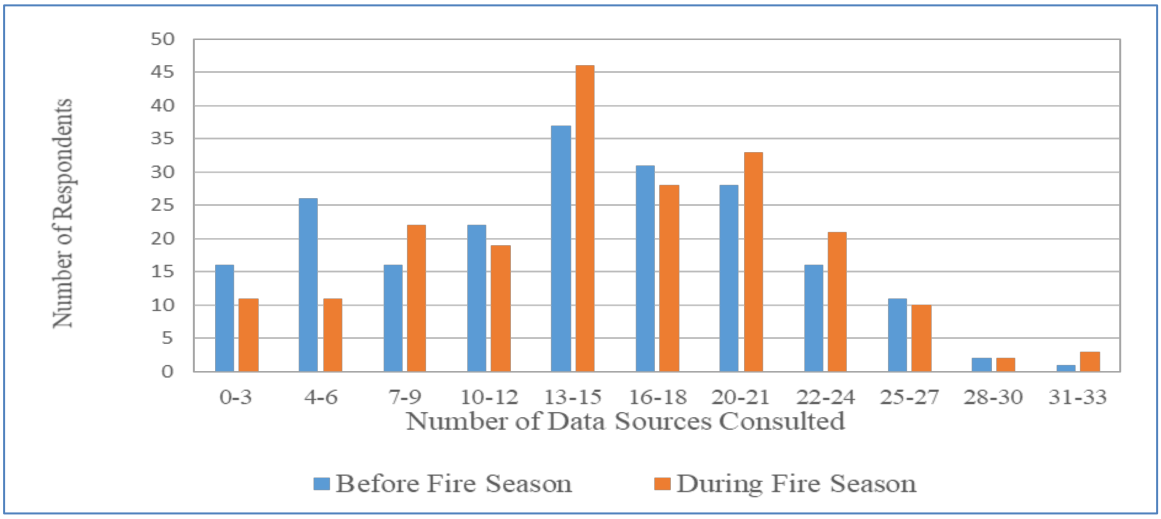
Figure 3.2. Effects of changes in the marginal benefits of information use



Results

Respondents were asked about their use of 33 different information sources for wildland fire management before and during the fire season. There was wide variation in the number of information sources respondents used, ranging from zero to 33 per season (Figure 3.3)

Figure 3.3. Distribution of data sources consulted by fire managers before and during fire season



While there were 206 respondents in the survey, 31 did not respond fully. Although they reported on their use of information sources they did not report on their personal characteristics such as age, experience, job / role, or education level. There was data on the agency and dispatch center where all 206 respondents worked. Four regression analysis, two different specifications were used. One (the sub-sample) included age, experience, job / role, and education variables in a regression with 350 observations (175 respondents using information in two different seasons. The other regression (full sample) used all 412 observations (206 respondents using information in two seasons) but had a smaller number of explanatory variables.

Table 3.1 shows the distribution of information source in both the full sample and the sub-sample. In the full sample, respondents consulted an average of 13.9 sources before and 15.2 sources during the fire season. The median was 15 sources in both periods. While 25% of respondents consulted 19 sources or more (75th percentile) another 25% consulted 11 sources or fewer (25th percentile). In the sub-sample, median information as well as minimum and maximum values were the same as for the full sample. Average source use was less than one source greater in the sub-sample.

Table 3.1. Distribution of the number of data sources used by fire managers before and during fire season

	Full Sample, n = 412		Sub-sample, n = 350	
	During Fire Season	Before Fire Season	During Fire Season	Before Fire Season
Mean	15.2	13.9	15.8	14.3
Standard Deviation	6.7	7.1	6.9	6.9
Minimum	0	0	0	0
Maximum	33	33	33	33
25th Percentile	11	8	12	9
Median	15	15	15	15
75th Percentile	20	19	20	19

Table 3.2 reports results of a multiple regression model that examines how respondent personal characteristics and place in the fire management system affect the number of information sources they use. For the sub-sample, with fewer observations but more explanatory variables, the simple model value of information model explains nearly 30% of the variation in manager uses of information sources ($R^2 = 0.296$). Each additional decision a respondent made increased use by about one source per decision (consistent with hypothesis **H1**). On average, respondents used 1.53 more sources during the fire season than before it. Hypothesis **H2** suggested that more resources at risk would increase demand for information, but also that time constraints might limit information gathering during fire season. Our results suggest that the resources-at-risk effect dominates. The baseline respondent was a Forest Service employee working in the SWCC, aged 40-49 years, with 20-29 years of experience, a bachelor's degree, and job of fire manager, fuels and fire. The model coefficients measure effects of deviations from this baseline profile. Working at the Bureau of Indian Affairs increased information use by more than two sources, working at NOAA increased use by more than five sources, and working at the Arizona Department of Forestry and Fire Management reduced use by more than five sources. Respondents younger than 30 years used more than 13 additional sources. Other age groups were no different from the default. Those with 15-19 years of experience used 2.7 more sources, while Agency administrators used nearly five fewer sources. Those with just a high school degree used about three fewer sources than college graduates.

Table 3.2. Multiple regression analysis of factors affecting total number of information sources used by wildland fire managers (variable coefficients significant at p <0.10 in **boldface**)

Dependent Variable: Total information sources used in a season	R^2 adjusted = 0.2818			R^2 adjusted = 0.2962		
	Full Sample, n = 412			Sub-sample, n =350		
	Coefficient	Std. err	P>|t|	Coefficient	Std. err	P>|t|
During fire season	**1.33**	**0.58**	**0.021**	**1.53**	**0.60**	**0.011**
Total decisions made	**1.28**	**0.15**	**0.000**	**1.07**	**0.20**	**0.000**
Agency variables						
BLM	-1.01	0.96	0.295	-0.94	1.05	0.374
Bureau of Indian Affairs	**2.27**	**1.01**	**0.025**	**2.68**	**1.08**	**0.014**
National Park Service	-1.48	1.40	0.291	-2.30	1.60	0.152
AZ Dept of Forestry & Fire Management	**-5.54**	**1.37**	**0.000**	**-4.56**	**1.55**	**0.004**
NM Forestry Division	2.33	1.58	0.141	2.92	2.09	0.163
US Fish & Wildlife Service	0.07	1.52	0.962	0.55	1.81	0.763
Tribal Organization	-3.27	2.56	0.202	0.15	3.30	0.965
NOAA	**5.18**	**2.72**	**0.058**	4.98	3.70	0.180
AZ Dept of Env Quality	3.40	3.26	0.297	1.20	4.27	0.779
Age variables						
<30 years old				**13.62**	**6.05**	**0.025**
30-39 years old				0.85	1.04	0.411
50-59 years old				-0.55	0.88	0.532
≥60 years old				0.60	1.42	0.672
Experience variables						
<5 years of experience				-2.17	2.34	0.356
5-9 years of experience				1.03	1.76	0.557
10-14 years of experience				0.10	1.15	0.932
15-19 years of experience				**2.70**	**1.00**	**0.008**
≥30 years of experience				1.43	1.15	0.216
Job / role variables						
Agency administrator				**-4.77**	**2.14**	**0.026**
Fire manager, suppression				0.95	0.82	0.248
Other job				0.18	0.88	0.839
Education variables						
High school graduate				**-3.07**	**1.39**	**0.027**
Some college				1.16	0.74	0.115
Masters / professional degree				1.66	1.06	0.120
Doctoral degree				0.85	3.27	0.794
Dispatch center variables						
AZ-Flagstaff	**-4.83**	**1.42**	**0.001**	**-3.44**	**1.57**	**0.029**
AZ-Phoenix	**-4.69**	**1.63**	**0.004**	**-4.76**	**1.75**	**0.007**
AZ-Prescott	0.84	1.51	0.578	0.79	1.77	0.655
AZ-Springerville	-0.65	1.56	0.677	0.20	1.72	0.909
AZ-Tucson	**-5.20**	**1.38**	**0.000**	**-5.10**	**1.47**	**0.001**
AZ-Williams	**-6.17**	**2.18**	**0.005**	**-5.35**	**3.08**	**0.083**
NM-Alamogordo	**-3.64**	**1.33**	**0.007**	**-2.96**	**1.55**	**0.058**
NM-Albuquerque	-0.25	1.44	0.860	1.59	1.58	0.313
NM-Santa Fe	-1.50	1.33	0.260	0.08	1.43	0.953
NM-Silver City	**-3.17**	**1.36**	**0.020**	**-3.05**	**1.43**	**0.033**
NM-Taos	**-6.65**	**1.48**	**0.000**	**-5.18**	**1.73**	**0.003**
Other	**-6.95**	**3.24**	**0.033**	**-10.30**	**4.27**	**0.017**
Constant	**11.82**	**1.17**	**0.000**	**10.55**	**1.46**	**0.000**

Table 3.3. Negative binomial regression analysis of factors affecting total number of information sources used by wildland fire managers (variable coefficients significant at p <0.10 in **boldface**)

Dependent Variable: Total information sources used in a season	Pseudo $R^2 = 0.0480$ Full Sample, n = 412			Pseudo $R^2 = 0.0633$ Sub-sample, n =350		
	Coefficient	Std. err	P>|z|	Coefficient	Std. err	P>|z|
During fire season	**0.10**	**0.04**	**0.023**	**0.11**	**0.04**	**0.008**
Total decisions made	**0.10**	**0.01**	**0.000**	**0.08**	**0.01**	**0.000**
Agency variables						
BLM	-0.11	0.07	0.154	-0.09	0.07	0.196
Bureau of Indian Affairs	**0.13**	**0.08**	**0.078**	**0.16**	**0.07**	**0.027**
National Park Service	-0.10	0.11	0.338	-0.16	0.11	0.132
AZ Dept of Forestry & Fire Management	**-0.45**	**0.11**	**0.000**	**-0.36**	**0.11**	**0.001**
NM Forestry Division	0.12	0.12	0.297	0.13	0.14	0.354
US Fish & Wildlife Service	-0.03	0.12	0.829	-0.01	0.12	0.932
Tribal Organization	-0.28	0.20	0.174	0.03	0.24	0.906
NOAA	**0.36**	**0.20**	**0.077**	0.41	0.27	0.125
AZ Dept of Env Quality	0.23	0.25	0.342	0.13	0.31	0.666
Age variables						
<30 years old				**0.99**	**0.44**	**0.025**
30-39 years old				0.04	0.07	0.542
50-59 years old				-0.04	0.06	0.481
≥60 years old				0.05	0.10	0.602
Experience variables						
<5 years of experience				-0.16	0.17	0.372
5-9 years of experience				0.02	0.12	0.866
10-14 years of experience				0.01	0.08	0.914
15-19 years of experience				**0.20**	**0.07**	**0.004**
≥30 years of experience				0.09	0.08	0.241
Job / role variables						
Agency administrator				**-0.43**	**0.16**	**0.007**
Fire manager, suppression				0.05	0.06	0.385
Other job				0.00	0.06	0.948
Education variables						
High school graduate				**-0.29**	**0.10**	**0.004**
Some college				0.06	0.05	0.221
Masters / professional degree				0.10	0.07	0.159
Doctoral degree				0.04	0.24	0.876
Dispatch center variables						
AZ-Flagstaff	**-0.38**	**0.11**	**0.001**	**-0.23**	**0.11**	**0.034**
AZ-Phoenix	**-0.34**	**0.12**	**0.006**	**-0.33**	**0.12**	**0.007**
AZ-Prescott	0.03	0.11	0.780	0.04	0.12	0.739
AZ-Springerville	-0.14	0.12	0.235	-0.04	0.12	0.738
AZ-Tucson	**-0.39**	**0.11**	**0.000**	**-0.37**	**0.11**	**0.000**
AZ-Williams	**-0.48**	**0.17**	**0.004**	**-0.39**	**0.21**	**0.068**
NM-Alamogordo	**-0.29**	**0.10**	**0.004**	**-0.21**	**0.11**	**0.050**
NM-Albuquerque	-0.06	0.11	0.603	0.09	0.11	0.414
NM-Santa Fe	-0.14	0.10	0.167	0.00	0.10	0.978
NM-Silver City	**-0.22**	**0.10**	**0.035**	**-0.20**	**0.10**	**0.044**
NM-Taos	**-0.58**	**0.12**	**0.000**	**-0.41**	**0.12**	**0.001**
Other	**-0.49**	**0.25**	**0.047**	**-0.81**	**0.31**	**0.009**
Constant	**2.46**	**0.09**	**0.000**	**2.40**	**0.10**	**0.000**

Table 3.3 presents results estimating the models from Table 3.2 as negative binomial regressions. Technically, our dependent variable, number of sources used is count data. All observations are non-negative integers. So, the dependent variables are the not a continuous variable as is assumed in least squares regression. Count data regressions, therefore, may be more appropriate. The negative binomial specification is used because it is a more general specification than the frequently-used Poisson regression model. Poisson regressions assume the mean and variance of the dependent variable are equal. From Table 3.1, one can see this is not the case. We therefore use the negative binomial specification, which does not require this restriction Comparing results in Tables 3.2 and 3.3, the results are similar across models. Variables that are statistically significant in the least squares regressions are also significant (and have the same sign) in the negative binomial regressions. While the dependent variable is count data, there are a large number of integer values (34 in total) and the histogram of the data (Figure 3.3) appears as an approximation to a normal curve.

For the sub-sample, there were statistically significant and negative coefficients for managers at eight dispatch centers, who used between 3.17 and 6.95 fewer sources than managers in the default category, SWCC (Table 3.2). The SWCC is the focal point for logistical support between the other Southwest Area Dispatch Centers and with the National Coordination Center. As such, it covers the entire Southwest Area. Recall **H3:** Managers operating at a broader, regional scale will access more information. Conversely, respondents in Dispatch Centers outside SWCC would use fewer data sources.

Results for the full sample were quite similar to the sub-sample. Dropping fire manager characteristics (except agency and dispatch center) reduced the adjusted R^2 only slightly, from 0.2962 down to 0.2818). The variables that were significant in the full sample were also significant in the sub-sample. The magnitude of the regression coefficients are roughly the same. The results are robust across sample sizes for common variables.

Table 3.3 reports results of F-tests on the joint significance of respondent personal characteristic and place-of-work effects. The null hypothesis is that all the regression coefficients for a given category equal zero (e.g. all agency coefficients, or all age coefficients, or all experience coefficients, etc., equal zero). Except for age, we reject the null hypothesis that the grouped variables have no effect on information use. For the fire manager job type variable, the null hypothesis is rejected at the 10% significance level, but we fail to reject the null at the 5% level.

Table 3.4. Joint hypothesis tests for groups of variable coefficients measuring combined effects

Null hypothesis	t test statistic	p-value	Hypothesis test result
Information use is independent of number of decisions made	5.34	0.0000	Rejected (consistent with H1)
Information use does not increase during fire season even though risks are greater	2.56	0.0108	Rejected (consistent with H2)
Information use does not decrease during fire season because time is limited	2.56	0.0108	Rejected (consistent with H2)
Joint null hypothesis	F test statistic	p-value	
No dispatch center effects	F(12, 310) = 3.87	0.0000	Rejected (consistent with H3 and H7)
No education effects	F(4, 310) = 3.01	0.0184	Rejected (consistent with H4)
No age effects	F(4, 310) = 1.53	0.1936	Fail to reject
No experience effects	F(5, 310) = 2.26	0.0485	Rejected (consistent with H5)
No job description effects	F(3, 310) = 2.30	0.0775	Rejected at 10% level, fail to reject at 5% level (consistent with H6)
No agency effects	F(9, 310) = 3.04	0.0017	Rejected (consistent with H75

The overall results are generally consistent with the hypotheses generated from our simple value of information model. The results are consistent with the JWWZ framework (Just et al. 2002) for examining decision maker demand for information as a function of the decision maker's occupation or role within a system, characteristics of the system in which the decision maker participates, and the decision maker's the firm's or individual's level of human capital.

Chapter 4. How Information User and Source Attributes Affect Use of Fire Management Information

This chapter presents a more complex model than the previous chapter. Here, the goal is to examine how the use or non-use of an individual fire management information source *j* is affected by fire manager attributes as well as the attributes of the information sources themselves. The approach is similar to recreation demand models that attempt to predict individuals travel to particular recreation sites based on individual and site characteristics (Loomis, 1995; Massey et al., 2006; Peterson et al., 1983). In this chapter, we are trying to predict individual "visits" to websites rather than campsites. This chapter develops a random utility model to predict use of information source *j* by fire manager *i*. It uses data from the same internet survey described in Chapter 2. It then estimates the model using both logistic and linear probability model specifications.

Value of Information Use: A Conceptual Model

A fire manager's expected utility function V_i depends on the expected outcomes of a vector of *n* decisions (or actions), $\boldsymbol{x}_n$. The manager can consult *j* different information sources, represented by vector $\boldsymbol{s}_j$. Let $b\ [\boldsymbol{x}_n\ (\boldsymbol{s}_j)]$ be the expected benefit of making the n^{th} decision after using information source j. Let $b_0\ [x_n\ (\boldsymbol{s}_{j0})]$ be the expected benefit of making the nth decision without using information source *j*. One may express the value of information V_i to an individual fire manager making a particular decision *i* as

(1) $$V_i\ \{b_i\ [k_i, \boldsymbol{r}_i, a_i, \delta_i, \boldsymbol{x}_n\ (\boldsymbol{s}_j), \boldsymbol{z}_j] - b_{i0}\ [k_i, \boldsymbol{r}_i, a_i, \boldsymbol{x}_n\ (\boldsymbol{s}_{j0}), \boldsymbol{z}_j] - c_{in}\ (\boldsymbol{s}_j, k_i, \boldsymbol{r}_i, a_i, \delta i, \boldsymbol{z}_j)\}$$

where

c_i = manager i's costs of processing information for decision *n*, include time costs and costs of delay in making a decision

k_i = a measure of manager i's knowledge or technical capacity

r_i = a vector of attributes characterizing manager i's job or role within the fire management system

a_i = the agency that the individual works for

δ_i = the dispatch center where the individual works

$\mathbf{z}_j$ = a vector of attributes of the individual information sources

We can use the model above to examine which factors help explain fire manager *i*'s use (or non-use) of information source *j*. We can rewrite (1) as a reduced-form random utility model as follows. Utility when a fire manager does not use the information source is

(2) $V_0 = V\{b_{i0}\,[k_i, \boldsymbol{r}_i, a_i, \boldsymbol{x}_n\,(\mathbf{s}_{j0}), z_j]\} + \varepsilon\,[k_i, \boldsymbol{r}_i, a_i, \boldsymbol{x}_n\,(\mathbf{s}_{j0}), z_j, \boldsymbol{e}_{ij0}]$

where b_{i0} and ε are real valued functions. The vector $\boldsymbol{e}_{ij0}$ represents unmeasured attributes of the fire manager, the system where the manager operates, or the information source. Utility when the manager uses information source *j* is

(3) $V_1 = V\{b_i\,[k_i, \boldsymbol{r}_i, a_i, \delta_i, \boldsymbol{x}_n\,(\mathbf{s}_j), z_j] - c_{in}\,(\mathbf{s}_j, k_i, \boldsymbol{r}_i, a_i, \delta i, z_j)\} + \varepsilon\,[k_i, \boldsymbol{r}_i, a_i, \boldsymbol{x}_n\,(\mathbf{s}_j), z_j, \boldsymbol{e}_{ij}]$

where $\boldsymbol{e}_{ij0}$ represents unmeasured attributes of the fire manager, the system where the manager operates, or the information source.

Random Utility Model of Information Use

If the population is drawn from a random sample with common socioeconomic characteristics, the vectors $\boldsymbol{e}_{ij0}$ and $\boldsymbol{e}_{ij}$ will be random, and the utility function value will be stochastic (Domencich and McFadden 1975). We assume that the random components can be expressed as $\varepsilon(\boldsymbol{e}_{ij})$ and $\varepsilon(\boldsymbol{e}_{ij0})$. The value of weather information V* can be expressed as

(4) $V^* = \{b_i\,[k_i, \boldsymbol{\rho}_i, a_i, \delta_i, \boldsymbol{x}_n\,(\mathbf{s}_j), z_j] - c_{in}\,(\mathbf{s}_j, k_i, \boldsymbol{\rho}_i, a_i, \delta i, z_j)\} + \varepsilon\,(\boldsymbol{e}_{ij})$
$- \{b_{i0}\,[k_i, \boldsymbol{\rho}_i, a_i, \boldsymbol{x}_n\,(\mathbf{s}_{j0}), z_j] + \varepsilon\,(\boldsymbol{e}_{ij0})\}$

A utility maximizing fire manager will use information source *j* if $V^* > 0$ (i.e. if the expected net benefit is positive)

(5) $V^* = \{b_i\,[k_i, \boldsymbol{\rho}_i, a_i, \delta_i, \boldsymbol{x}_n\,(\mathbf{s}_j), z_j] - c_{in}\,(\mathbf{s}_j, k_i, \boldsymbol{\rho}_i, a_i, \delta i, z_j)\} - \{b_{i0}\,[k_i, \boldsymbol{\rho}_i, a_i, \boldsymbol{x}_n\,(\mathbf{s}_{j0}), z_j]$
$+ [\varepsilon\,(\boldsymbol{e}_{ij}) - \varepsilon\,(\boldsymbol{e}_{ij0})]\} > 0$

and not, otherwise.

We do not observe the expected value of using information source *j* to fire manager *i*. We do, however, observe the discrete choice of whether manager i uses the information source. If $\varepsilon(\boldsymbol{e}_{ij})$ and $\varepsilon(\boldsymbol{e}_{ij0})$ each have a Gumbel distribution, then their difference $\eta = \varepsilon(\boldsymbol{e}_{ij}) - \varepsilon(\boldsymbol{e}_{ij0})$ will have a logistic distribution (Kaoru, et al., 1995). If we assume that V^* can be written as a linear function

(6) $V_{ij}^* = \alpha + \mathbf{k}'\boldsymbol{\beta}_k + \mathbf{a}'\boldsymbol{\beta}_a + \mathbf{r}'\boldsymbol{\beta}_r + \boldsymbol{\delta}'\boldsymbol{\beta}_\delta + \boldsymbol{z}'\,\boldsymbol{\beta}_z + n\beta n + d\beta_d + \eta$

where terms $\boldsymbol{\beta}_k$, $\boldsymbol{\beta}_a$, $\boldsymbol{\beta}_r$, $\boldsymbol{\beta}_\delta$, $\boldsymbol{\beta}_z$, β_n, β_d are regression coefficients to be estimated and

α = is a regression constant term

k = is a vector of categorical variables for age, experience, and education level, which may influence the costs and benefits of using particular information sources

a = a vector of dummy variables denoting where the fire manager works

r = a vector of dummy variables for different jobs or roles in the fire management system a fire manager may have

$\boldsymbol{\delta}$ = a vector of dummy variables denoting the dispatch center where a fire manager operates

$\mathbf{z}$ = a vector of dummy variables characterizing attributes of each information source *j*

n = the total number of decisions a fire manager makes

d = a dummy variable = 1 if the choice of using or not using an information source is made during the fires season and = 0 if the choice is made before the fire season

Variable Description

Table 4.1 shows descriptive statistics for variables used in the regression analysis along with those for omitted default variables. Except for the total decisions made by a manager, all other variables are binary, 0-1 categorical variables. To avoid perfect multicollinearity one of the categories must be left out. Regression coefficients in the model show effects of difference from these reference categories.

Many of the variables used here are the same as those used in Chapter 2. Their description is not repeated here. Individual fire managers work for different agencies (e.g. Forest Service, Bureau of Land Management), but are stationed a particular dispatch center with authority to over fire management over specific regions. So, managers from different agencies may work together in at a common dispatch center. In the sample, fire managers operated out of dispatch centers in Flagstaff, Phoenix, Prescott, Springerville, Tucson, and Williams in Arizona and Alamogordo, Albuquerque, Santa Fe, Silver City, and Taos in New Mexico. A small number of respondents were primarily assigned to other dispatch centers in adjoining states. Fire managers can work across dispatch center boundary areas or states to reallocate and pool resources to manage fire. There is also a Southwest Coordination Center (SWCC), which as its name suggests, coordinates activities among the other, smaller dispatch centers. The SWCC is treated as the default variable in the regression analysis.

In the survey, different sources of information were grouped into broad categories:

- general websites and portals
- forecasts and outlooks
- situation reports and information products
- decision support tools

Tab1e 4.1. Descriptive statistics for regression variables (all values are proportions except for Total Decisions)

Proportion of times information source used	0.441	Self-described job within agency	
During fire season	0.500	Agency administrator	0.034
Total Decisions, mean	4.223	Fire Manager (fuels and fire)	0.417
Total Decisions, standard deviation	1.800	Fire Manager (suppression)	0.274
Agency		Other job	0.274
Forest service	0.451	Researcher-defined job categories	
BLM	0.143	Modelers	0.114
Bureau of Indian Affairs	0.126	Implement	0.360
National Park Service	0.057	Environmental Specialist	0.040
AZ Dept. of Forestry & Fire Mgmt.	0.109	Aviation	0.097
NM Forestry Division	0.029	Logistics	0.131
Other agency	0.051	Age (years)	
NOAA	0.017	less than 30	0.006
AZ Dept. of Environmental Quality	0.017	30-39	0.171
Dispatch Center		40-49	0.451
AZ-ADC	0.109	50-59	0.269
AZ-FDC	0.080	60 or more	0.103
AZ-PHC	0.063	Experience	
AZ-PDC	0.046	0-4 years	0.029
AZ-SDC	0.063	5-9 years	0.057
AZ-TDC	0.091	10-14 years	0.109
AZ-WDC	0.011	15-19 years	0.177
NM-ADC	0.086	20-29 years	0.486
NM-ABC	0.074	30 and more years	0.143
NM-SFC	0.091	Education	
NM-SDC	0.097	High school graduate	0.069
NM-TDC	0.046	Some college	0.337
Other	0.023	College Graduate	0.451
NM-SWC	0.120	Masters/Professional degree	0.126
Type of information source		Doctoral degree	0.017
Fire	0.424		
General	0.303		
Outlook	0.273		
Situation	0.303		
Drought	0.152		
ENSO	0.091		
DSS	0.121		

For the regression, the sources in the forecast and outlook category were treated as the default variable, while dummy variables were created to denote whether source was in one of the other categories.

Information sources were also categorized in terms of whether they provided more tailored fire management information or whether they provide more generally applicable weather and climate information. Three separate dummy variables were created for cases where (i) the information source provided tailored information for fire management, (ii) it provided data more generally on drought, or (iii) it provided data more generally on El Niño-

Southern Oscillation (ENSO) patterns. Drought data provide information about soil moisture and precipitation, which can affect wildland fire risk.

Fire managers in the survey self-identified their jobs/roles as one of Agency Administrator, Fire Manager (fuels and fire), Fire Manager (suppression), or Other. Managing fuels is related to prevention, while suppression is "putting fires out." Administrators were treated as the omitted default category, while dummy variables for the other jobs/roles were included in the regression. The research team also classified fire managers into the following groupings: Modelers, Environmental Specialists, Aviation, Logistics, and Implementation. Those in Implementation were treated as the omitted default category, while dummy variables for the other categories were included in the regression.

Results

Below we report results for six different regression specifications. Equation (6) is estimated both as a logistic regression and as a linear probability model (OLS). These regressions were run for the full sample, pooling choices made both before and during the fire season and in separate regressions for before and during the fire season.

Odds ratios (ORs) and their significance levels were reported for variables in the logistic regressions. In the context of this study, the OR measures how a respondent being in a particular category (e.g., age category, education category) changes their odds of using an information source relative to a reference category. The odds are the probability of use divided by the probability of non-use (UCLA, 2023). An OR equal to one (1) means that being in that category has no effect on the odds of use relative to the reference category. An OR = 2 means that being in the category doubles the odds of use. An OR = 0.5 means that being in the category cuts the odds of use in half. For the linear probability models, the regression coefficients simple represent the change in the probability of use with a change from the reference category.

Output from the logistic regressions predict use or non-use of each information source *j* by each fire manager *i*. The adjusted count R^2 (ACR^2) was reported for each logistic regression for information source use

(7)

$$\mathrm{ACR}^2 = \frac{\text{Total correct predictions from regression model} - \text{Count of most common response}}{\text{Total number of observations} - \text{Count of most common response}}$$

The ACR^2 compares the logistic regression predictions to a "naive" model where one predicts that all responses were the same as the most common response. For example, suppose 75% of observations were "yes," for adoption. If someone naively predicted that all observations were yes, they would be correct 75% of the time. The ACR^2 measures the percentage reduction in prediction error from using the regression model relative to this naive model. If the regression predictions were no better than the naive model, then $ACR^2 = 0$. If the regression predicts perfectly, then $ACR^2 = 1$.

Table 4.2 shows the results of the logistic regression, pooling information for before and during fire season. In the Arizona and New Mexico, the fire season has historically been defined as beginning in April (in low desert areas) and May (to the north) and running through October. For respondents, operationally the main difference is between a period of preparation and fire fuels management and a period of fire suppression. Results for variables significant at the 5% level (or less) are shown in boldface.

The odds of using a given information source during fire season is nearly 24% greater than using it before (OR = 1.235). Every additional decision a fire manager makes increases the odds of using an information sources by 15% (OR = 1.15). For types of data source, the default category was general websites and data portals. Compared to this category, the odds of using an information source specifically tailored to fire management is more than double (OR = 2.3). The odds of using Outlook information are about 5% greater, while the odds of using Situation, Drought-specific, or ENSO-specific sources are lower than for the general sites. The odds of a fire manager using a Decision Support System (DSS) is less than a third of the odds of general sites (OR = 0.318).

The agency default category is for managers working for the Forest Service. Comparatively, those at the Bureau of Indian Affairs, the New Mexico Forestry Division, and NOAA have greater odds of using a given information source. In contrast, those at the National Park Service and the Arizona Department of Forestry and Fire Management have lower odds of using information. For dispatch centers, several have significantly lower odds that the default, SWCC. In Chapter 2, we posited that information use among those at SWCC would be greater because they are responsible for a larger geographical area. So, the gains from better information could be applied across a larger area.

Results for age and experience are complex. Those younger than 40 have greater odds of use than those 40-49 years old. Yet those with experience of 30 or more years have greater odds of use than those with 20-28 years of experience. Compared to college graduates, those with only a high school diploma have lower odds, while those with some college or a masters/professional degree have higher odds. Turning to job type, Fire Managers (fuels and fire), Fire Managers (suppression) and those in Other Jobs have roughly double the odds of use as Administrators. Based on the other job categories, Modelers have 32% greater odds of use compared to the default, Implementers.

Table 4.2. Logistic regression of fire manager use of individual information sources before and during fire season (variables with odds ratios significant at $p < 0.05$ shown in bold face)

Number of observations = 11,550	Adjusted count R^2 = 0.186			
Regression Variables	Odds ratio	Std. error	z	P>|z|
During fire season	**1.236**	**0.049**	**5.30**	**0.0000**
Fire	**2.305**	**0.133**	**14.45**	**0.0000**
Total decisions	**1.151**	**0.016**	**9.84**	**0.0000**
Outlook	1.065	0.056	1.20	0.2320
Situation	**0.807**	**0.052**	**-3.36**	**0.0010**
Drought	**0.849**	**0.057**	**-2.45**	**0.0140**
ENSO	**0.600**	**0.059**	**-5.16**	**0.0000**
Decision Support System	**0.318**	**0.025**	**-14.38**	**0.0000**
BLM	0.904	0.066	-1.37	0.1710
Bureau of Indian Affairs	**1.408**	**0.103**	**4.66**	**0.0000**
National Park Service	**0.788**	**0.085**	**-2.21**	**0.0270**
AZ Dept. of Forestry & Fire Mgmt.	**0.533**	**0.057**	**-5.93**	**0.0000**
NM Forestry Division	**1.646**	**0.239**	**3.44**	**0.0010**
Other agency	1.164	0.121	1.46	0.1450
NOAA	**2.919**	**1.110**	**2.82**	**0.0050**
AZ Dept. of Env. Quality	1.683	0.694	1.26	0.2070
Age (< 30)	**5.769**	**2.420**	**4.18**	**0.0000**
Age (30-39)	**1.168**	**0.081**	**2.25**	**0.0250**
Age (50-59)	0.971	0.057	-0.50	0.6200
Age (≥60)	1.098	0.105	0.97	0.3310
Experience (< 5 years)	0.778	0.128	-1.52	0.1280
Experience (5-9 years)	1.028	0.125	0.22	0.8230
Experience (10-14 years)	0.975	0.079	-0.31	0.7530
Experience (15-19 years)	**1.341**	**0.090**	**4.35**	**0.0000**
Experience (> 30 years)	**1.249**	**0.096**	**2.89**	**0.0040**
Fire Manager (fuels & fire)	**1.896**	**0.282**	**4.30**	**0.0000**
Fire Manager (suppression)	**2.164**	**0.333**	**5.02**	**0.0000**
Other job	**1.883**	**0.273**	**4.36**	**0.0000**
High school graduate	**0.693**	**0.068**	**-3.74**	**0.0000**
Some college	**1.253**	**0.062**	**4.58**	**0.0000**
Masters / professional degree	**1.192**	**0.085**	**2.45**	**0.0140**
Doctoral degree	1.124	0.261	0.50	0.6140
AZ-Flagstaff Dispatch Center (DC)	**0.622**	**0.067**	**-4.44**	**0.0000**
AZ-Phoenix DC	**0.495**	**0.058**	**-6.04**	**0.0000**
AZ-Prescott DC	1.105	0.127	0.87	0.3850
AZ-Springerville DC	1.011	0.118	0.09	0.9260
AZ-Tucson DC	**0.460**	**0.046**	**-7.75**	**0.0000**
AZ-Williams DC	**0.437**	**0.090**	**-4.04**	**0.0000**
NM-Alamogordo DC	**0.678**	**0.073**	**-3.60**	**0.0000**
NM-Albuquerque DC	1.174	0.123	1.53	0.1260
NM-Santa Fe DC	0.932	0.090	-0.73	0.4650
NM-Silver City DC	**0.685**	**0.064**	**-4.03**	**0.0000**
NM-Taos DC	**0.460**	**0.056**	**-6.43**	**0.0000**
Other DC	**0.241**	**0.070**	**-4.87**	**0.0000**
Modeler	**1.322**	**0.098**	**3.76**	**0.0000**
Environmental Specialist	0.818	0.232	-0.71	0.4780
Aviation	0.983	0.083	-0.20	0.8420
Logistics	1.101	0.091	1.15	0.2490
Constant	**0.194**	**0.034**	**-9.30**	**0.0000**

Table 4.3. Linear probability model of fire manager use of individual information sources before and during fire season (variables with odds ratios significant at $p < 0.05$ shown in bold face)

Number of observations = 11,550	Adjusted R^2 = 0.1044			
Regression Variables	Coefficient	Std. error	t statistics	P>|t|
During fire season	**0.047**	**0.009**	**5.29**	**0.000**
Fire	**0.192**	**0.013**	**14.99**	**0.000**
Total decisions	**0.030**	**0.003**	**9.86**	**0.000**
Outlook	0.014	0.012	1.23	0.220
Situation	**-0.048**	**0.014**	**-3.37**	**0.001**
Drought	**-0.036**	**0.015**	**-2.43**	**0.015**
ENSO	**-0.104**	**0.021**	**-4.94**	**0.000**
Decision Support System	**-0.260**	**0.017**	**-14.95**	**0.000**
BLM	-0.022	0.016	-1.34	0.180
Bureau of Indian Affairs	**0.077**	**0.016**	**4.74**	**0.000**
National Park Service	**-0.054**	**0.024**	**-2.26**	**0.024**
AZ Dept. of Forestry & Fire Mgmt.	**-0.137**	**0.023**	**-5.91**	**0.000**
NM Forestry Division	**0.114**	**0.032**	**3.62**	**0.000**
Other agency	0.039	0.023	1.70	0.089
NOAA	**0.230**	**0.085**	**2.70**	**0.007**
AZ Dept. of Env. Quality	0.110	0.091	1.21	0.228
Age (< 30)	**0.380**	**0.089**	**4.26**	**0.000**
Age (30-39)	**0.032**	**0.015**	**2.13**	**0.033**
Age (50-59)	-0.007	0.013	-0.55	0.580
Age (≥60)	0.017	0.021	0.82	0.415
Experience (< 5 years)	-0.052	0.035	-1.49	0.136
Experience (5-9 years)	0.013	0.027	0.48	0.634
Experience (10-14 years)	-0.004	0.018	-0.23	0.818
Experience (15-19 years)	**0.064**	**0.015**	**4.31**	**0.000**
Experience (> 30 years)	**0.051**	**0.017**	**2.98**	**0.003**
Fire Manager (fuels & fire)	**0.136**	**0.031**	**4.34**	**0.000**
Fire Manager (suppression)	**0.164**	**0.032**	**5.07**	**0.000**
Other job	**0.136**	**0.030**	**4.50**	**0.000**
High school graduate	**-0.076**	**0.021**	**-3.66**	**0.000**
Some college	**0.051**	**0.011**	**4.62**	**0.000**
Masters / professional degree	**0.040**	**0.016**	**2.53**	**0.011**
Doctoral degree	0.030	0.049	0.61	0.540
AZ-Flagstaff Dispatch Center (DC)	**-0.107**	**0.024**	**-4.51**	**0.000**
AZ-Phoenix DC	**-0.159**	**0.026**	**-6.13**	**0.000**
AZ-Prescott DC	0.025	0.026	0.97	0.334
AZ-Springerville DC	0.007	0.026	0.27	0.790
AZ-Tucson DC	**-0.170**	**0.022**	**-7.89**	**0.000**
AZ-Williams DC	**-0.186**	**0.045**	**-4.09**	**0.000**
NM-Alamogordo DC	**-0.084**	**0.024**	**-3.5**	**0.000**
NM-Albuquerque DC	0.038	0.023	1.62	0.105
NM-Santa Fe DC	-0.015	0.022	-0.67	0.502
NM-Silver City DC	**-0.085**	**0.021**	**-4.03**	**0.000**
NM-Taos DC	**-0.169**	**0.026**	**-6.49**	**0.000**
Other DC	**-0.306**	**0.063**	**-4.87**	**0.000**
Modeler	**0.059**	**0.016**	**3.60**	**0.000**
Environmental Specialist	-0.047	0.064	-0.73	0.463
Aviation	-0.003	0.019	-0.16	0.870
Logistics	0.020	0.018	1.08	0.282
Constant	**0.140**	**0.038**	**3.74**	**0.000**

Table 4.4, Logistic regression of fire manager use of individual information sources before fire season (variables with odds ratios significant at $p < 0.05$ shown in bold face)

Number of observations = 5,775	Adjusted count R^2 = 0.156			
Regression Variables	Odds ratio	Std. error	z	P>|z|
Fire	**2.002**	**0.161**	**8.62**	**0.000**
Total decisions	**1.158**	**0.024**	**7.24**	**0.000**
Outlook	1.076	0.081	0.97	0.333
Situation	**0.681**	**0.062**	**-4.20**	**0.000**
Drought	0.901	0.095	-0.99	0.321
ENSO	0.805	0.112	-1.56	0.119
Decision Support System	**0.294**	**0.034**	**-10.65**	**0.000**
BLM	0.847	0.088	-1.60	0.111
Bureau of Indian Affairs	**1.396**	**0.145**	**3.22**	**0.001**
National Park Service	0.763	0.116	-1.77	0.076
AZ Dept. of Forestry & Fire Mgmt.	**0.566**	**0.085**	**-3.78**	**0.000**
NM Forestry Division	**1.769**	**0.361**	**2.80**	**0.005**
Other agency	1.250	0.184	1.51	0.130
NOAA	2.230	1.199	1.49	0.136
AZ Dept. of Env. Quality	1.591	0.925	0.80	0.425
Age (< 30)	**7.121**	**4.212**	**3.32**	**0.001**
Age (30-39)	1.142	0.112	1.35	0.176
Age (50-59)	0.949	0.080	-0.63	0.531
Age (≥ 60)	1.055	0.144	0.39	0.698
Experience (< 5 years)	**0.595**	**0.146**	**-2.12**	**0.034**
Experience (5-9 years)	1.076	0.185	0.42	0.671
Experience (10-14 years)	0.963	0.110	-0.33	0.741
Experience (15-19 years)	1.182	0.113	1.75	0.080
Experience (> 30 years)	**1.370**	**0.149**	**2.89**	**0.004**
Fire Manager (fuels & fire)	**1.946**	**0.420**	**3.08**	**0.002**
Fire Manager (suppression)	**2.099**	**0.467**	**3.33**	**0.001**
Other job	**2.043**	**0.432**	**3.38**	**0.001**
High school graduate	**0.706**	**0.099**	**-2.48**	**0.013**
Some college	**1.195**	**0.083**	**2.55**	**0.011**
Masters / professional degree	1.167	0.118	1.53	0.127
Doctoral degree	0.998	0.330	0.00	0.996
AZ-Flagstaff Dispatch Center (DC)	**0.676**	**0.102**	**-2.58**	**0.010**
AZ-Phoenix DC	**0.511**	**0.084**	**-4.06**	**0.000**
AZ-Prescott DC	1.234	0.200	1.30	0.195
AZ-Springerville DC	1.062	0.174	0.37	0.715
AZ-Tucson DC	**0.497**	**0.071**	**-4.90**	**0.000**
AZ-Williams DC	**0.417**	**0.121**	**-3.01**	**0.003**
NM-Alamogordo DC	0.746	0.114	-1.92	0.055
NM-Albuquerque DC	1.248	0.185	1.50	0.135
NM-Santa Fe DC	1.002	0.137	0.02	0.985
NM-Silver City DC	**0.731**	**0.097**	**-2.36**	**0.018**
NM-Taos DC	**0.419**	**0.073**	**-4.98**	**0.000**
Other DC	**0.260**	**0.108**	**-3.25**	**0.001**
Modeler	**1.313**	**0.138**	**2.59**	**0.010**
Environmental Specialist	0.945	0.377	-0.14	0.888
Aviation	0.886	0.106	-1.01	0.311
Logistics	1.066	0.126	0.54	0.589
Constant	**0.204**	**0.051**	**-6.30**	**0.000**

Table 4.5. Linear probability model of fire manager use of individual information sources before fire season (variables with odds ratios significant at $p < 0.05$ shown in bold face)

Number of observations = 5,775   Adjusted R^2 = 0.0925

Regression Variables	Coefficient	Std. error	t statistic	P>|t|
Fire	**0.159**	**0.018**	**8.86**	**0.000**
Total decisions	**0.032**	**0.004**	**7.27**	**0.000**
Outlook	0.017	0.017	1.03	0.305
Situation	**-0.086**	**0.020**	**-4.26**	**0.000**
Drought	-0.021	0.023	-0.89	0.375
ENSO	-0.040	0.030	-1.35	0.178
Decision Support System	**-0.271**	**0.025**	**-11.01**	**0.000**
BLM	-0.035	0.023	-1.53	0.126
Bureau of Indian Affairs	**0.076**	**0.023**	**3.29**	**0.001**
National Park Service	-0.062	0.034	-1.82	0.069
AZ Dept. of Forestry & Fire Mgmt.	**-0.121**	**0.033**	**-3.70**	**0.000**
NM Forestry Division	**0.132**	**0.045**	**2.96**	**0.003**
Other agency	0.056	0.033	1.71	0.087
NOAA	0.166	0.121	1.38	0.169
AZ Dept. of Env. Quality	0.087	0.129	0.67	0.500
Age (< 30)	**0.425**	**0.126**	**3.36**	**0.001**
Age (30-39)	0.029	0.021	1.33	0.184
Age (50-59)	-0.011	0.018	-0.62	0.533
Age (≥ 60)	0.009	0.029	0.32	0.752
Experience (< 5 years)	**-0.102**	**0.049**	**-2.08**	**0.037**
Experience (5-9 years)	0.022	0.038	0.60	0.551
Experience (10-14 years)	-0.006	0.025	-0.25	0.805
Experience (15-19 years)	0.035	0.021	1.67	0.096
Experience (> 30 years)	**0.071**	**0.024**	**2.96**	**0.003**
Fire Manager (fuels & fire)	**0.138**	**0.044**	**3.12**	**0.002**
Fire Manager (suppression)	**0.154**	**0.046**	**3.35**	**0.001**
Other job	**0.151**	**0.043**	**3.54**	**0.000**
High school graduate	**-0.071**	**0.029**	**-2.41**	**0.016**
Some college	**0.040**	**0.015**	**2.56**	**0.011**
Masters / professional degree	0.034	0.022	1.52	0.129
Doctoral degree	0.007	0.070	0.10	0.922
AZ-Flagstaff Dispatch Center (DC)	**-0.088**	**0.034**	**-2.61**	**0.009**
AZ-Phoenix DC	**-0.151**	**0.037**	**-4.13**	**0.000**
AZ-Prescott DC	0.051	0.037	1.40	0.162
AZ-Springerville DC	0.021	0.037	0.59	0.558
AZ-Tucson DC	**-0.152**	**0.031**	**-4.99**	**0.000**
AZ-Williams DC	**-0.196**	**0.064**	**-3.04**	**0.002**
NM-Alamogordo DC	-0.062	0.034	-1.82	0.069
NM-Albuquerque DC	0.055	0.033	1.66	0.098
NM-Santa Fe DC	0.003	0.031	0.10	0.919
NM-Silver City DC	**-0.070**	**0.030**	**-2.34**	**0.019**
NM-Taos DC	**-0.185**	**0.037**	**-5.05**	**0.000**
Other DC	**-0.288**	**0.089**	**-3.24**	**0.001**
Modeler	**0.057**	**0.023**	**2.45**	**0.014**
Environmental Specialist	-0.011	0.091	-0.12	0.906
Aviation	-0.025	0.026	-0.97	0.335
Logistics	0.012	0.026	0.46	0.648
Constant	**0.153**	**0.053**	**2.89**	**0.004**

Table 4.6. Logistic regression of fire manager use of individual information sources during fire season (variables with odds ratios significant at $p < 0.05$ shown in bold face)

Number of observations = 5,775   Adjusted count R^2 = 0.244

Regression Variables	Odds ratio	Std. error	z	P>|z|
Fire	**2.758**	**0.230**	**12.14**	**0.000**
Total decisions	**1.146**	**0.023**	**6.71**	**0.000**
Outlook	1.067	0.080	0.87	0.387
Situation	0.938	0.085	-0.71	0.477
Drought	0.864	0.076	-1.66	0.097
ENSO	**0.465**	**0.066**	**-5.39**	**0.000**
Decision Support System	**0.334**	**0.037**	**-9.84**	**0.000**
BLM	0.965	0.100	-0.34	0.731
Bureau of Indian Affairs	**1.428**	**0.150**	**3.39**	**0.001**
National Park Service	0.812	0.124	-1.36	0.174
AZ Dept. of Forestry & Fire Mgmt.	**0.499**	**0.075**	**-4.64**	**0.000**
NM Forestry Division	**1.541**	**0.320**	**2.08**	**0.037**
Other agency	1.085	0.161	0.55	0.580
NOAA	**3.905**	**2.122**	**2.51**	**0.012**
AZ Dept. of Env. Quality	1.796	1.060	0.99	0.321
Age (< 30)	**4.881**	**2.929**	**2.64**	**0.008**
Age (30-39)	1.197	0.118	1.83	0.067
Age (50-59)	0.991	0.083	-0.11	0.916
Age (≥60)	1.140	0.154	0.97	0.333
Experience (< 5 years)	0.992	0.226	-0.04	0.970
Experience (5-9 years)	0.981	0.171	-0.11	0.914
Experience (10-14 years)	0.987	0.113	-0.12	0.907
Experience (15-19 years)	**1.530**	**0.147**	**4.43**	**0.000**
Experience (> 30 years)	1.141	0.125	1.21	0.226
Fire Manager (fuels & fire)	**1.877**	**0.389**	**3.03**	**0.002**
Fire Manager (suppression)	**2.269**	**0.488**	**3.81**	**0.000**
Other job	**1.759**	**0.355**	**2.79**	**0.005**
High school graduate	**0.677**	**0.094**	**-2.82**	**0.005**
Some college	**1.319**	**0.093**	**3.95**	**0.000**
Masters / professional degree	**1.222**	**0.125**	**1.96**	**0.050**
Doctoral degree	1.279	0.419	0.75	0.452
AZ-Flagstaff Dispatch Center (DC)	**0.568**	**0.086**	**-3.72**	**0.000**
AZ-Phoenix DC	**0.475**	**0.079**	**-4.50**	**0.000**
AZ-Prescott DC	0.988	0.163	-0.08	0.939
AZ-Springerville DC	0.961	0.160	-0.24	0.809
AZ-Tucson DC	**0.423**	**0.060**	**-6.09**	**0.000**
AZ-Williams DC	**0.454**	**0.132**	**-2.72**	**0.007**
NM-Alamogordo DC	**0.612**	**0.094**	**-3.20**	**0.001**
NM-Albuquerque DC	1.102	0.165	0.65	0.515
NM-Santa Fe DC	0.864	0.119	-1.06	0.287
NM-Silver City DC	**0.638**	**0.085**	**-3.36**	**0.001**
NM-Taos DC	**0.497**	**0.084**	**-4.13**	**0.000**
Other DC	**0.221**	**0.091**	**-3.65**	**0.000**
Modeler	**1.340**	**0.142**	**2.76**	**0.006**
Environmental Specialist	0.700	0.285	-0.88	0.381
Aviation	1.091	0.130	0.73	0.464
Logistics	1.139	0.134	1.11	0.269
Constant	**0.218**	**0.054**	**-6.18**	**0.000**

Table 4.7. Linear probability model of fire manager use of individual information sources during fire season (variables with odds ratios significant at $p < 0.05$ shown in bold face)

Number of observations = 5,775   Adjusted R^2 = 0.1166

Regression Variables	Coefficient	Std. error	t statistic	P>|t|
Fire	**0.231**	**0.018**	**12.68**	**0.000**
Total decisions	**0.029**	**0.004**	**6.69**	**0.000**
Outlook	0.014	0.017	0.87	0.384
Situation	-0.014	0.020	-0.69	0.488
Drought	-0.033	0.019	-1.70	0.089
ENSO	**-0.157**	**0.030**	**-5.31**	**0.000**
Decision Support System	**-0.251**	**0.025**	**-10.22**	**0.000**
BLM	-0.008	0.023	-0.37	0.712
Bureau of Indian Affairs	**0.078**	**0.023**	**3.41**	**0.001**
National Park Service	-0.047	0.034	-1.38	0.168
AZ Dept. of Forestry & Fire Mgmt.	**-0.153**	**0.033**	**-4.67**	**0.000**
NM Forestry Division	**0.096**	**0.044**	**2.16**	**0.031**
Other agency	0.022	0.032	0.69	0.490
NOAA	**0.295**	**0.120**	**2.45**	**0.014**
AZ Dept. of Env. Quality	0.133	0.128	1.03	0.301
Age (< 30)	**0.335**	**0.126**	**2.66**	**0.008**
Age (30-39)	0.036	0.021	1.69	0.090
Age (50-59)	-0.003	0.018	-0.16	0.873
Age ($\geq$60)	0.025	0.029	0.84	0.401
Experience (< 5 years)	-0.001	0.049	-0.03	0.980
Experience (5-9 years)	0.003	0.038	0.08	0.939
Experience (10-14 years)	-0.002	0.025	-0.08	0.937
Experience (15-19 years)	**0.093**	**0.021**	**4.44**	**0.000**
Experience (> 30 years)	0.030	0.024	1.26	0.208
Fire Manager (fuels & fire)	**0.133**	**0.044**	**3.02**	**0.003**
Fire Manager (suppression)	**0.175**	**0.046**	**3.82**	**0.000**
Other job	**0.120**	**0.043**	**2.83**	**0.005**
High school graduate	**-0.081**	**0.029**	**-2.77**	**0.006**
Some college	**0.062**	**0.015**	**3.98**	**0.000**
Masters / professional degree	**0.046**	**0.022**	**2.07**	**0.039**
Doctoral degree	0.053	0.069	0.77	0.441
AZ-Flagstaff Dispatch Center (DC)	**-0.127**	**0.034**	**-3.77**	**0.000**
AZ-Phoenix DC	**-0.166**	**0.036**	**-4.55**	**0.000**
AZ-Prescott DC	-0.001	0.037	-0.04	0.972
AZ-Springerville DC	-0.008	0.036	-0.21	0.834
AZ-Tucson DC	**-0.188**	**0.030**	**-6.18**	**0.000**
AZ-Williams DC	**-0.176**	**0.064**	**-2.74**	**0.006**
NM-Alamogordo DC	**-0.106**	**0.034**	**-3.13**	**0.002**
NM-Albuquerque DC	0.021	0.033	0.64	0.522
NM-Santa Fe DC	-0.032	0.031	-1.05	0.292
NM-Silver City DC	**-0.100**	**0.030**	**-3.36**	**0.001**
NM-Taos DC	**-0.152**	**0.037**	**-4.14**	**0.000**
Other DC	**-0.324**	**0.089**	**-3.65**	**0.000**
Modeler	**0.061**	**0.023**	**2.65**	**0.008**
Environmental Specialist	-0.084	0.091	-0.92	0.357
Aviation	0.019	0.026	0.74	0.462
Logistics	0.028	0.026	1.07	0.286
Constant	**0.169**	**0.053**	**3.20**	**0.001**

Table 4.8. Differences in odds ratios between pooled, before-fire-season, and during-fire-season regressions

	Pooled Sample			Before Fire Season			During Fire Season		
		95% Confidence Interval			95% Confidence Interval			95% Confidence Interval	
Regression Variables	Odds ratio	Lower	Upper	Odds ratio	Lower	Upper	Odds ratio	Lower	Upper
Type of Information Source									
Fire	**2.305**	**2.058**	**2.581**	**2.002**	**1.710**	**2.345**	**2.758**	**2.341**	**3.248**
Total decisions	**1.151**	**1.119**	**1.184**	**1.158**	**1.113**	**1.205**	**1.146**	**1.101**	**1.192**
Outlook	1.065	0.960	1.182	1.076	0.928	1.247	1.067	0.921	1.236
Situation	**0.807**	**0.712**	**0.914**	**0.681**	**0.569**	**0.814**	0.938	0.786	1.119
Drought	**0.849**	**0.745**	**0.968**	0.901	0.734	1.107	0.864	0.728	1.027
ENSO	**0.600**	**0.494**	**0.729**	0.805	0.613	1.057	**0.465**	**0.352**	**0.614**
Decision Support System	**0.318**	**0.272**	**0.372**	**0.294**	**0.235**	**0.369**	**0.334**	**0.268**	**0.415**
Agency									
BLM	0.904	0.783	1.044	0.847	0.690	1.039	0.965	0.787	1.183
Bureau of Indian Affairs	**1.408**	**1.219**	**1.626**	**1.396**	**1.140**	**1.710**	**1.428**	**1.162**	**1.754**
National Park Service	**0.788**	**0.638**	**0.974**	0.763	0.566	1.029	0.812	0.602	1.096
AZ Dept. of Forestry & Fire Mgmt.	**0.533**	**0.433**	**0.657**	**0.566**	**0.421**	**0.760**	**0.499**	**0.371**	**0.669**
NM Forestry Division	**1.646**	**1.239**	**2.188**	**1.769**	**1.186**	**2.637**	**1.541**	**1.026**	**2.314**
Other agency	1.164	0.949	1.427	1.250	0.937	1.667	1.085	0.812	1.451
NOAA	**2.919**	**1.386**	**6.150**	2.230	0.777	6.399	**3.905**	**1.346**	**11.328**
AZ Dept. of Env. Quality	1.683	0.749	3.778	1.591	0.509	4.974	1.796	0.565	5.712
Age									
Age (< 30)	**5.769**	**2.535**	**13.128**	**7.121**	**2.234**	**22.698**	**4.881**	**1.505**	**15.824**
Age (30-39)	**1.168**	**1.020**	**1.338**	1.142	0.942	1.383	1.197	0.987	1.452
Age (50-59)	0.971	0.865	1.090	0.949	0.805	1.119	0.991	0.841	1.168
Age (≥ 60)	1.098	0.910	1.324	1.055	0.807	1.379	1.140	0.874	1.485
Experience									
Experience (< 5 years)	0.778	0.563	1.075	**0.595**	**0.368**	**0.962**	0.992	0.635	1.549
Experience (5-9 years)	1.028	0.809	1.305	1.076	0.768	1.506	0.981	0.697	1.381
Experience (10-14 years)	0.975	0.832	1.142	0.963	0.769	1.205	0.987	0.789	1.234
Experience (15-19 years)	**1.341**	**1.175**	**1.530**	1.182	0.980	1.426	**1.530**	**1.268**	**1.846**
Experience (> 30 years)	**1.249**	**1.074**	**1.453**	**1.370**	**1.107**	**1.696**	1.141	0.921	1.414
Self-Reported Job Type									
Fire Manager (fuels & fire)	**1.896**	**1.417**	**2.538**	**1.946**	**1.274**	**2.971**	**1.877**	**1.250**	**2.819**
Fire Manager (suppression)	**2.164**	**1.601**	**2.925**	**2.099**	**1.356**	**3.248**	**2.269**	**1.489**	**3.458**
Other job	**1.883**	**1.417**	**2.503**	**2.043**	**1.350**	**3.091**	**1.759**	**1.184**	**2.614**
Education									
High school graduate	**0.693**	**0.572**	**0.840**	**0.706**	**0.537**	**0.929**	**0.677**	**0.516**	**0.887**
Some college	**1.253**	**1.138**	**1.380**	**1.195**	**1.042**	**1.370**	**1.319**	**1.150**	**1.514**
Masters / professional degree	**1.192**	**1.035**	**1.371**	1.167	0.957	1.423	1.222	1.000	1.492
Doctoral degree	1.124	0.714	1.771	0.998	0.522	1.910	1.279	0.673	2.429
Dispatch Center									
AZ-Flagstaff	**0.622**	**0.504**	**0.767**	**0.676**	**0.502**	**0.910**	**0.568**	**0.421**	**0.765**
AZ-Phoenix	**0.495**	**0.394**	**0.622**	**0.511**	**0.370**	**0.706**	**0.475**	**0.344**	**0.657**
AZ-Prescott	1.105	0.882	1.386	1.234	0.898	1.696	0.988	0.715	1.364
AZ-Springerville	1.011	0.805	1.270	1.062	0.770	1.463	0.961	0.693	1.331
AZ-Tucson	**0.460**	**0.378**	**0.560**	**0.497**	**0.376**	**0.657**	**0.423**	**0.321**	**0.558**
AZ-Williams	**0.437**	**0.293**	**0.653**	**0.417**	**0.236**	**0.736**	**0.454**	**0.257**	**0.802**
NM-Alamogordo	**0.678**	**0.549**	**0.838**	0.746	0.553	1.007	**0.612**	**0.454**	**0.827**
NM-Albuquerque	1.174	0.956	1.443	1.248	0.934	1.670	1.102	0.822	1.479
NM-Santa Fe	0.932	0.771	1.126	1.002	0.767	1.310	0.864	0.659	1.131
NM-Silver City	**0.685**	**0.570**	**0.823**	**0.731**	**0.563**	**0.949**	**0.638**	**0.491**	**0.829**
NM-Taos	**0.460**	**0.363**	**0.582**	**0.419**	**0.298**	**0.590**	**0.497**	**0.357**	**0.693**
Other dispatch center	**0.241**	**0.136**	**0.427**	**0.260**	**0.115**	**0.586**	**0.221**	**0.098**	**0.497**
Researcher-Defined Job									
Modeler	**1.322**	**1.143**	**1.530**	**1.313**	**1.069**	**1.612**	**1.340**	**1.088**	**1.649**
Environmental Specialist	0.818	0.469	1.426	0.945	0.433	2.065	0.700	0.314	1.557
Aviation	0.983	0.834	1.160	0.886	0.700	1.120	1.091	0.863	1.380
Logistics	1.101	0.935	1.295	1.066	0.846	1.343	1.139	0.904	1.436

Values reported in boldface if lower bound of 95% confidence interval is greater than one or if the upper bound of the 95% confidence interval is less than one.

Results for the linear probability model LPM are about the same as those of the logistic model (Table 4.3). While there are problems with LPMs (e.g., predicted values may lay outside the [0-1] range, heteroscedasticity), there are also justifications on theoretical grounds, under certain conditions (Heckman and Snyder, 1996). LPMs also have the advantage of simplicity of interpretation. The coefficient for tailored, fire-specific sources is 0.19, while the coefficient for Decision Support Systems (DSS) is -0.26. DSSs, however, are also fire-specific sources. In the LPM, the interpretations is that being a non-DSS fire-specific source increases the probability of use by 19%, but that being a DSS reduces the probability by 7% (19% - 26%).

Tables 4.4 – 4.7 repeat the logistic an LPM estimation but divide the sample into choices made before and during the fire season. In general, results are very similar between the pooled sample and the season-specific regressions. The adjusted count R^2 for the pooled model is 0.186, while it was 0.156 for the before fire season model and 0.244 for the during fire season model. This suggests the model fits the data slightly better for choice made during fire season.

Table 4.8 shows side-by-side comparisons of the odds ratios for the pooled and season-specific logistic regressions. Values in the table are reported in boldface if the lower bound of 95% confidence interval is greater than one or if the upper bound of the 95% confidence interval is less than one. There were 20 variables where the 95% confidence intervals did not include one before fire season, during fire season, and with pooled data. There was only one case of a variable where the 95% confidence intervals did not include one before fire season, but not in during fire season or in the pooled sample. This was for respondents younger than 30, who had and odds ratio of 0.595. In general, the odds ratios were relatively stable across before fire season, during fire season, and pooled samples.

Chapter 5. Discussion and Conclusions

Despite significant resources dedicated to the supply of information, less attention has been paid to understanding the actual information needs of fire managers. This thesis has investigated the demand for information by wildland fire managers in the U.S southwest, focusing on how they use data products and information sources specially tailored to wildland fire management in their decision-making processes.

The study employed a comprehensive survey and targeted a well-defined and small population, collecting their characteristics. The responses were a representative sample that was close to the distribution for the target population. The framework of this thesis is based on three types of literature to analyze the demand for information and the value of information introduced into wildfire management. We grounded in the Just-Wolf-Wu-Zilberman (JWWZ) framework to understand the factors influencing information use among these managers.

The findings indicate that the demand for information is significantly shaped by several key factors. For the first model predicting total information sources used, managers who made more decisions used more information sources. For every additional decision made, managers used about one additional information source. More sources were used during fire season than before. The specific roles of the fire managers and their systems (agencies, dispatch centers) were found to be crucial in determining their information use. Managers working in broader systems tend to use more information sources. The level of education of fire managers also played a significant role. The effects of age and education did not follow easy-to-interpret patterns. Information use among managers under 30 was significantly greater.

We note some limitations of our total information use model in Chapter 3. Because several respondents did not provide information on personal characteristics, we estimated two regression equations. One had a smaller sample size, but included personal characteristics. The other had a larger sample size but did not include personal characteristics. The adjusted R^2 was relatively low for each model. It was 0.2818 for the model without personal characteristics and 0.2962 in the model without them. Adding personal characteristics and dropping observations did not improve the predictive power of the model much. The agency effect variables and dispatch center variables were robust to changing sample size and adding or omitting personal characteristics.

Our result suggest that the agency a fire manager works for and the dispatch center where the fire manager works significantly affects total information use. In the present study, these differences were captured only by dummy variables for agency and dispatch center. An area of future research would be to investigate which specific features of agencies or dispatch centers lead to greater information use.

Our experience variable only measured years of experience. Future research could explore what types of experiences fire managers have had. Did they work on especially large fires in the past? What was the history of their decision-making responsibilities? How much training in information product use had they had in the past? Did they have any problematic experiences that may have influenced their information use? More detailed qualitative studies could explore these factors in greater detail and aid in developing questions for future quantitative surveys.

In chapter 4, this thesis developed a sophisticated random utility model to predict the use of information source *j* by fire manager *i* and employed both logistic regression and linear probability model (LPM) specifications to understand these dynamics. The limitations of the total information use model also apply to this random utility model. Adjusted R^2 and adjusted count R^2 were low for different specifications, although the model fits were somewhat better in sub-samples just during fires season.

Use of information source tailored specifically for fire management had a greater odds of use, but this was not the case for fire-management-specific decision support tools (DSTs). The linear probability model results suggest that the combined effect of fire specificity and DST reduced the odds of use. Further research is needed to explore why fire managers are less likely to use decision support tools to support their decisions.

There are also paradoxical results concerning the effects age and experience. The odds of information use are greater for younger managers, but also greater for more experienced managers, which seems to be a contradiction. Further research could explore this issue (including looking at types of experiences and not just years of experience).

In both models, many of the variables suggested by simple economic models of the value of information were significant, while results were generally consistent with hypotheses generated by these models. In both Chapter 3 and Chapter 4 models, agency and dispatch center effects were highly significant predictors of fire manager information use. Future research could explore the internal dynamics of agencies and dispatch centers.

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