Valuing Geospatial Information: Using the Contingent Valuation Method to Estimate the Economic Benefits of Landsat Satellite Imagery

John Loomis, Steve Koontz, Holly Miller, and Leslie Richardson

Abstract

While the U.S. government does not charge for downloading Landsat images, the images have value to users. This paper demonstrates a method that can value Landsat and other imagery to users. A survey of downloaders of Landsat images found: (a) established US users have a mean value of $912 USD per scene; (b) new US users and users returning when imagery became free have a mean value of $367 USD per scene. Total US user benefits for the 2.38 million scenes downloaded is $1.8 billion USD. While these benefits indicate a high willingness-to-pay among many Landsat downloaders, it would be economically inefficient for the US government to charge for Landsat imagery. Charging a price of $100 USD a scene would result in an efficiency loss of $37.5 million a year. This economic information should be useful to policymakers who must decide about the future of this and similar remote sensing programs.

Introduction

Geospatial information is ubiquitous in everyday life through online mapping, social media, and other applications, many of which are available for free. These applications frequently incorporate free geospatial data, often collected and distributed by government entities. Additionally, geospatial data is used extensively in research and development, in both the private and public sectors. The widespread use of geospatial information suggests the data are very valuable, but without a market price, it can be difficult to estimate that value. It becomes even more challenging to estimate value once the original data has been incorporated into value-added products. Landsat satellite imagery is one such source of geospatial data that is currently provided at no cost by the United States (US) Federal government to all users.

We present a method of eliciting the economic value of a public good in an application to Landsat satellite imagery. We use well-established procedures for valuing goods not sold in competitive markets, and are able to elicit values across different types of users. Combined with information on representative users, we are then able to construct a conservative aggregate benefit to society for the Federal government having provided this service in 2011. We answer the question: what is Landsat imagery worth to the community of direct imagery users? We believe this information, and the processes used, will be useful to the community of satellite imagery users, as well as decision and policymakers who may find the results helpful in deliberations about the future of this and similar programs.

Landsat satellites have been operating since 1972, providing a continuous global record of the Earth's land surface. The more than 40-year record of imagery is unique among satellite imagery today, and this archive of data is among the most important attributes of Landsat to users (Miller *et al.*, 2013). Apart from a failed attempt at privatization in the 1980s, the Federal government has built, launched, and operated the satellites, and archived and distributed the images provided by those satellites. For most of the duration of the program, Landsat scenes were available for a fee, ranging from $200 USD to over $4,000 USD per scene. Beginning in 2008, the imagery became available at no cost through the US Geological Survey (USGS). This free and open data policy resulted in a huge increase in the number of scenes downloaded from USGS, from a few thousand scenes per year to millions of scenes per year. The current user community includes users in every sector (e.g., private, academic, and government) employing the imagery in more than 40 diverse applications, from forestry and water resources to humanitarian aid and urban planning (Miller *et al.*, 2013). The vast number of scenes downloaded and breadth of users and applications infers a substantial societal benefit is being generated, but little generalizable research has been conducted to determine the economic value of the imagery. Since 1999, there have been two Landsat satellites operating concurrently, providing imagery every eight days. One of the current satellites, Landsat-7, is nearing the end of its lifespan, and to maintain the frequency of return that users have become reliant upon, a new satellite will be needed soon. Given the cost of building and launching a typical Landsat satellite (almost a billion US dollars), estimating the benefits of the imagery is critical to ensuring the continuity of data for users.

The societal benefits derived from the use of Landsat imagery have been well-documented qualitatively (e.g., NASA, 2012; Serbina and Miller, 2014), but few studies have been conducted on the quantitative value of the imagery. The majority of these studies have focused on the cost savings associated with using Landsat (e.g., Morse *et al.*, 2008; Serbina and Miller, 2014) or cost-benefit analyses which incorporate cost savings (e.g., Booz Allen Hamilton, 2012). For example, the Landsat Advisory Group (2012) estimated a savings of $178 to 235 million USD over 10 Federal and state government applications of Landsat, ranging from consumptive water use and forestry, to agriculture and flood mitigation. The gain or loss of revenue has also been used to assess value. Bernknopf *et al.* (2012) projected a potential increased profit of more than

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\$850 million USD annually if Landsat was used to maximize crop yield in northeast Iowa. A survey conducted in 2006 by the American Society for Photogrammetry and Remote Sensing estimated a loss of \$936 million USD to users who completed the survey: if Landsat imagery was no longer available (Green, 2008). Each of these analyses pertains only to the application and/or user group in which they were conducted, which makes generalizing the results to other areas difficult.

As the above literature shows, monetizing the economic value of this publically provided good beyond a specific group or application can be challenging, partly because there is no market price to reflect the value of the imagery to society. Similar to many other sources of data and information, Landsat imagery has characteristics of a public good: (a) once provided to one user, there is little or no cost to provide it to additional users; and (b) one person's use of a Landsat image does not consume or "use up" the image, so the same image is available to others. As is well known in the economics literature, markets often fail in providing goods that have characteristics of a public good. Markets tend to provide less than the economically efficient or the socially optimal level of provision of public goods, whether national defense or air quality (Krugman and Wells, 2013, p. 479; Nicholson, 1992, p 758). As a result, public goods are more frequently provided by group action through government or associations of users. Even when the USGS had priced Landsat images, this price did not accurately reflect economic benefits because the price was administratively set. To capture the economic benefits provided, user's net willingness-to-pay or consumer surplus is needed. This is the standard measure of benefits in benefit-cost analysis (Sassone and Schaffer, 1978) and is recommended by the Office of Management and Budget to capture the societal benefits from a government program or project (1992).

An Economic Method to Measure the Value of Landsat Images

A variety of methods can be used to value earth science information (Macauley, 2005 and 2006). Economists apply a specific set of methods to monetize the economic benefits provided by goods and services that are not traded in markets (see Freeman, 2003 for a review of these methods). One of the most commonly applied methods and one most suitable for valuing Landsat images is a stated preference or intended behavior technique known as the Contingent Valuation Method (CVM). CVM is a survey-based approach used to estimate the economic benefits individuals receive from a non-market good or service. This method is recommended for use by Federal agencies (US Environmental Protection Agency, 2000; US Water Resources Council, 1983). While the method has been used worldwide with more than a thousand studies, nearly all of these involve environmental public goods or outdoor recreation (see Carson, 2012). To our knowledge, only a handful of studies have applied CVM to value publically provided sources of information, such as weather warnings and forecasts (for instance, Lazo and Chestnut, 2002; Cavlovic *et al*., undated). The work herein is the first application of CVM to satellite imagery and specifically, Landsat imagery.

CVM is a survey-based approach in which individuals are asked what they would pay to have access to a particular public good. There are several design features of such surveys. The first is determining how the willingness-to-pay (WTP) question is to be asked. Since the 1990s most such questions do not involve directly asking an open-ended "fill in the blank" WTP question format. Instead, users are asked if they would "buy or not buy" the public good at a particular price that varies across the sample of potential respondents. This dichotomous choice format has several advantages. First, it essentially simulates a market, where the individual is confronted with a price and asked if they will pay that amount or not. Second, there is less opportunity for "strategic" behavior (e.g., inflating or understating WTP). As argued by Carson and Groves (2007), this question format potentially provides the appropriate incentive structure to get respondents to reveal whether they value the good more or less than the price they are asked to pay. When using this dichotomous choice survey format, an important issue becomes having a large enough sample to vary the bid amounts within different potential groups of respondents that themselves may have different valuations. Finally, whether the sample responses exhibit economically rational behavior can be tested by determining whether respondents facing a higher price have a lower probability of "buying" (responding *Yes*), than those facing lower prices. For these reasons, as well as the recommendation of the US National Oceanic and Atmospheric Administration's (NOAA) blue ribbon panel (Arrow *et al*., 1993), we use the dichotomous choice CVM approach.

We also implemented the NOAA panel's suggestion to remind users of their budget constraint when answering the WTP question. In this study the budget constraint was not the usual household budget constraint but rather the user's project and/or agency budget constraint. Since we were sampling from the entire spectrum of imagery users (which include for-profit businesses; academics; Federal, State, and local governments; and non-profit organizations), we emphasized that the money to pay for the Landsat images would have to come out of their current project or agency budgets.

Nonetheless, a longstanding issue in CVM has been the concern over hypothetical bias, e.g., will respondents overstate their WTP since they do not actually have to pay. While the literature is voluminous on this topic (see Loomis, 2014 for a summary), recent evidence suggests that use of the dichotomous choice WTP question format can help minimize this tendency. The overstatement is also less for users of a public good than non-users (see Carson *et al*., 1996). When users are valuing a well-defined product for which they have had past "consumption" experience with, hypothetical bias is also minimized (Cummings *et al*., 1986; List and Lucking-Reiley, 2000). The advantages and disadvantages of CVM have been recently summarized by Kling *et al*. (2012), and will not be dealt with here other than to say best practices were implemented wherever possible.

2009 Pilot Survey

The survey wording and range of WTP bid dollar amounts were originally pretested on a large sample of users in 2009 (see Miller *et al*., 2011, for more details). In particular, the sample was drawn from a web search of self-identified Landsat users. Convenience samples such as this are often used to pretest surveys.

The pilot survey was administered online, as was the 2012 survey; the results of which are reported here. Based on the pilot, the dollar amounts asked in the dichotomous choice WTP question at the upper end were increased for the 2012 survey. In the dichotomous choice framework, high bids need to be high enough so that almost all respondents answer that they are not willing to pay, and similarly, low bids need to be low enough so that typical respondents are willing to pay. Due to the fact that a large portion of the respondents were willing to pay the highest bid amount in the 2009 survey, high bids in the final survey were increased. Further, the magnitude of the step up in bids for initial *Yes* responses and step down in bids to initial *No* responses were adjusted from the traditional doubling and halving to less obvious increments and decrements.

2012 Survey

Sample Frame and Sample Design

With the advent of the USGS Earth Resource Observation Science Center (EROS) providing free access to Landsat imagery, a requirement was made for users to register with EROS in order to download images. This provided a complete sample frame of direct or initial users of Landsat images. We say direct or initial users, as we are aware that there may be literally millions of subsequent users of the images produced by the initial users (e.g., users of Google™ maps, GPS programs). Thus, our estimates of the benefits of Landsat images are conservative as only the initial direct users were sampled.

The sample frame was 44,731 unique working email addresses of registered Landsat users worldwide. Because the survey was being conducted online, we chose to do a census of all the users rather than a sample. A variety of questions were asked of the respondents in addition to the WTP questions, including questions related to the specific use and qualitative value of satellite imagery. Additional questions were used to elicit conditioning information with respect to the respondents. The respondents are direct users registered with EROS, and information was sought so as to be able to describe how the value of imagery varied across categories of these direct users.

Survey Implementation

The survey was launched in April of 2012. The implementation followed the Dillman (2007) repeat contact method to attain as high a survey response rate as feasible. A total of 13,473 individuals responded to the survey, for a response rate of 30 percent. This response rate is equivalent to the average response rates for online surveys reported in several meta-analyses (for example, Lozar Manfreda, 2008; Sheehan, 2001; Shih and Fan, 2008). This number includes both completed surveys (n = 11,749) and partially completed surveys (n = 1,724).

A non-response survey was conducted among those who did not respond to the initial survey to ascertain if those who did not respond were different than those who did. This short survey contained four questions: current or past Landsat user; new, established, or returning user; sector (government, private sector, academia, etc.); and citizenship. A total of 1,622 individuals responded to the non-response survey. These results were compared to those of the respondent sample, and it was determined that there were no statistically significant differences in the distribution of the four variables between respondents and non-respondents.

Willingness-to-Pay Question

The CVM question in the 2012 survey was very similar to that in the 2009 survey in that it was a hypothetical but realistic scenario and included an explicit budget restriction. At the time the 2012 survey was administered, Landsat-5, one of the two satellites operating at the time, had stopped acquiring imagery. Some users had already replaced Landsat-5 imagery with data from other sources, so they had recent experience with paying for replacement information. The specific question asked on the survey was:

> *"At the moment, current Landsat 5 imagery is not available (expected to be available again in spring of 2012) and you may have already obtained imagery elsewhere to replace Landsat 5. If both Landsat 5 and 7 became permanently inoperable before the next Landsat satellite is operational (scheduled to launch in early 2013), you may have to obtain imagery elsewhere again. Assume that you are restricted to your current project or agency budget level and that the money to pay this cost would have to come out of your existing budget. If such a break in continuity did occur and you had to pay for imagery that was equivalent to the Landsat standard product typically available (which assumes both Landsat 5 and 7 imagery are available), would you pay $X for one scene covering the area equivalent to a Landsat scene?"*

The "$X" was randomly filled in with one of 20 different dollar, or bid, amounts, ranging from a low of $10 to a high of $20,000 (this range was set after the 2009 pilot survey). Respondents were instructed to answer *Yes* or *No*.

Some assessment of the downstream value of Landsat imagery is implicit but not the main focus of the question. The question asks the user whether they would pay $X to replace the lost imagery. Thus, the respondent values the information based on a comparison of cost or lost revenue of replacing the imagery. For example, if a for-profit firm sells an interpretive service of Landsat imagery for $Y and has an in-house cost of $Z for developing that service, then presumably the business user would be willing to pay some portion of $(Y – Z) for alternative imagery. Likewise, if a government agency is mandated to provide a service, such as reporting crop forecasts, they must obtain information to fulfill that requirement. If they have a budget of $A for the use of satellite imagery and replacing the information provided by the imagery would cost $B, the government user would presumably be willing to pay up to $B.

After the first WTP question was asked and answered, a follow-up second question was asked. If the respondent answered *Yes* to the first question, they were asked if they would pay a second higher bid amount. If the respondent answered *No* to the first question, they were asked if they would pay a second lower bid amount. This follow-up question provides more information about the respondent's underlying WTP and enables more efficient estimation of the distribution of WTP across users (Hanemann *et al.*, 1991). Lastly, if the respondent answered *No*/*No* then a final bid amount of $1 per scene was asked. An answer of *No* to this trivial amount indicates a protest bid; that is, the respondent is not willing to reveal their valuation of the imagery and may be offended by being asked to value the information hypothetically. As is customary, protest bidders are not included in the statistical analysis (Mitchell and Carson, 1988).

Statistical Analysis

Using the results of the CVM question, a measure of economic benefits received by direct users for the equivalent of a Landsat scene can be obtained. Responses to the first CVM question provide the data necessary to estimate a single-bounded estimate of WTP. The underlying distribution of WTP, which is unknown, can be specified as:

$$\mathrm{WTP}_i^* = x_i'\delta + \varepsilon_i \tag{1}$$

where x_i is a vector of independent variables, including the dollar bid amount, that are expected to influence individual i's willingness-to-pay for the imagery, δ are a vector of weights associated with these attributes, and ε_i is a random error term. This dollar amount varies across the sample to provide insights about the distribution that representative respondents would pay. Whether or not an individual is willing to pay a particular bid amount is observed, so the probability that individual i responds *Yes* to a specified bid amount, bid_i, is equal to the probability that the random willingness-to-pay function is greater than or equal to that bid amount:

$$\Pr(\mathrm{WTP}_i^* \geq \mathrm{bid}_i \mid x_i) = \Pr(\mathrm{Y} = 1 \mid x_i) = 1 - F\,(\mathrm{bid}_i \mid x_i) \tag{2}$$

where F is a cumulative distribution function (CDF). Likewise, there is a similar relationship for individuals responding *No* to their specific bid amount:

$$\Pr(\mathrm{WTP}_i^* < \mathrm{bid}_i \mid x_i) = \Pr(\mathrm{Y}=0 \mid x_i) = F(\mathrm{bid}_i \mid x_i). \tag{3}$$

Aggregating over individuals creates sample measures of underlying population parameters. Specifically, the model is estimated by the method of maximum likelihood, where the likelihood function is specified as:

$$\mathrm{L} = \Pi_{y_i=0}[1 - F(x_i'\delta)]\ \Pi_{y_i=1}[F(x_i'\delta)] \tag{4}$$

and the log-likelihood is

$$\ln\mathrm{L} = \textstyle\sum_{i=1}^{N}\{y_i\, lnF(x_i'\delta) + (1 - y_i)\ln[1 - F(x_i'\delta)]\} \tag{5}$$

where N is the sample size of respondents, y_i takes a value of 1 if the i^{th} individual responds *Yes* to bid_i and 0 otherwise, $(1 - y_i)$ takes a value of 1 if the i^{th} individual responds *No* to bid_i and 0 otherwise. A distributional assumption is necessary for estimation. Logistic models, used here, make use of the logistic CDF. The logistic has been commonly used because the CDF has a closed form expression and does not require integration within the process of maximizing the log-likelihood function. In essence, the maximum likelihood procedure fits the weights associated with the attributes (δ) to most closely match actual choices (y_i) by survey respondents. The intercept and slope coefficient within the δ vector summarize the WTP response across individuals within the sample to different bid amounts. With a large enough sample, the distribution of WTP is measured and through the parameters can be summarized.

From the responses to the initial WTP question, all the analyst knows is whether the benefits users receive are greater than or less than the bid amount offered to the survey respondent. Using a second follow-up CVM question allows for improved inference of economic benefits. The response to these two questions leads to a series of *Yes*/*Yes*, *Yes*/*No*, *No*/*Yes*, and *No*/*No* answers. These responses provide the data necessary to calculate a more precise "double-bounded" estimate of economic benefits (Hanemann *et al.*, 1991). The likelihood function is comprised of four pieces instead of two in Equations 4 and 5, but the underlying δ vector with the intercept (α), slope (β), and parameters for the other attributes (θs) have the same interpretation and use.

Specifically, the model used in the Landsat valuation can be represented as follows using the details of our application:

$$\Pr(\mathrm{bid}_i \mid d_{ki}) = F(\alpha + \beta\ln(\mathrm{bid}_i) + \textstyle\sum_{k=1}^{K}\theta_k d_{ki}) \tag{6}$$

where α is the intercept, β is the slope parameter on the bid amount variable, θs are parameters associated with other conditioning information variables (ds), and F is the logistic CDF. In our application, the natural logarithm of the bid amount is used to restrict the value of Landsat imagery from being negative, as it is illogical that a user would take the time and effort to download something they did not have at least some positive value for. Specific to the logistic model:

$$\Pr(\mathrm{bid}_i \mid d_{ki}) = \frac{\exp(\alpha + \beta\ln(\mathrm{bid}_i) + \sum_{k=1}^{K}\theta_k d_{ki})}{[1 + \exp(\alpha + \beta\ln(\mathrm{bid}_i) + \sum_{k=1}^{K}\theta_k d_{ki})]}. \tag{7}$$

In the application to Landsat valuation, the conditioning information variables d_k are limited to zero-one variables for different industry sectors; these will be discussed later. In addition, we estimate separate models for different groups within the sample that display substantially different sets of parameter estimates. Again, these will also be discussed later. With a set of parameter estimates and a specific set of attributes d_{ki}, a given bid amount can be used to calculate the probability that a representative individual will agree to the bid amount. Varying the bids amounts produces a probabilistic demand function for the imagery: given the specifics of the attributes of the representative individual chosen.

The probabilistic demand function Equation 7 is essential in economic valuation. It describes WTP and can be used to summarize *net* WTP or what is also called consumer surplus. Consumer surplus is the value of a good, i.e., Landsat imagery less any cost to the user. Economic valuation of the good hinges on relative comparisons and probabilities of choosing. We know the number of scenes that were acquired, or consumed, when the imagery was free of charge.

The following is an example where individuals respond to charging for imagery. Using a 50-50 probability:

$$\Pr(\mathrm{bid}_i \mid d_{ki}) = 50\% = F(\alpha + \beta\ln(\mathrm{bid}_i) + \textstyle\sum_{k=1}^{K}\theta_k d_{ki}) \tag{8}$$

and choosing a set of attributes; for example, a specific user group could be chosen or non-bid variables could be set at their sample mean. Then, with the parameter estimates for α, β, and θs, the bid amount can be solved for:

$$\text{Median WTP} = \exp[(\alpha + \textstyle\sum_{k=1}^{K}\theta_k d_{ki})/\beta]. \tag{9}$$

For this log-bid-amount model, the solution is the median willingness-to-pay. If the bid amount was used linearly in the model then the median and the mean are identical with the symmetric logistic distribution. However, with the nonlinear bid amount the median and mean are different. The median WTP amount is the price where, if charged, 50 percent of the respondents would chose to pay, and 50 percent would choose not to pay and would not acquire the imagery. In other words, half the imagery that was acquired when the imagery was free would not be acquired if the median was charged. The probabilistic demand function converts immediately into a typical demand function with price and quantity. Alternative quantile amounts can be similarly calculated.

The mean WTP is the expected value of the underlying WTP random variable that is observed through the answers to the dichotomous choice question. This expected value is the integral:

$$\text{Mean WTP} = \textstyle\int_0^\infty [1 - F(\mathrm{WTP}^* < bid)]d(bid)$$

which is:

$$\text{Mean WTP} = \textstyle\int_0^\infty [1 - F(\alpha + \beta\ln(bid) + \sum_{k=1}^{K}\theta_k d_k]d(bid) \tag{10}$$

(see Hanemann, 1984). However, the integral is bounded only if the slope coefficient (β), which should be negative for a demand function, is less than -1. While the bid coefficient is always negative in our estimated models, the estimated slope coefficient is greater than -1. The situation of $-1 < \beta < 0$ is not an unusual result in CVM applications. The approach then is to choose a high-bid amount representative of the sample, and perform the integration numerically (see Bishop and Heberlein, 1979; Hanemann, 1984). Specifically,

$$\text{Mean WTP} = \textstyle\int_0^{highbid} [1 - F(\alpha + \beta\ln(bid) + \sum_{k=1}^{K}\theta_k d_k)]d(bid). \tag{11}$$

We make use of the high-bid amount for the first WTP question, which is $10,000 USD, and thus our results are relatively conservative from this aspect.

The median bid amounts, or other price-probability-and-quantity amounts, and the mean WTP amounts are useful information for interpreting behavior of individuals and constructing aggregate economic values. The median bid amount is the value of imagery at which, if charged by the US Federal government, half of the users would pay and half would forgo

Table 1. 2012 Landsat User Survey Results from Double-Bounded Dichotomous Choice Models[1]

	U.S. Users			
	Established Users		New/Returning Users	
	Estimate	Std Err	Estimate	Std Err
Intercept	4.3041***	0.2630	3.4689***	0.2066
$ Bid Slope	-0.8788***	0.0411	-0.9071***	0.0374
Federal Gov Shifter	0.6779***	0.1871	0.4685**	0.2100
State & Local Gov Shifter	0.4517	0.3084	0.2790	0.2755
Private Business Shifter	0.3868**	0.1964	0.4014**	0.1876
Non Gov Organizations Shifter	0.9066**	0.3771	0.3738	0.3244
% Correct Predictions	76.5%		85.8%	
	International Users			
	Established Users		New/Returning Users	
	Estimate	Std Err	Estimate	Std Err
Intercept	4.1325***	0.1323	3.1537***	0.1165
$ Bid Slope	-0.8475***	0.0216	-0.8030***	0.0207
Federal Gov Shifter	0.4563***	0.1433	0.4694***	0.1574
State & Local Gov Shifter	0.6218***	0.1634	0.3710**	0.1770
Private Business Shifter	0.7042***	0.1134	0.6317***	0.1228
Non Gov Organizations Shifter	0.1196	1.1626	0.2144	0.1805
% Correct Predictions	74.4%		81.5%	

[1]Academic sector is implicit within the intercept and all sectors shifter coefficients are measured relative to academics (i.e., positive signs on the shifter variables indicate a higher value than academics).

*, ** and *** indicate statistically significant at the 10 percent, 5 percent and 1 percent level.

use of the imagery. Similarly, other bid amounts can be used to determine the proportion of users that would forgo use of the imagery if those amounts were charged. Finally, the mean value of a scene to a group of representative users can be multiplied by the number of scenes obtained by that group over a given time period and then aggregated across all groups.

Results

Descriptive Results

The majority of respondents were current Landsat users (84 percent; users who had used Landsat in their work in the year prior to the survey) and the remainder were past Landsat users (16 percent). The results reported here apply to current Landsat users registered with USGS EROS. We accounted for three variables within the analyses: sector, residence, and type of user. Based on the results from the 2009 pilot survey, we expected to find differences in WTP by sector. The majority of users in the 2012 survey were from academic institutions (slightly more than 50 percent), and about 15 percent of the users were each from private business and Federal government. About 5 percent were each from state/local government and non-profit organizations. Additionally, we wanted to separate US and international users to note any WTP differences between those two groups, especially since US users download the majority of scenes from USGS. Slightly more than one-quarter (27 percent) of the current Landsat users were US residents and 73 percent were from other countries (international users). Finally, we divided users into three types: established (those who used Landsat regularly both before and after it became available at no cost), new (those who had never used Landsat imagery before it became available at no cost), and returning (those who had used Landsat in the past, but had not used Landsat for at least a year prior to it becoming available at no cost). We hypothesized that established users would report greater benefits from using Landsat imagery than new or returning users, based on their consistent use of the imagery over time. New users were the largest group of users (43 percent), followed by established users (41 percent), and returning users (16 percent). In the analysis, new and returning users were combined due to their similarities across a variety of variables. Based on these variables, we report results for four groups of users: (a) US established users, (b) US new/returning users, (c) international established users, and (d) international new/returning users. The variation in WTP by sector is also taken into account within each of these groups.

Economic Valuation Results

Statistical Results

Table 1 presents the dichotomous choice double-bounded logit valuation model results. There is a separate logit regression model for each of the four groups: US established users, US new/returning users, international established users, and international new/returning users. Within each group, the model incorporates a variable in the form of dummy intercept shifter variables for the type of sector to which the user belonged: academic, Federal government, state and local government, private for-profit business, and non-governmental organizations. These dummy or shifter variables information results in a separate intercept parameter for each group. Changes in the slope coefficient by group were also tested for and found to not be statistically significant. Within each of the four models, separate valuations are allowed for each of the user types since the intercepts strongly differ across user types within each group. Slope parameters differ strongly across established versus new/returning and US versus international groups.

As can be seen in Table 1, the sign coefficient for the dollar bid amount the user was asked to pay is negative and significant for each of the user groups. This indicates internal validity of results, i.e., the higher the dollar amount (bid) a user is asked to pay, the lower the probability they will pay this amount to download a scene. This intuitive pattern exhibits economic behavior consistent with economists' law of

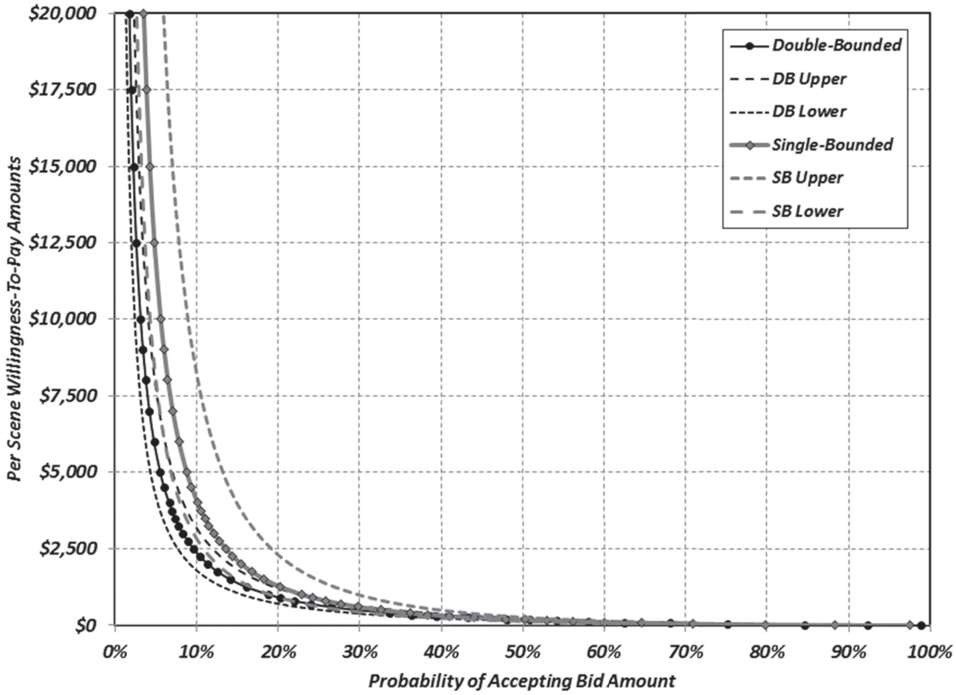

Figure 1. Logit Function Demand Curve for Landsat imagery for the Full Range of Alternative Bid Amounts asked of US Established Users.

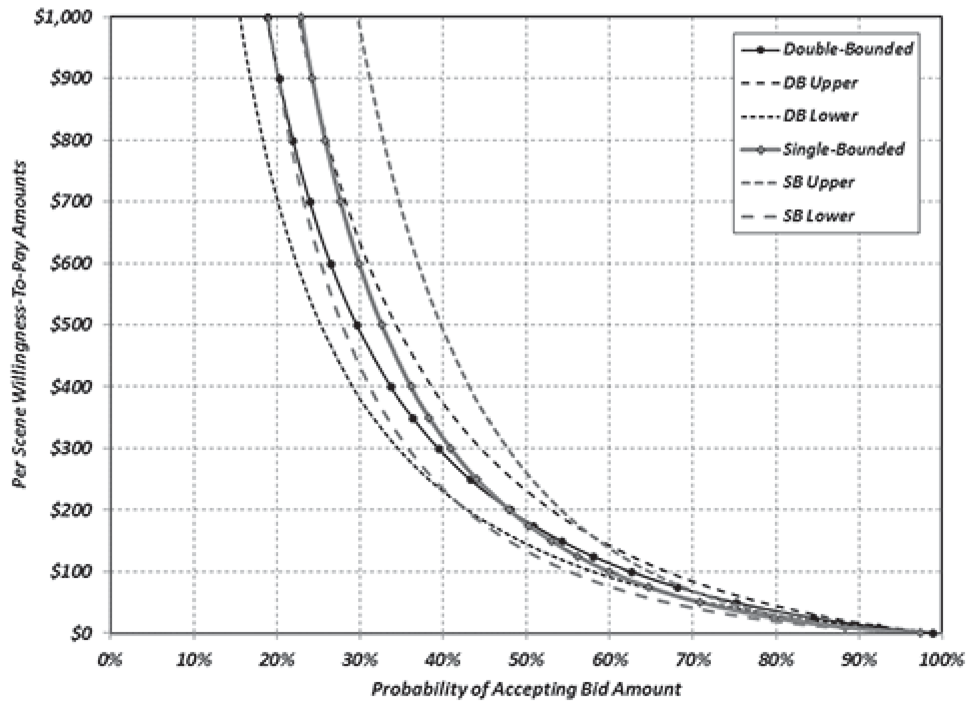

Figure 2. Logit Function Demand Curve for Landsat Imagery Expanded View of the Low-Bid Range for US established users.

demand. The fit of the models is also reasonably strong. The models predict the actual user's first choice correctly between 74 percent and 85 percent of the time depending on the model. Within the set of survey respondents, the largest set of responses was *No/No* (a No response to the first bid amount they were asked to pay and a No response to the second lower bid amount they were asked to pay). The next largest set of responses was *Yes/Yes* (Yes to the first bid amount they were asked to pay and a Yes response to the second higher bid amount they were asked to pay). There were smaller proportions of *No/Yes* and *Yes/No*.

Figures 1 and 2 present the quasi demand function for Landsat satellite imagery aggregated by percentage across all sector types for US established users. Figure 1 is the function represented across all bid amounts presented to survey respondents. The functions associated with both the single-bounded model and the double-bounded model, as well as associated confidence intervals, are presented. The single-bounded and double-bounded are visually rather similar, but the confidence interval is noticeably narrower for the double-bounded model, as expected. Figure 2 zooms into the lower bid amounts so that the bid amount for the median WTP can be observed. As can be seen in Figure 2, the median WTP estimates with the single- and double-bounded models are nearly identical.

Figure 1 communicates two intuitive ideas. First, the large majority of users value Landsat imagery at very low amounts. The median WTP amount is $182 USD per scene, so by definition, half of the users value it less than that. However, there is a not-so-small proportion of users that find Landsat imagery incredibly valuable. Five and a half percent of users are willing to pay $5,000 USD per scene or more. Most US established users are willing to pay a small amount to maintain access to the imagery but there is a minority of the same set of users that appear to find the information almost irreplaceable.

Within Figure 2, we see that choosing a percentage different from 50 percent will result in different valuations. For example, 74.5 percent of respondents value Landsat imagery at $50 per scene or higher and 92.3 percent of respondents value it at least $10 per scene. Likewise, the model results can determine the number of Landsat users that would no longer acquire imagery if the USGS resumed charging. Half the users, as represented by the sampling in 2012, would no longer acquire imagery if the median was charged. Charging $100 USD per scene or $10 USD per scene would result in 37.5 percent and 7.7 percent of US established users not acquiring imagery, respectively.

WTP Amounts

Results from this analysis show that the median value of the economic benefits obtained from Landsat imagery is $182 USD per scene for US established users and $49 USD per scene for US new/returning users (Table 2). This is not the value of the scene to the typical user but the value where a majority (>50 percent) of the sampled users would purchase a scene equivalent to a Landsat scene. The mean or average value of the economic benefits is $912 USD per scene for US established users and $367 USD per scene for US new/returning users (Table 2: means were weighted by the number of users in each of the four groups and the integration truncated at the highest dollar amount asked in the survey). The mean is substantially less for new and returning users than for established users, as would be expected for a group of users that was not accustomed to paying for Landsat imagery. The mean is much higher than the median for both groups of users because there is that small, but significant group, which values Landsat imagery very highly. This may be due to the type of respondents to this survey who are generally technically oriented, professional, and knowledgeable about the good they were asked to value. This type of respondent is not typical of many other CVM studies that tend to sample the general public and consider non-market goods with which the survey respondents may not actually use.

As expected, there are significant differences in WTP across sectors, particularly for established users. Academic users report the lowest values and non-government organizations (NGO) report the highest values for the imagery among US established users (Table 3). Among US new/returning users, state, and local government users report the lowest values, and private sector users report the highest. Sector does not seem to play as large a role in determining value among new/returning users as it does among established users. For example, the mean value for US established users from non-profit organizations is more than double that of academic users. However, the mean value for new/returning users from private businesses is only 58 percent more than that of state and local government users. This may indicate that longer-term use of the imagery in certain sectors has created an increased dependency among some users which translates into greater benefits.

Thus, within the sets of models examined, the strata that appear to be the most important are, as expected: US versus international users, established versus new/returning users, and the sector within these groups. Other variables within the survey offered little improvement to predicting the response to the WTP bid amounts.

Table 2. Overall Median and Mean Values of Economic Benefits from a Landsat Scene by User Group

Value per Landsat scene	U.S. users		International users	
	Established	New/returning	Established	New/returning
Median	$182	$49	$171	$59
Mean	$912	$367	$930	$463

Table 3. Mean and Median Values in USD of Economic Benefits from a Landsat Scene to US Users by Sector

	Established users		New/returning users	
Sector	Mean	Median	Mean	Median
Academic	$704	$123	$331	$43
Federal Gov	$1,181	$264	$354	$47
State and Local Gov	$940	$187	$307	$39
Private Business	$1,057	$223	$484	$72
NGO	$1,490	$379	$380	$52

Table 4. Estimated Annual Aggregate Economic Benefits in USD to Landsat Users Registered with the USGS from Landsat Imagery Distributed by USGS in 2011

Landsat user group	Number of scenes obtained in 2011 from EROS	Mean economic benefit per scene	Annual economic benefit (millions)
U.S. users			
Established	1,687,600	$912	$1,539.091
New/returning	692,508	$367	$254.151
U.S. total	***2,380,108***		***$1,793.242***
International users			
Established	377,749	$930	$298.086
New/returning	160,969	$463	$101.025
International total	***538,718***		***$399.111***
TOTAL	**2,918,826**		**$2,192.353**

An Estimate of Total Economic Benefits of Landsat

The aggregate value of Landsat imagery is a relatively straightforward calculation. We have estimated the average value of a scene for US and international established and new/returning users. Using information from the survey on the average number of scenes that each of these four groups obtains annually from EROS and combining that information with the total number of scenes distributed by EROS in 2011 (the last full year before the survey was administered), the value of Landsat is the sum of the mean value per scene for each group multiplied by the total number of scenes each group obtained in 2011 (Table 4). The annual economic benefit from Landsat imagery is just over $1.79 billion USD per year for US users and almost $400 million USD per year for international users, resulting in an annual economic benefit of $2.19 billion USD for the Landsat scenes which were obtained from EROS in 2011. This estimate is conservative and does not represent the entire societal benefit from Landsat imagery, since it accounts only for the benefits received by direct users registered with EROS. A more complete survey of end users of Landsat imagery would likely result in a valuation that is substantially higher.

Economic Loss to Society from Charging for Landsat Imagery

Although Landsat imagery is currently available at no cost, user fees are sometimes charged to access goods provided by the US Federal government, as well as state and local governments. In this section, we evaluate the economic effects to society of charging a positive price for the use of Landsat imagery. In a market for a particular good, the demand curve is a graphical representation of the relationship between the

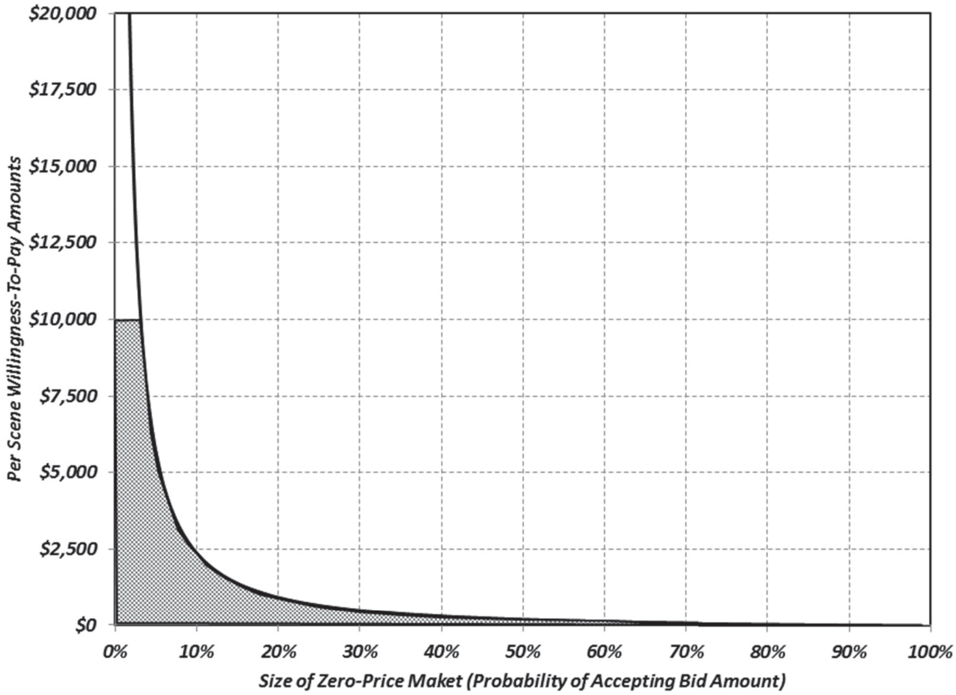

Figure 3. Shaded Area of the Conservative Willingness-to-Pay Amount for US Established Users

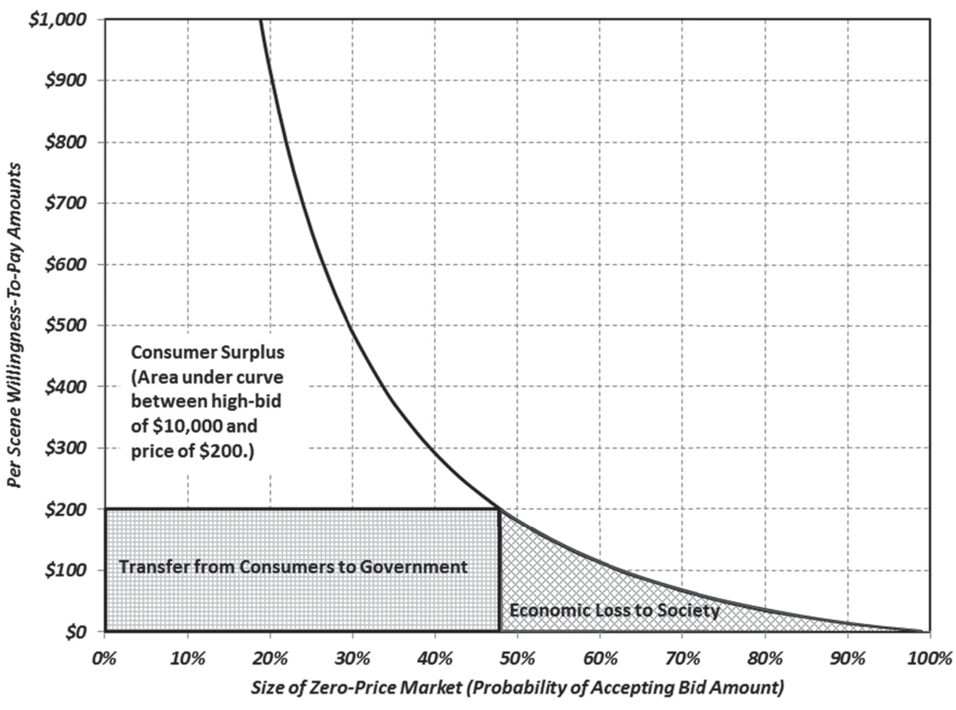

Figure 4. Demand function for Landsat imagery illustrating changes in consumer surplus (net WTP), the transfer to the government, and economic loss if price increases from $0 USD per scene to $200 USD per scene for US established users.

price of the good and the quantity demanded. The area below the demand curve and above the price paid for the good represents consumer surplus (net WTP), the net economic gain that consumers receive from participating in the market. It is a dollar value and can be thought of as an aggregation of the price and quantity within the demand function. Regarding the demand for Landsat imagery, focusing on US established users, this user group obtained 1,687,600 scenes from EROS in 2011 when it was offered at no cost (Table 4). This represents one price and quantity point on the demand curve for Landsat imagery for this particular user group. At a price of $0 USD, this is the number of scenes acquired. Assuming the percentage of US established users who said that they would purchase a scene at a particular price in the 2012 survey is representative of the percentage of the total scenes downloaded at that price (e.g., if 63 percent of users said they would purchase a scene at a price of $100 USD, it is assumed that the quantity of scenes demanded at that price would be equivalent to 63 percent of 1,687,600), Figure 3 illustrates the demand curve, also referred to as the marginal social benefit curve, for

TABLE 5. ESTIMATED ANNUAL ECONOMIC LOSS IN USD TO SOCIETY FROM CHARGING A POSITIVE PRICE FOR THE USE OF LANDSAT IMAGERY

Landsat user group	Annual economic loss to society at a price per scene of $10	Annual economic loss to society at a price per scene of $100	Annual economic loss to society at a price per scene of $1,000
U.S. users			
Established	$565,000	$24,211,000	$288,600,000
New/returning	$593,000	$13,285,000	$73,091,000
U.S. total	***$1,158,000***	***$37,496,000***	***$361,691,000***
International users			
Established	$119,000	$4,626,000	$52,816,000
New/returning	$168,000	$3,959,000	$25,222,000
International total	***$287,000***	***$8,585,000***	***$78,038,000***
GRAND TOTAL	**$1,445,000**	**$46,081,000**	**$439,729,000**

the imagery. This curve shows the percent of users that would pay various prices per scene. At a price of $0 USD, 100 percent of the current 1,687,600 scenes would be downloaded by US established users, and the entire area under the demand curve represents the net economic gain that consumers receive from the use of Landsat imagery at the current zero price.

As can be seen in Figure 4, charging user fees creates an economic loss to society that can be measured, and would have the greatest impact on the potentially large number of low-value users. The average bid amount is different if there is a cost, and can be calculated as follows:

$$\text{Average Bid Net Cost} = \int_{cost}^{highbid} [1 - F(\alpha + \beta\ln(bid) + \sum_{k=1}^{K} \theta_k d_k)]d(bid). \qquad (12)$$

We examine this loss for costs of $1,000 USD per scene, $100 USD per scene, and $10 USD per scene. The loss to society from charging for downloading Landsat images is the aggregate difference between the average bid amount and average bid net of costs, and this difference per scene is aggregated over scenes obtained.

Based on the same demand curve, Figure 4 graphically illustrates the effect of increasing the price of Landsat imagery from $0 USD per scene to $200 USD per scene, for example. Under this scenario, the area below the demand curve and above the price of $200 USD represents the total consumer surplus, or net economic gain, received by those users who continue to purchase Landsat scenes at a price of $200 USD per scene. The light shaded gray area represents the loss in consumer surplus to these same users who continue to use Landsat imagery but now have to pay a price of $200 USD per scene to do so. This loss in consumer surplus accrues to the government as revenue, and therefore represents a transfer from imagery users to government. The dark shaded area represents the loss in consumer surplus that arises due to users who are not willing to pay $200 USD per scene exiting the market and no longer using Landsat imagery. This represents a complete loss in economic benefits to society as this money is not gained by anyone. This loss is sometimes referred to in economics as a deadweight efficiency loss. To minimize deadweight loss, price should be set at the marginal cost of providing another scene to a user, which in this case is nearly zero (actually 10 cents; see *http://remotesensing.usgs.gov/landsat_fees.php*).

The deadweight loss associated with charging various prices for Landsat imagery can be determined by integrating the area under the demand curve. The economic loss to society at a price per scene of $10 USD, $100 USD, and $1,000 USD is calculated for each of the four user groups in the 2012 survey (Table 5). Charging $10 USD per scene for the use of Landsat imagery results in an economic loss to society of $1.16 million USD per year if the analysis is restricted to US users only and $1.45 million USD per year if the analysis includes both US and international Landsat imagery users. At a price of $100 USD per scene, this loss would increase to $46.08 million USD based on the effects to both US and international users, and at a price of $1,000 USD per scene, this loss would increase to $439.73 million USD per year based on the effects to both U.S. and international users. This deadweight loss would continue to increase as the price per scene increases. Again, it should be noted that this estimate is based on the assumption that users within a particular user group are downloading an equal proportion of scenes. If the users who drop out of the market more quickly as the price per scene increases (i.e., they are not willing to pay as much per scene) obtain a greater share of the scenes than those users who stay in the market as the price increases, the results in Table 5 represent a lower bound on the annual economic loss to society associated with increasing the price of the imagery. Alternatively, if the users who drop out of the market more quickly as the price per scene increases obtain a smaller share of the scenes than those users who stay in the market as the price increases, the results in Table 5 represent an upper bound on the annual economic loss to society associated with increasing the price of the imagery.

It is also important to note that Landsat imagery has been available at no cost since 2008 and the losses calculated in Table 5 are based on the number of scenes downloaded free of charge from EROS in 2011 and the percentage of 2012 survey respondents who stated that they would still be willing to purchase a scene at various prices. Given the substantial increase in the number of scenes downloaded after the imagery became available at no cost (see Miller *et al.*, 2013), charging a positive price could result in a larger decrease in the number of scenes downloaded than what has been estimated here. In addition, the losses in Table 5 are based on the impacts to direct users of the imagery only. Moving away from a free and open data policy would likely result in greater economic losses than those estimated here due to the fact that the analysis does not account for the impact to downstream users of Landsat imagery and imagery-derived products.

Conclusions

This paper demonstrates an approach that can in principle be used to value a variety of non-market geospatial and other information. The Contingent Valuation Method is applied to provide the first aggregated estimate of economic benefits to US and international direct users of Landsat images. Not surprisingly, established users of Landsat tend to value the imagery more than new/returning users, with a small portion of these users valuing the imagery very highly. As newer users continue to use and become more reliant on Landsat imagery, it seems likely the value they ascribe to Landsat will increase. The annual benefit to US users in 2011 was estimated at approximately $1.8 billion USD, which is two times greater than the cost of building and launching Landsat-8, the newest Landsat satellite expected to operate for at least five years. Much of the value stems from the free and open data policy which allows users to access as much imagery as they need at no cost. Charging even small fees would result in an immediate loss of users and most likely, a steep decline in the amount of imagery downloaded. The impacts of charging for Landsat imagery would be felt by downstream users as well, through increased prices for value-added products as well as more intangible effects, such as reduced monitoring of environmental hazards. Future research efforts could continue to assess the value of a growing archive of Landsat satellite imagery and evaluate the increasing number of users and uses of this unique resource.

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