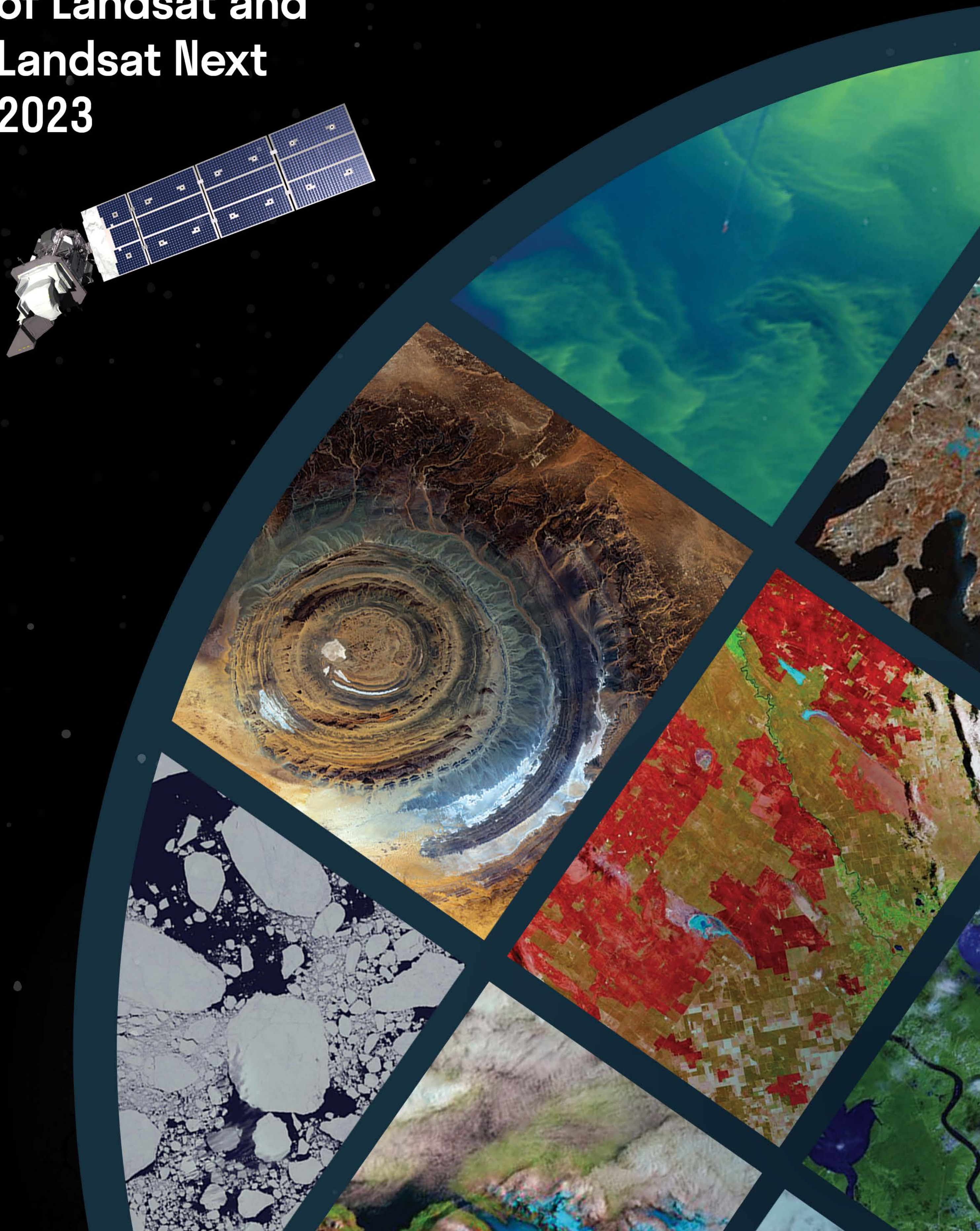
Economic Valuation of Landsat and Landsat Next 2023



ECONOMIC VALUATION OF LANDSAT AND LANDSAT NEXT (2023)

Authored By:

John B. Loomis and Stephen R. Koontz

Department of Agricultural and Resource Economics

Colorado State University*

Co-Authored By:

Aravind Ravichandran

Earth Observation Consultant & Communicator

TerraWatch Space

Work directed by Cori Kelly, Native American Technology Corporation**

under contract with the United States Geological Survey.

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NATECH Native American Technology Corporation

* The views represent those of the authors and not of Colorado State University.

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ACRONYMS AND DEFINITIONS

AGB	aboveground biomass
BAER	Burn Area Emergency Response
CA	Coastal Aerosol
CDF	cumulative distribution function
CPI	Consumer Price Index
CVM	contingent valuation method
EROS	Earth Resources Observation and Science (Center)
ESRI	Environmental Systems Research Institute
ET	evapotranspiration
GIS	geographic information system
HAB	harmful algal bloom
m	meter
MSS	multispectral scanner
NDSI	Normalized Difference Snow Index
NDVI	Normalized Difference Vegetation Index
NGO	nongovernmental organization
NIR	near infrared radiation
NLCD	National Land Cover Database
nm	nanometers
OLI	Operational Land Imager
OMB	Office of Management and Budget
SWE	snow water equivalent
SWIR	short-wave infrared radiation
TIR	thermal infrared radiation
TM	Thematic Mapper
USGS	U.S. Geological Survey
WTP	willingness to pay
μm	micrometers

BACKGROUND

Satellite data is a pervasive technology that runs in the background and powers the modern digital economy with cross-sectoral applications across mapping, location-based services, disaster management, business intelligence, environmental monitoring, climate change, and more. It is a fundamental tool that does not grab headlines as much as the applications it enables. Satellites designed to collect information about Earth's atmosphere, land, and oceans have been in operation for more than 50 years. While these satellites were originally mostly owned and operated by governments, commercial entities have increasingly launched and managed their own. Satellite data unlocks a wealth of benefits, enhancing scientific discoveries, driving economic growth, enriching society, protecting the environment, and much more.

The Landsat series of Earth observation satellites, a joint program of National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey (USGS), has been continually monitoring the Earth for more than 50 years. The program has been so influential for our understanding of the planet that prior to the Landsat program, detailed, comprehensive depictions of the Earth's surface were scarce, mainly due to the lack of tools for capturing and processing large-scale datasets. Over the last five decades, as a result of several technological breakthroughs and pioneering remote sensing techniques, Landsat became a template for other global Earth observation missions and programs.

During most of the program's history, Landsat scenes were available for a fee, ranging from $200 USD to $4,000 USD per scene. The 2008 policy allowing free and open access to Landsat data was a game-changer for the program and the wider Earth observation sector (Zhum, et al. (2019))[1]. It not only democratized medium spatial resolution satellite data but also led to a substantial increase in the usage of Landsat data. While the USGS distributes millions of these free Landsat images to thousands of users, numerous other sources, such as Google Earth Engine, the Environmental Systems Research Institute (ESRI), and Microsoft Planetary Computer, among others, also provide access to Landsat data. This increased access to Landsat data has, in turn, sparked a rapid proliferation of scientific and commercial applications serving the public and private sectors. The societal and environmental benefits of this shift are vast, largely because the usage of Landsat data transitioned from single images to time-series analyses over large areas. Freeing up access to satellite imagery set an example for other space agencies and led to the adoption of similar policies worldwide, including the Copernicus Program from the European Union, which provides a new supply of open-access satellite imagery through the Sentinel-2A and Sentinel-2B satellites.

The growing use of Landsat data has produced major scientific and economic benefits in the areas of agricultural crop mapping, water use, disaster support (including for floods and wildfires), land-cover and land-use change mapping, ecosystem and habitat mapping, and continuous monitoring

[1] https://www.sciencedirect.com/science/article/pii/S0034425719300719

of climate change and its impact. The societal and scientific benefits derived from the use of Landsat imagery have been well-documented (Wulder, et al. (2022))[2].

While the widespread use of Landsat data underscores its high value, it is a challenge to estimate its full economic worth. This difficulty arises not only from the inherent complexity of empirically estimating the economic value of a good without a price but also from the fact that much of the data's value is derived from downstream value-added products and services. Moreover, the Earth observation sector has seen rapid evolution over the past decade, with the continued growth of commercial satellite imaging companies providing data at high spatial, temporal, and spectral resolutions. As of May 2023, about 1,275 out of the 7,560 satellites in orbit are Earth-observing satellites, of which almost 90 percent belong to the private sector (UCS Satellite Database (2023))[3].

The Landsat program is evolving with the upcoming Landsat Next mission, a constellation of three satellites that will provide observations with higher spatial, spectral, and temporal resolutions compared to Landsat 8 and 9. This mission, set to launch in 2030 or 2031, aims to meet the emerging needs of land-imaging users across sectors while maintaining Landsat data continuity and providing synergies with the Sentinel satellites. Landsat Next is expected to continue Landsat's legacy of providing highly calibrated data that has become a gold standard of global satellite imaging and will support new applications for water quality assessment, cryospheric (e.g., snow and ice) science, geology, agricultural science, and more (USGS (2024))[4].

The purpose of this report is to provide an update on the economic benefits of Landsat imagery, following the previous update in 2019 and determine the relative increase in potential economic value offered by Landsat Next (Straub, et al. (2019)). In addition to quantifying the value through direct use, the report provides an overview of the indirect cost savings and indirect value that Landsat generates. The report also includes an analysis of the potential long-term value of Landsat Next and its complementarity with the growing commercial satellite imagery market, emphasizing the value of the Landsat's long lifespan and the high-quality data that is considered a benchmark for satellite imagery. Finally, the report includes some areas of future work that could lead to uncovering additional benefits of Landsat and enable the continuous monitoring of the economic, societal, scientific, and environmental value of the Landsat program.

[2] https://www.sciencedirect.com/science/article/pii/S0034425722003054

[3] https://www.ucsusa.org/resources/satellite-database

[4] https://www.usgs.gov/landsat-missions/landsat-next

EXECUTIVE SUMMARY

CHAPTER 1: Landsat Imagery's Economic Benefits to Direct Users

This chapter estimates the economic benefits of Landsat imagery to its direct users based on data obtained in 2018 (Economic Valuation of Landsat Imagery, Straub, et al. 2019), which is the latest survey that measured the value of Landsat data to direct users. Direct users are defined as Landsat users registered with the USGS EarthExplorer user interface for accessing remote sensing data and products.

Because Landsat imagery has been free since 2008, the Contingent Valuation Method (CVM) was used to estimate the value of Landsat imagery to direct users. CVM is a frequently used method to estimate the value of a wide variety of nonmarket goods, such as publicly provided recreation or improvements in water quality. This method is recommended for use by federal agencies (U.S. Office of Management and Budget (1992, 2017, 2023), the U.S. Environmental Protection Agency (2000), and in the academic literature for benefit-cost analysis (Young and Loomis (2014: 30-32)). The 2018 survey asked whether users would pay a specific dollar amount to download a standard Landsat scene. The dollar amounts varied across the sub-samples of 4,454 users. The responses showed that as the cost per scene increased, users would download fewer scenes. Analyzing these responses, we traced out a demand-curve-like relationship and calculated the average amount users would pay for a scene. The resulting dollar values were well below what Landsat users were paying when a private company had taken over selling Landsat imagery during the 1980s. The lower values also reflected the availability of free imagery from the European Space Agency's Sentinel satellites and users' strategic behavior in sending a signal about the possible return of the federal government's charging for downloading scenes.

After adjusting for strategic behavior using calibration factors derived from the literature, the average value per scene that U.S. registered Landsat users would pay is $378 in 2023 dollars. International users would pay $418 per scene. The weighted average value between U.S. and international users is $390.41 per scene.

In 2017, 22.1 million scenes were downloaded from USGS EarthExplorer. In order to update the number of scenes downloaded to 2023, we first obtained the total terabytes accessed in 2023 from the EROS Tracking, Reporting and Metrics system. The volume of Landsat accessed from the USGS in FY2023 includes all publicly available datasets directly used in the cloud and downloaded from the cloud and on premise. Then we divided that number by the average number of megabytes in a typical scene from each Landsat satellite. This calculation yielded a result that 65.65 million scene-equivalents were accessed in 2023, a nearly three-fold increase from 2017. The product of 65.65 million scene-equivalents times $390.41 per scene yields an estimated value to direct registered Landsat users of $25.63 billion in 2023. However, this estimate only accounts for a portion of the total direct benefits from Landsat imagery and does not include other economic benefits it provides. Landsat's benefits for indirect users and other applications are detailed in Chapter 2.

The last section of Chapter 1 presents the economic inefficiency that would result from charging for Landsat imagery. This would happen because Landsat imagery has both of the characteristics of a public good: (a) a person accessing an image does not use it up, unlike a product like a gallon of gasoline that can be used only once, and (b) once the image is downlinked from the Landsat satellite to the USGS archive, there is no extra cost to let more people access an image, unlike the cost of producing more gasoline. As such, the federal government does not save costs by charging a price per image that causes users to decrease the number of images they access. The fewer images accessed, the smaller the economic benefits are to direct users (and indirect users, as discussed in Chapter 2), and thus, the benefits to the economy and society are also lost, with no offsetting savings to the federal government.

CHAPTER 2: Benefits of Landsat to Indirect Users

This chapter examines Landsat's value to indirect users who are unlikely to be direct (registered) users. The indirect users' benefits arise from Landsat imagery accessed by registered users for application by others in an organization or from other platforms, such as Google Earth Engine, and used to reduce costs in addressing real-world problems, in scientific and commercial applications, or for other purposes, e.g., patent applications. Indirect users' benefits can be measured in two ways: the economic value generated to public and private sectors from using Landsat, and the cost savings achieved by government agencies, companies, and others around the world that use Landsat data or related products. The chapter also details scientific, environmental, and commercial applications of Landsat that are not quantified, yet may be significant to society and the economy.

The economic value generated by Landsat includes benefits across several sectors. For example, it was estimated that as many as 36,750 articles and reports were published in 2023 that used data from Landsat, or a derived product, in their research. This led to an estimated $583 million in annual economic value resulting from the improved productivity of other researchers and the benefits from journal articles or other publications, even without considering the broader implications of the research. Similarly, the economic value of patents citing Landsat was estimated to be $40.8 million for the 42 such patents granted in 2023, based on returns to the inventor (or the inventor's company). The economic value of Landsat also extends to commercial sectors such as mining, in which Landsat imagery information led to mineral discoveries that would not have been possible otherwise. Across the continental United States, this has a potential revenue of $277.6 million of value from additional gold production.

Examples of cost savings to society from using Landsat data can be found in various applications across the public and private sectors. The U.S. Department of Agriculture uses Landsat to update and make more accurate maps of the potential flood risks to farmers, saving farmers about $300 million in crop insurance premiums. Similarly, the Idaho Department of Water Resources saves up to $20 million a year by utilizing Landsat's thermal infrared data to estimate water used by unmetered groundwater wells. The U.S. government uses Landsat data to keep global maps up to date, saving more than $100 million in taxpayer money annually. Landsat's resources help the U.S. Forest Service and Bureau of Land Management to improve the targeting of post-wildfire restoration activities ($2 million to $9 million). The U.S. Department of Agriculture saves from not paying fraudulent crop insurance claims ($100 million). The National Oceanic and Atmospheric Administration saves on shoreline mapping ($90 million).

In addition to the economic values generated and the cost savings associated with Landsat, the chapter also describes other applications that are not quantified. Landsat plays a substantial role in measuring carbon emissions and sequestration, tracking changes in biodiversity and deforestation, helping with urban planning, and monitoring water usage. Landsat's importance for the private sector is valuable as it acts as the gold standard, enabling cross-sensor calibration of commercial imaging satellites. Finally, Landsat is important for developing artificial intelligence-based models using satellite imagery, which has the potential for multiple downstream applications across domains such as crop detection, flooding, and wildfire monitoring.

CHAPTER 3: Landsat Next's Value

Chapter 3 starts by reviewing the new features of the planned Landsat Next mission as compared to current Landsat satellites and discussing the many ways Landsat Next's improved capabilities (particularly a more frequent revisit cycle, increased spatial resolution, and more spectral bands) can be used and the benefits we expect from them. These benefits include enhanced crop condition assessment, which is useful for the U.S. Department of Agriculture's crop forecasts, and to cryospheric science for surface snow and ice monitoring that can help predict the water supply for crop irrigation, as well as municipal water supplies. In addition, Landsat Next would aid improved wildfire management through more detailed burned-area and severity mapping. It is also expected that there will be increased synergistic applications of Landsat Next, both in combination with other public satellites such as Sentinel-2 and with commercial satellites due to the longevity of the Landsat program and its imagery.

With regard to the economic value of Landsat Next, valuing improvements in satellite imagery that does not yet exist is somewhat challenging. Therefore, we first used a technique widely used in market research that is called conjoint analysis (Louviere, 1988) and in economics is called stated preference (Louviere, et al. 2000). In 2018, we conducted a stated preference survey where registered EarthExplorer Landsat users were asked to prioritize their most important improvements. The stated preference questions were part of the same survey of U.S. and international registered Landsat users discussed in Chapter 1. The stated choice questions asked users to choose between two options with different improvements in spatial resolution, cloud-free usable imagery (as a proxy for revisit time), and particular additions of spectral bands (e.g., thermal infrared, Red Edge) and thermal band resolution. Based on the trade-offs from users, we found that both U.S. and international Landsat users had the strongest preference for improvements in spatial resolution, more frequent revisit time, and an increase in thermal band resolution. The stated preference results were used as a check on the validity of the dollar valuations obtained from the application of commercial software prices to Landsat Next.

To estimate the incremental dollar values for Landsat Next improvements, we analyzed data collected on what commercial satellite companies charge for their imagery, along with specific improvements of that imagery, such as spatial resolution, number of bands, revisit time, and whether the image was "sharpened," often using other bands, such as panchromatic. A multiple regression price equation was estimated from that data, where the price of a one square kilometer ($1km^2$) image was the dependent variable, and the explanatory variables were the features of imagery, to estimate implicit prices of these features. We then applied the respective prices to the increases in spatial resolution, number of bands, and faster revisit time associated with Landsat Next versus the current Landsat 8/9 missions. Scaling up the increase in value per $1km^2$ to the larger usual Landsat 8/9 scene size, the gain in value per Landsat Next scene is $117-$139. When we add this gain to the average value of $390 for a Landsat 8/9 scene (described in Chapter 1), the value of a scene generated by Landsat Next would be between $507-$529 per scene. In 2023, there were 65.65 million scene-equivalents accessed, so the value added for Landsat Next scene-equivalents in 2023 would be $7.69-$9.15 billion more than Landsat 8/9. Adding this to the estimate of the direct registered Landsat user value of $25.63 billion that we reported in Chapter 1 and holding the number of scene-equivalents constant at 2023 levels, the total value to direct registered users of Landsat Next would be between $33.32-$34.78 billion annually. This represents a 30-35.7 percent increase in value over Landsat 8/9. It is also important to note that the benefits of Landsat Next's improved imagery would be received by millions of other users who access their Landsat images with other services. Thus, the total value of Landsat Next is likely to be much larger than the above estimate to direct users.

CHAPTER 1: LANDSAT BENEFITS TO DIRECT USERS

1.1. Chapter Synopsis

To estimate the benefit to registered Landsat users, a valuation survey was conducted in 2012 and in 2018. We relied upon the most recent survey results, even though those values per Landsat user were more conservative than the 2012 results, for the reasons explained in this chapter. Nonetheless, the value was $390 per scene downloaded. We applied that value figure to the estimated 65.65 million scene-equivalents accessed in 2023. This figure only includes user imagery accessed through USGS EarthExplorer and not access through commercial cloud providers or Landsat data replicated on other platforms. Based on this, we estimated the total direct Landsat value to registered Landsat users was $25.63 billion in 2023. However, the economic benefits to direct users are just one part of the total benefit generated by Landsat imagery. The economic benefits to indirect users are detailed in Chapter 2.

1.2. Introduction

Given the wide range of Landsat imagery users and its various uses, direct Landsat users likely receive significant economic benefits. By direct users we mean those registered with the USGS and who can access data directly from the USGS-associated platforms but does not include those who access or download imagery from other commercial tools such as Google Earth Engine, , Microsoft Planetary Computer, and ESRI software, among others. In some sense, the imagery's initial users tend to be those with the technical knowledge needed to process remote sensing data like Landsat. Users may also include the end users in that they take the images and conduct direct analysis, such as comparing the images over time to see what types of changes have occurred to natural areas, urban areas, areas in crop production, etc. In some cases, they may be providing these images to their research team, for other joint research into these topics, or a wider range of analyses – for example, using Geographic Information System (GIS) mapping to assess what the changes in a forest mean for particular wildlife species' habitat.

In most of their uses, the value that direct users of Landsat images have is what economists call a derived demand. In this case, Landsat images are used as a starting point to create something valuable for society. This value to the direct users can be in terms of their basic research for understanding processes that generate natural phenomena or applied research, such as when the direct user is asked to evaluate the existing density of buildings around an airport or additional runways to minimize the number of people exposed to jet noise. Knowledge is created where it did not exist before, and it has economic value. Knowledge can also create new value, as illustrated in Chapter 2 on indirect use. For example, the imagery may create value through savings or efficiency improvements as indirect or "downstream" users apply the imagery by the direct users.

Landsat imagery has the characteristics of what economists define as a public good[5]: (a) once provided to one user, there is little or no cost to provide the imagery 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 technically available for others to use. Public goods are contrasted to the more familiar private goods, such as food, which is costly to produce additional units, and consumption uses up the product. Competitive market prices can efficiently allocate food or housing, but not imagery, due to the differences in the characteristics of the two goods. As will be explained in more detail at the end of this chapter, establishing a price for Landsat imagery will result in less than the maximum benefits to society from the imagery being accessed. Thus, government provision of public goods, whether imagery, national defense, or air quality, is usually optimal (Nicholson (1992: 758)).

Even when Landsat images were sold during the 1980s and 1990s, this price did not accurately reflect the economic benefits of the imagery purchased. First, the price was usually administratively set. Second, for nearly all goods that have a price, the price paid reflects just the value of the last unit of the good purchased. The prior units may in fact have a much higher benefit to them than the last unit they buy. Economists call the benefit received on the prior units a consumer surplus value. In this case, the direct Landsat user may have been willing to pay two to three times the price to download the first few images. Later in this chapter, we will illustrate this relationship graphically and also empirically estimate this relationship for Landsat imagery using our direct-user survey data.

To completely reflect the economic benefits provided to the user, the user's net willingness to pay (WTP), or the consumer surplus over all the units purchased, is needed. This is the standard measure of benefits in cost-benefit analysis (Sassone & Schaffer (1978); Young and Loomis (2014: 30-32)). In fact, the U.S. Office of Management and Budget (OMB) also recommends using WTP as a measure of benefits, stating, "When it can be determined, consumer surplus provides the best measure of the total benefit to society from a government program or project." (OMB (1992: 7)) The OMB confirmed its continued usage of WTP in its cost-benefit analysis in 2017 (OMB (2017: 52)) and 2023 (OMB (2023: 30)).

If there is a market price, valuing a good is related to the price of it per unit and the number of units of the good purchased. However, this approach only provides the basic starting point. Across users of a good, such as Landsat or any satellite or remote sensing imagery, there may not necessarily be a single value. There is a distribution of values and also a distribution of quantities used. A more comprehensive valuation recognizes the distribution of value across diverse types of users, e.g., government or private sector. In the end, the valuation of imagery to direct users is substantially bigger than a simple price/quantity combination.

[5] The term public good is not necessarily synonymous with a government good. That is, the inherent characteristics of the good and who provides it are technically separate issues. But the characteristics of the public good affect whether markets or government provides the optimal or benefit-maximizing amount to society.

Indirect users are those for which the source of the imagery access is not necessarily known, but for which an economic value of the imagery can be estimated. These indirect benefits would be, e.g., cost savings from the administration of government functions, such as Farm Bill programs, or the monitoring of environmental impacts or quality. The use of remote sensing imagery allows considerable cost savings due to the need for fewer personnel and other program costs. Private businesses and industry are also potential indirect users that benefit through increased efficiency and the offering of services at lower costs.

1.3. Past Prices Direct Landsat Users Paid

Prior to the USGS making Landsat images free, there were significant prices that direct users had to pay to access imagery. This was true for individuals and companies, as well as state and federal agencies (e.g., the U.S. Department of Agriculture). Table 1-1 compiles the evidence of prices that were charged, starting with the Reagan Administration, for Landsat satellite images, including from the Multispectral Scanner (MSS), and Thematic Mapper (TM), the latter of which yields higher resolution. For much of this period, the sole private government contractor, the Earth Observation Satellite Company, set these prices. Data on prices were compiled from publications including the American Society for Photogrammetry and Remote Sensing (2017: 176-180, 240) and the Congressional Research Service (1991). As seen in Table 1-1, these prices per scene (adjusted to 2023 constant dollars using the Consumer Price Index (CPI) were substantial, especially for TM scenes. These prices provide three important insights. First, even at the margin, for the last scene bought direct users would pay a substantial amount, indicating a Landsat scene was worth a great deal to them. Any project requiring dozens of TM scenes to allow for a longitudinal analysis could cost well over $50,000. Second, when the USGS moved to providing scenes for free in 2008, there was a substantial “surplus value” captured by direct users. That is, they were sacrificing several thousands of dollars for a single Landsat image before and now could get them for free. Third, when the scenes became free, scenes downloaded skyrocketed from about 19,000 a year to more than 7 million in just 10 years (American Society for Photogrammetry and Remote Sensing (2017: 345)). As will be evident in the chapters that follow, this unleashed a huge amount of research and applications of Landsat imagery not just to a growing number of direct users but also millions of indirect users. Lastly, the prices in Table 1-1 that were actually paid helps validate the survey results from 2012 and 2018 on the amounts that current direct Landsat users would pay for a scene.

Nagaraj, et al. (2020: 23495) studied the effect of free access to Landsat imagery on the broadening of scientific topics and geographic regions. Their paper was titled, “Improving data access democratizes and diversifies science.” Using a sample of 24,000 Landsat publications by over 34,000 authors, they found that free access resulted in a more diverse set of topics and geographic areas being studied. Newly entering Landsat users played a prominent role in this expansion. There was a significant expansion of Landsat use in low- and middle-income countries that could not previously afford the imagery.

Table 1-1 Prices Paid by Direct Landsat Users Per Scene 1979–2000 in 2023 Constant Dollars[6]

Year	MSS Price/Scene[a]	TM Price/Scene[b]
1979	$699	–
1980	$625	–
1981	$582	–
1982	–	–
1983	$1,217	$5,244
1984	$1,329	$6,189
1985	$1,328	$8,004
1986	$1,202	$6,012
1987	$1,171	$5,853
1988	$1,662	$5,483
1989	$1,593	$5,736
1990	$1,581	$5,691
1991	$315	$6,937
1992	–	$6,908
1993	–	$6,804
1994	–	$5,275
1995	–	$3,553
1996	–	$3,563
1997	–	$3,560
1998	–	$3,595
1999	–	$3,613
2000	–	$3,525

a. MSS (Multispectral Scanner)
b. TM (Thematic Mapper)

[6] From the U.S. Federal Reserve Bank of St. Louis in 2015 dollars, i.e., 2015=100. https://fred.stlouisfed.org/series/CPALTT01USA661S

This is not surprising since Nagaraj (2024) estimated that a typical study during the "privatization" era of the 1980s to 1990s would cost at least $26,400. This would likely be beyond research budgets available to scientists in low-income countries during the 1990s. One of Nagaraj's conclusions (2024: 16) from this very recent paper is, "These findings suggest that policies that improve access to valuable scientific data promote scientific progress, reduce inequality among scientists, and increase the diversity of scientific research."

1.4. Measuring the Monetary Benefits of Currently Free Access to Landsat Imagery

Despite the fact that Landsat users no longer have to pay per image downloaded, the concept of economic benefits to these direct users is still the maximum amount they would pay; the value of a good can be clearly linked to the price a consumer would be willing to pay whether or not payment was required. Value and price are linked in practice and concept. Thus, the concept of economic surplus, what is sometimes called consumer surplus or WTP, is still the appropriate measure of value.

Economists use a range of methods to monetize the economic benefits provided by goods and services that are not traded in markets. One of the most commonly used is the Contingent Valuation Method (CVM). CVM is a survey-based approach to estimate the economic benefits individuals receive from a non-market good or service. This method is recommended for use by federal agencies (OMB (1992, 2017, 2023); U.S. Environmental Protection Agency (2000); U.S. Water Resources Council (1983); and Young and Loomis (2014: 30-32)).

Given the three-month period for this project, it would be impossible to set up and conduct an original CVM survey. Such a survey requires pre-tests and multiple contacts with non-responding users to minimize nonresponse bias to survey questions. As such, we rely upon two contingent valuation method studies: updating the values and applying them to the most recent data on imagery accessed. We provide some validation of these dollar estimates by comparing the statistical results to economic principles and to the prices previously paid by Landsat users when there were prices.

There have been two CVM surveys, conducted in 2012 and 2018, using probability sampling of registered USGS Landsat users to estimate the consumer surplus, or WTP. Both surveys used a widely recommended type of WTP question: the dichotomous choice question format (Boyle (2017); Johnston, et al. (2017)). In this format, respondents are asked if they would or would not pay a given amount of money for a typical Landsat image. Thus, the user simply has to judge whether they value a Landsat image more or less than the dollar amount they are asked to pay. The dollar amount is varied across the sample, such that a variation of the standard demand-curve-like relationship between the price of the good and the probability they will pay can be calculated using a statistical model. From the coefficients in the statistical model, three pieces of information are obtained:

(a) a statistical test of whether the coefficient on the dollar amount users are asked to pay is negative and statistically significant to confirm (or reject) that as the price rises, the percent of users that would pay decreases, as would be consistent with the demand for any good. This is a form of validation to indicate that surveyed Landsat users are taking seriously the dollar amount they are asked to pay.

(b) coefficients from the entire logistic regression allows calculation of the median and mean WTP per scene; and

(c) derivation of a curve showing the percentage of all Landsat users, or each Landsat user group, would pay for each price. This method communicates the distribution of valuations across sampled users. From this analysis, the numerical percentage of users that would pay each price per image can be calculated.

The remainder of this section is organized as follows: We first present information about the sampling and wording of the 2012 CVM survey. This is followed by a rigorous presentation of the statistical analysis method used in both the 2012 and 2018 surveys. Then the valuation results of the 2012 survey are presented. This is followed by a description of the 2018 survey, the valuation results of the 2018 survey, and the likely reasons for differences between 2012 and 2018 in the values per scene. Lastly, the total value of Landsat imagery to registered Landsat users is presented.

A. 2012 CVM Study Using a Census of Landsat Users

The population of interest for the 2012 survey involved a complete census of all Landsat users registered with the USGS EROS Center. Thus, the census included established users, new/returning users, as well as domestic and international users. It was a large sample with nearly 7,000 respondents and 6,619 answering the CVM WTP question toward the end of the rather long survey.

The CVM WTP scenario question was as follows:

"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 imageries are available), would you pay $X for one scene covering the area equivalent to a Landsat scene?"

The $X was randomly assigned to each survey respondent and had 20 different dollar amounts, varying from a low of $10 to a high of $10,000, to find a dollar amount low enough that almost all users would respond with "Yes" and high amounts that almost all users would respond with "No."

B. Method of Statistical Analysis of the CVM WTP Question for the 2012 and 2018 Surveys

Responses to the CVM dichotomous choice question in both surveys provided the data necessary to estimate WTP. Therefore, this section provides the detailed statistical model used to analyze those responses to the WTP question and which allowed us to calculate the overall sample median and average WTP. The general form of the underlying distribution of WTP can be specified as:

$$WTP_i^* = x_i'\delta + \varepsilon_i$$

where x_i is a vector of independent variables that influence individual *i's* WTP for the Landsat imagery, δ are a vector of weights associated with these attributes, and ε_i is a random error term. The star on WTP implies that the true willingness to pay of each respondent is unobserved. One of the independent variables is the dollar bid amount the individual is asked to pay. This dollar amount varies across the sample to provide insights about the distribution that a representative respondent would pay. The dollar amount varies within the sample of respondents to provide insight about how the population of users, as represented by the sample, values Landsat imagery. Whether or not an individual is willing to pay a specified bid amount is observed in their survey response, so the probability that individual *i* responds "Yes" to a specified bid amount (bid_i) is equal to the probability that the WTP function is greater than or equal to that bid amount the respondent is asked to pay:

$$Pr(WTP_i^* \geq bid_i|x_i) = Pr(Y=1|x_i) = 1 - F\,(bid_i|x_i)$$

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

$$Pr(WTP_i^* < bid_i|x_i)\,) = Pr(Y=0|x_i) = F\,(bid_i|x_i)$$

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:

$$L = \prod_{y_i=0}[1 - F(x'_i\delta)]\ \prod_{y_i=1}[F(x'_i\delta)]$$

and the log-likelihood is . . .

$$\ln L = \sum_{i=1}^{N}\{y_i\ lnF(x'_i\delta) + (1 - y_i)\ \ln\,[1 - F(x'_i\delta)]\}$$

where N is the sample size of respondents, y_i takes a value of 1 if the individual *i* responds "Yes" to bid_i and 0 otherwise, $(1 - y_i)$ takes a value of 1 if individual *i* responds "No" to bid_i and 0 otherwise. A distributional assumption is necessary to empirically estimate the log-likelihood function. A logistical distribution of the CDF results in the logit models used here. The logistic distribution has been commonly used because the CDF 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 summarizes the WTP response across individuals within the sample to different bid amounts. With a large enough sample, the distribution of WTP is measured and can be summarized through the parameters.

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

$$\Pr(bid_i|d_{ki}) = F(\alpha + \beta \ln(bid_i) + \sum_{k=1}^{K} \theta_k d_{ki})$$

where α is the intercept, β is the slope parameter on the bid amount variable, θ's are parameters associated with other conditioning information variables d's, and F is the logistic CDF. In our application, the natural logarithm of bid amount is used. This functional form specification is used frequently, and our data resembles this specification more than other usable alternatives. Our logistic model is:

$$\Pr(bid_i|d_{ki}) = \exp(\alpha + \beta\ln(bid_i) + \sum_{k=1}^{K} \theta_k d_{ki})/[1 + \exp(\alpha + \beta\ln(bid_i) + \sum_{k=1}^{K} \theta_k d_{ki})].$$

In the application to Landsat valuation, the conditioning information variables d_k are limited to zero-one variables describing characteristics of survey takers. If the other variables are specified, then the θ's are multiplied by their means and added into the intercept. Similarly, and as needed, separate models for different groups within the sample that display substantially different behavior can be estimated. The bottom line is that with a set of parameter estimates and a specific set of attributes d_{ki}, then a given bid amount can be used to calculate a probability that that a representative individual will agree to the bid amount.

C. Logistic Regression Results from the 2012 User Survey

Table 1-2 presents the results of the logistic regressions based on the 2012 registered Landsat user survey. Recall that the sample frame was a complete census of all Landsat users. In Table 1-2, established users were defined as longtime users of Landsat for at least a decade, i.e., those who used Landsat regularly both before and after it became available for free in 2008. New and returning users were those who had not used Landsat for at least a year prior to it becoming available at no cost. The independent or explanatory variables are a series of intercept shifters for federal government employees, state and local government employees, private businesses, and nongovernmental organizations (NGOs). As seen in Table 1-2, all coefficients are statistically significant, with the exception of the state and local government employees. Most importantly, the BidAmt($), which is the dollar amount the direct user was asked to pay, is negative and statistically significant. This indicates the internal validity of results, which was that the higher the dollar amount users are asked to pay, the lower the probability they will pay. This result indicates the users were paying attention to the dollar amount they were asked to pay and taking it seriously. This intuitive pattern exhibits economic behavior consistent with economists' law of demand.

Table 1-2 Logistic Regression Results from the 2012 Survey Responses

	Established User (High Years)		New/Returning User (Low Years)	
	Coefficient	**Std Error**	**Coefficient**	**Std Error**
Intercept	4.3041***	0.2630	3.4689***	0.2066
Federal Gov=1	0.6779***	0.1871	0.4685**	0.2100
State & Local Gov=1	0.4517	0.3084	0.2790	0.2755
Private Business=1	0.3868**	0.1964	0.4014**	0.1876
NGO=1	0.9066**	0.3771	0.3738	0.3244
Ln(BidAmt$)	-0.8788***	0.0411	-0.9071***	0.0374

*** is significant at the 1 percent level

** significant at 5 percent level

D. Graphical Results of the Registered Landsat User Demand for a Scene

The logistic regression results in Table 1-2 can be converted into a demand function with price and quantity. To do this, we use the regression coefficients from the more recent 2018 study discussed more below, which are qualitatively similar to Table 1-2.[7] Using the logistic regression coefficients and varying the levels of dollar bid amounts will produce a probabilistic demand function for Landsat imagery, i.e., a distribution of valuations. The probabilistic demand function is essential in economic valuation. It describes economic WTP for a scene and can be used to calculate the overall mean and median WTP, or consumer surplus. Since we know the number of scenes that were acquired, an aggregate valuation can be constructed.

Figure 1-1 presents the demand curve derived from the estimated logistic model. The horizontal axis of the probability of answering “Yes” to a given dollar amount can also be thought of as the percentage of users that would pay each dollar amount. This demand curve is consistent with the usual inverse relationship between price and quantity: The higher the price a user is asked to pay, the less likely an individual user would pay, or in the aggregate, the users who would pay that amount are fewer. Again, the statistical relationship represents valuations across the distribution of users. By far, the majority are low-value users while there are a minority of users that find the imagery essential and have a very high value for it. This is what the exponential curve communicates.

Figure 1-2 zooms in on the lower part of the demand curve to show more detail. From Figure 1-2 it is evident that 30 percent of the sample will pay $150 or more per scene. The median value, which is the amount that half the sample would pay, is about $50 per scene.

[7] These regression results are in Table 3-4.

Figure 1-1 Demand for Imagery – Landsat Scenes: Bid Price Amount is Matched with the Probability the User Would Pay the Specific Dollar Amount

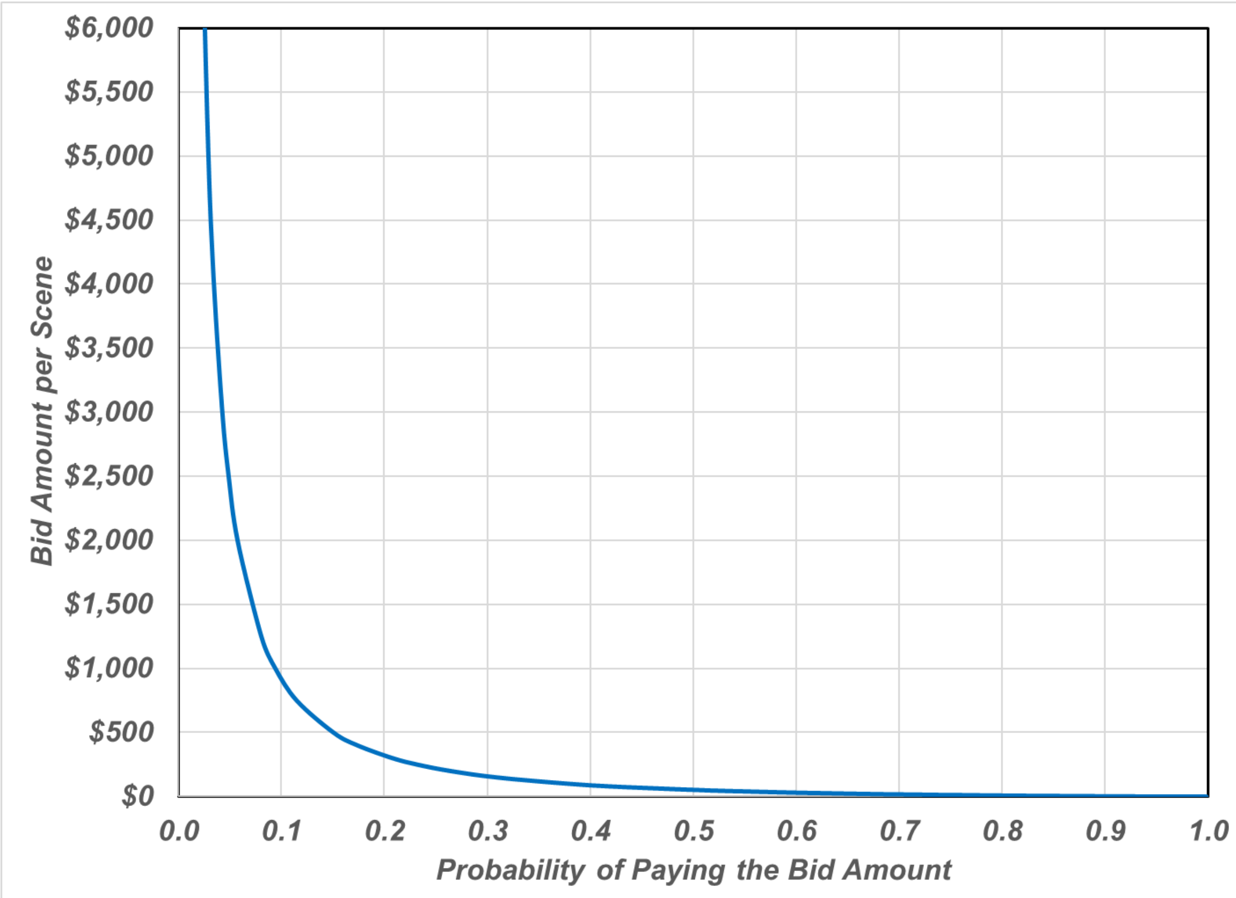
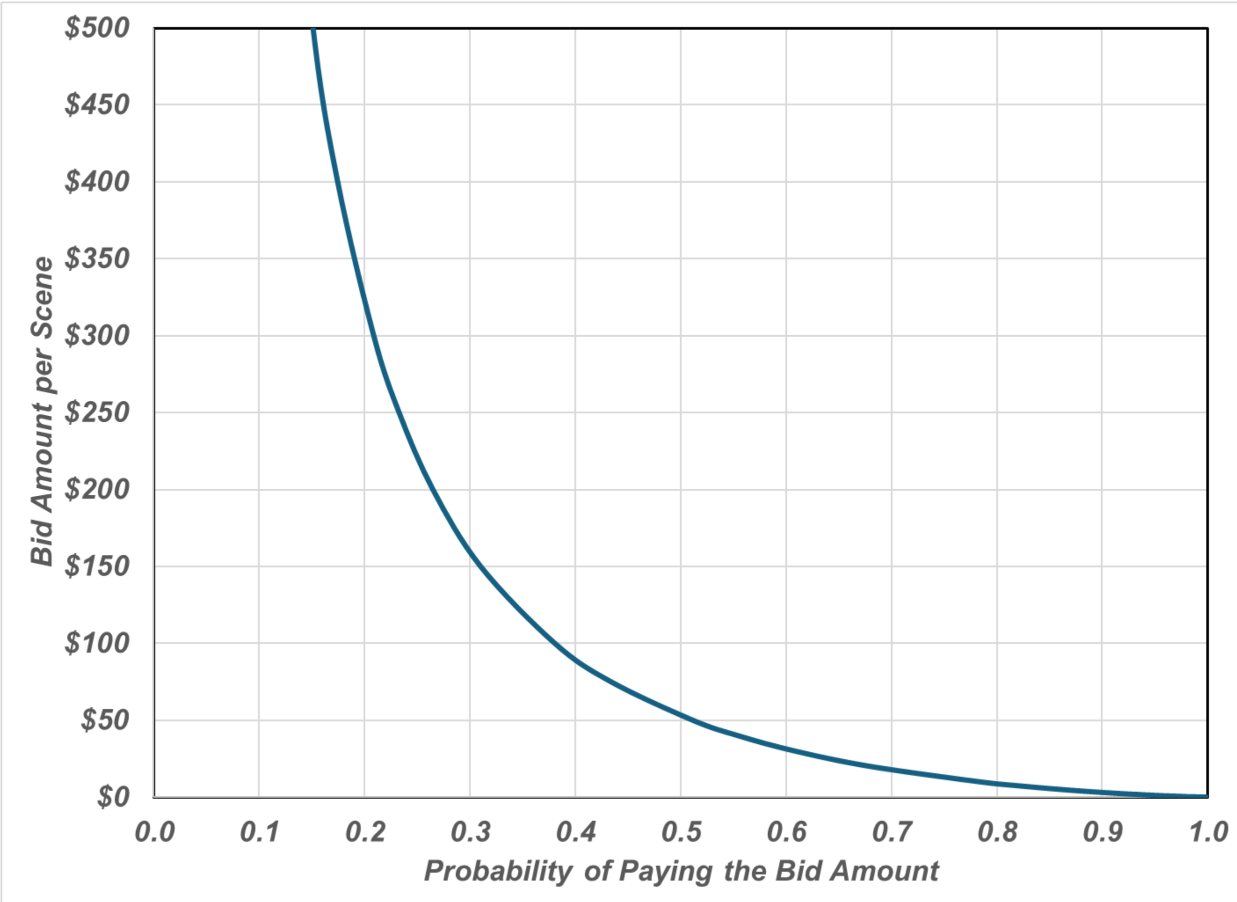


Figure 1-2 Demand for Imagery – View Zoomed to Lower Bid Amounts



E. Calculating Monetary Values of Landsat Imagery to Registered Landsat Users from the Regression Equation

Both the average (mean) and median WTP can be calculated from the logistic regression results. The median WTP is the amount that 50 percent of the users would pay and is calculated using a probability that what a user would pay is equal to 0.5. Formally,

$$\Pr(bid_i|d_{ki}) = 50\% = F(\alpha + \beta\ln(bid_i) + \sum_{k=1}^{K} \theta_k d_{ki})$$

To calculate the sample median, the independent variables in Table 1-2 would be set at the mean of the sample and use the logistic regression coefficients in Table 1-2 for α, β, and θ's, then the median WTP amount can be solved for:

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

For this log-bid-amount model, the solution is the median WTP. However, with this the nonlinear model median and mean WTP are different. This functional form and model imply that there are many imagery users that value the imagery at low amounts, but there is also a small but significant portion of users that find the imagery of very high value; there is also a very small portion that finds the imagery essential and who have an extremely high WTP for it. The nonlinear log-bid model makes it possible to fit a single demand curve that includes these types of high-valuing users, as well as those users with much smaller values. Thus, this model allows for this underlying condition in the user preferences and valuations. Because of these high and very high-value users, the average value of the scene is much higher than the median. Again, the distribution of valuations across the sampled population of users is captured in the overall aggregate evaluation methods employed.

The average 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:

$$\text{Average Value} = \text{Average Bid} = \int_0^{\infty} [1 - F(WTP^* < \text{bid})]d(bid)$$

which is:

$$\text{Average Bid} = \int_0^{\infty} [1 - F(\alpha + \beta\ln(\text{bid}) + \sum_{k=1}^{K} \theta_k d_k)]d(bid)$$

(Hanemann (1984). However, the integral is bounded only if the bid slope coefficient (β), which should be negative for a demand function, is less than -1. This is not the case in Table 1-2. Rather, -1 < β < 0; this is a common result in many CVM applications. The approach then is to choose a high-bid amount of the sample and perform the integration numerically (Bishop & Heberlein (1979); Hanemann (1984)). Specifically,

$$\text{Average Bid} = \int_0^{highbid} [1 - F(\alpha + \beta\ln(\text{bid}) + \sum_{k=1}^{K} \theta_k d_k)]d(bid)$$

We make use of the high bid amount for the WTP question in our survey, thus our WTP estimates are relatively conservative from this aspect. Essentially, we are omitting a portion of the WTP that the model implies are there for very high-value users, but that are also outside of our sample.

The average bid amounts are useful information for interpreting the behavior of individuals and constructing aggregate economic values when analysts wish to estimate the total benefits to registered Landsat users. Multiplying the average value per scene times the total number of scenes downloaded in a given year produces a conservative estimate of the total annual value of scenes to registered Landsat users[8].

We use the CPI to adjust the 2012 values per scene and the aggregate values to 2023. The reasoning is that the dollar values registered users of Landsat would pay in 2012 were grounded to prices in 2012. That is, when someone is asked if they would pay Bid x_i in 2012, their frame of reference is often the prices of other goods and services in 2012. Thus, if we want to know what their equivalent WTP is in 2023, we need to adjust upward to account for the rise in all other prices of goods and services between 2012 and 2023. Government agencies and private industry use the CPI to do this. Between 2012 and 2023, inflation was 32.7 percent, and we used this percentage to update the 2012 WTP dollar values to 2023.[9] However, this inflation adjustment is not the main determinant of the value of Landsat imagery reported in Table 1-3 and in the subsequent valuation tables.

F. Economic Values of 2012 CVM Study of Landsat Users

Table 1-3 presents the average WTP results from the 2012 survey for the U.S. Landsat users by whether they are established (longtime continuous users) versus new/returning users, and by sector. The average U.S. value weighted by the number of scenes downloaded for each sector across all established users was $1,210 and was $487 for new/returning users (updated to 2023 dollars).

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[8] The estimate is conservative since the upper limit of the integration for calculating the average WTP is truncated at the highest bid amount in the sample. There are some users with much higher values than this, as is evident in Figure 1-1.

[9] We feel that using the CPI to adjust our values over time may be underestimating the value of imagery, i.e., the relative imagery value may be increasing more than this percentage increase in the CPI indicates. As will be discussed in Chapter 2, Landsat imagery is often substituting skilled field data collection or aerial mapping work and other skilled office-related labor in the production of information. The amount of inflation in the CPI is substantially smaller than the increase in professional and skilled technical workers' wages that have risen over the same time period, which is about 45 percent, according to data from the Federal Reserve Bank of Atlanta (https://www.atlantafed.org/chcs/wage-growth-tracker).

Table 1-3 Estimates of the Average Amount a U.S. Landsat User Would Pay Per Scene from the 2012 CVM Survey (Updated to 2023 Dollars)

User Group	Established Users (High Years)	New/Returning Users (Low Years)
	Average Value/Scene	Average Value/Scene
Federal Government	$1,579	$473
State and Local Govt.	$1,257	$410
Private Business	$1,413	$647
Nonprofit Organization	$1,992	$508
Academic	$941	$443

Besides the statistical/economic model's consistency with economic principles as evidenced in Figure 1-1, providing confidence in the estimates of dollar values, we can also compare these values to what Landsat users were in fact paying for images when the federal government's contractor was charging for them. Table 1-1 indicates that in the mid- to late 1990s, Landsat users were actually paying the equivalent of $3,500 in today's dollars per scene. Thus, the estimates in Table 1-3 are credible estimates of the amount users would pay today per Landsat image.

Since the total benefits to registered Landsat users are calculated by multiplying the average values of a scene by the total number of scenes downloaded that year, it was necessary to calculate a weighted average of the values in Table 1-3. The weights were the proportion of U.S. Landsat users that identified themselves in one of those five categories. The overall U.S. user average value is $999 per scene. Given that U.S. users downloaded 2.38 million scenes in 2012, the total benefit to U.S. users in 2012 is $2.38 billion in 2023 dollars.

G. 2018 CVM Updated Valuation Study of Landsat Users

The 2018 survey was intended to provide an update to the 2012 survey because at the time the 2018 survey was designed, two changes were known to have occurred in the interim time period: a great deal more images were being downloaded, and there was a new supply of free imagery available from the European Space Agency's Sentinel-2A and -2B satellites. While Sentinel did not have the multi-decadal time series of satellite images that Landsat did, for some users it was another free source of high-quality (to 10-meter resolution) satellite imagery. As such, it acted as a substitute for some users. However, one unanticipated event occurred early in the implementation of the 2018 survey: a widely circulated article in April 2018 in the respected journal *Nature* indicated that discussions had started in 2017 in the U.S. Department of the Interior, the agency that oversees USGS, to prepare a "white paper" on "whether Landsat's costs could be recovered from users." (Popkin (2018: 418)) This would essentially return to the Reagan era of charging for Landsat imagery. As one might expect, such a prospect made Landsat users quite wary of answering survey questions on whether they would pay for Landsat imagery. We will return to the economic ramifications of these developments in the interpretation of the WTP results at the end of this section on the 2018 survey.

Contingent Valuation WTP Question: The prior 2012 Landsat survey (Loomis, et al. (2015); Miller, et al. (2015)) successfully used a closed-ended or dichotomous choice WTP approach. Therefore, we kept that dichotomous choice WTP question format as the primary valuation question. This approach allowed a longitudinal analysis of the 2012 and 2018 survey results. Any differences in value would be attributable to changes in the demand and supply of satellite imagery, as well as any information respondents may have on potential changes in Landsat pricing policy. The specific question asked on the survey was the following:

"In the event that Landsat imagery was no longer available, you may have to obtain imagery elsewhere. Assume that you are restricted to your current project or organization budget level and that the money to pay any cost for replacement imagery and additional software or training would have to come out of your existing budget. If you had to pay for imagery that was equivalent to currently available Landsat imagery, would you pay $X for one scene covering the area equivalent to a Landsat scene?"

The $X were the "bid" amounts that respondents were asked to pay. Following standard practice for the contingent valuation method, respondents were asked if they would pay one of several randomly assigned dollar amounts. For the 2018 survey, 13 dollar amounts were used that ranged from $55 to $4,400 per scene, based on the results of the 2012 CVM survey.

Survey Implementation: The survey was conducted throughout 2018. The implementation of the survey followed the Dillman (2017) repeat contact method (~10 repeat contacts) to attain as high a survey response rate as feasible. For the first wave, which was the U.S. federal user survey, a total of 251 individuals responded to the survey, for a response rate of 28 percent. This number includes both completed surveys (N = 205) and partially completed surveys (N = 46). For the nonfederal U.S. user plus international user survey, a total of 4,454 individuals responded, for a response rate of 16 percent. This number includes both completed surveys (N = 3,310) and partially completed surveys (N = 1,144). This response rate is comparable to recent email/web survey responses (Dillman (2017); Dillman, et al. (2014); National Research Council (2013); Petchenik and Watermolen (2011)).

Results from the 2018 Direct User Survey: Table 1-4 presents the results of the logistic regressions based on the 2018 registered Landsat user survey. As with the 2012 survey, the logistic regression specification for this survey involved regressing their "Yes/No" response to the natural log of bid amount (dollars asked to pay) but on a slightly different set of independent or explanatory variables. These included the natural logarithm of the number of scenes downloaded in the previous year, the logged number of years the user had downloaded images from the USGS Landsat website, and, as before, an intercept shifter for whether they were a federal employee or a private business employee. Academics, state and local government users, and NGOs were not statistically different from one another, and they were subsumed into the intercept. Similar to the logistic regression results for the 2012 survey, all the variables in Table 1-4 for the 2018 survey are statistically different from zero, and with intuitive signs. For example, the more scenes you download, the less you would pay per scene, which follows the law of demand: If you are buying a great deal, your "project budget constraint" cannot afford to pay a great deal per scene. The more years you have been using Landsat, the more you would pay, i.e., the longer you have been using Landsat imagery, no doubt you have developed your research program or "product" around Landsat. Importantly, the BidAmt($) is also negative and statistically significant. This again indicates the internal validity of results, i.e., the higher the dollar amount a user is asked to pay, the lower the probability they will pay. This indicates the users were paying attention to the dollar amount they were asked to pay and taking it seriously. Much of the same pattern is evident for international users: the negative and significant coefficient on the BidAmt($) and a positive coefficient and significant coefficient on the number of years using Landsat. However, whether they worked for the national government or private sector was not a significant determinant of the likelihood of responding "Yes" to their dollar amount.

Table 1-4 Logistic Regression Results from the 2018 Survey Responses from U.S. and International Registered Landsat Users

	U.S. Users		International	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Intercept	3.71015***	0.54944	3.05508***	0.6128
Ln[a] (Scenes)	-0.19822***	0.06704	-0.10646	0.0991
Ln (Years)	0.53294***	0.14807	0.30703*	0.1783
Federal/National Gov=1	0.73479***	0.26584	-0.08131	0.4757
Private=1	0.51404*	0.29682	-0.10710	0.3667
Ln(BidAmt$)	-1.1416***	0.10324	-0.90503***	0.0808

a. Ln refers to the natural logarithm.

*** Significant at the 1 percent level

** Significant at the 5 percent level

* Significant at the 10 percent level

Economic Values of 2018 CVM Study of Landsat Users: The coefficients from the logistic regression are used to calculate the median dollar amount that 50 percent of users would pay per scene. The mean value that users would pay per scene can be calculated by integration of the logistic curve, as was done in 2012. Results from this analysis are shown in Table 1-5 and indicate the median value for U.S. registered Landsat users is $58 per scene in 2023 dollars. The average value of the economic benefits obtained from Landsat imagery is $189 per scene in 2023 dollars for U.S. registered Landsat users.[10] For international registered Landsat users, there is the same pattern of the median being much lower than the mean: $42 in 2023 dollars for the median and a mean of $209 in 2023 dollars. The average is much higher than the median for both groups of users because there is that small, but significant, group that values Landsat imagery very highly. This may be due to the nature of the respondents who are generally technically oriented, professional, and knowledgeable about the good they were asked to value, much like when economists survey any longtime nonmarket good users.

[10] As in the 2012 analysis, calculation of the average required setting the upper limit of the integration at the highest dollar amount of the bid asked in the 2018 survey.

Table 1-5 2018 Survey Median and Mean Values of Economic Benefits from a Landsat Scene by U.S. Domestic and International Users

Value Per Landsat Scene[a]	U.S. Users		International Users	
	WTP	90% CI[b]	WTP	90% CI[b]
Median	$58	$45-$73	$42	$31-$61
Average	$189	–	$209	–

a. 2023 dollars

b. Confidence interval derivable statistically for median

H. Likely Reasons Why the 2018 Estimated Values per Scene are Lower than 2012

There were several reasons why the values per scene were lower in 2018 than 2012. One is the decade-long period in which Landsat had been free, specifically since 2008. This is a much longer time span in comparison to the 2012 Landsat survey. The users may now view this free Landsat access as a norm, unlike some longtime Landsat users in the 2012 survey that may have had experience with paying for Landsat. This lack of familiarity of many respondents to the 2018 survey could bring about uncertainty regarding how they would incorporate Landsat fees into current budgets and the mechanism by which they would pay for Landsat images. Beyond these logistical concerns some users might have, there were several more fundamental issues that likely caused differences between the 2018 and 2012 values.

Strategic Behavior May Understate 2018 Values: Respondents to the 2018 WTP survey were likely aware of and concerned about the potential policy change of charging for Landsat even prior to the well-publicized article by Popkin (2018) in *Nature*. Respondents may have heard about the possibility of charging before and during the survey release. This can induce strategic behavior on the part of the respondent to purposely understate the amount they would pay or simply refuse to pay so as to send a signal they were opposed to charging, especially when the good has been free for a decade (Campos, et al. (2007)). In these cases, respondents are worried that indicating any amount they would pay would result in charging for this previously free good. This phenomenon has been found in other CVM surveys (Campos, et al. (2007)). Even when the good has a current price, such as a hunting license, respondents tend to provide valuation responses to CVM WTP questions that are statistically lower than what demand estimates based on actual hunting license price increases indicate they would pay (Loomis, et al. (2000)). The users make this understatement of their WTP so as to send a message via the survey to try to avoid or at least minimize future fee increases.

Introduction of Sentinel as a No Cost Substitute for Landsat: When the 2012 survey was conducted, there was no close free substitute for Landsat satellite imagery. The 2012 Landsat CVM survey measured the entire value to the respondent of satellite imagery. During the time between the first survey in 2012 and the second survey in 2018, the European Space Agency introduced its satellite imagery with an open access policy in June 2014. The 2018 survey WTP question likely became a question about how much more or how much of a premium a user would pay for Landsat imagery compared to Sentinel-2 imagery. For some users, Landsat did offer some advantages. First, Landsat has an archive of satellite imagery that stretches back decades, which is not available for the Sentinel satellites. Second, although Sentinel-2 satellites have spectral bands mostly similar to Landsat 8's, Landsat 8 has thermal bands. Third, many of the analysts are familiar with using Landsat and have developed applications and software around Landsat. Thus, to some users (e.g., longtime users downloading a few images) these advantages of Landsat over Sentinel-2 are important, and they would pay a significant premium for Landsat imagery. For these types of users, we obtained a positive premium for Landsat but still not their total value of Earth observation imagery. For other users (e.g., relatively new users, downloading lots of images) who randomly were asked to pay relatively high prices per scene for Landsat, the advantages of Landsat over Sentinel-2 were just not worth the high added cost. Hence, they substituted Landsat at that price in the survey with the free

Sentinel-2, which is the classic economic substitution effect (Varian (1990: 111)). For some other users, Sentinel-2 was a perfect substitute, i.e., there was not really anything that Landsat offered that Sentinel-2 could not do as well for their particular purposes.

Presumption by Respondents that Sentinel Would Remain Free: There was no mention in the survey about any policy change or cost discussion related to the Sentinel-2 program. Therefore, respondents most likely assumed Sentinel-2 would remain free when responding to the survey.

An Influx of New Users Between 2012 and 2018 Surveys Often Valued Landsat Imagery Less Than Long-Established Users: While the total number of registered Landsat users was growing, including high-valuing users, the bulk of the new users likely had a lower value for Landsat imagery. This is consistent with the early adopter/late adopter timeline common to most new technologies. It is also consistent with the data from Straub, et al. Specifically, the valuation results of Straub, et al. (2019: 7) shows that both the median and the average value per scene of recent users (what was labeled Low Years in Tables 1-2 and 1-3) was, across all sectors of users, always lower than those who had been using Landsat for a long period of time (what was labeled High Years). For example, the value per scene of longtime users who downloaded a low number of scenes per year was twice what recent users who also downloaded a low number of scenes (Straub, et al. (2019: 7)). Thus, some of the decline in value from 2012 to 2018 may be attributable to the influx of new-user late adopters to what was at this point a mature technology. In addition, some new users were "playing catch-up" and downloading large numbers of scenes. This group had the lowest value per scene. Since some of these users received a randomly assigned bid amount that was quite high per scene, they responded with comments such as "there were just too many scenes to pay for." (Straub, et al. (2019: 9)).

I. Estimating the Value of Landsat Imagery in 2023 Given Sentinel-2 as a Substitute and Adjusting for Strategic Bias

In this section, we provide an approximate value of Landsat imagery in 2023 using the results of the 2018 WTP survey, adjusting for strategic bias. The other three changes (numbers 2 through 4 in the previous section) from 2012 to 2018 reflected sensible reasons to expect the values per scene to be lower in the 2018 survey results compared to 2012 survey results. Ideally, it would have been desirable to redo the 2018 survey in 2024 for this current study, as for the time being the threat of charging is now six years in the past. However, the amount of time available for this overall study did not allow for that, so we are drawing upon the literature on strategic bias cited above to adjust the 2018 value.

The Campos, et al. study comparing WTP via the imposition of entrance fees versus increased trip expenditures at a forest preserve and a national park illustrates the degree of understatement in WTP when one asks for willingness to pay for a good that has been free for at least a decade. There has been no entrance fee at these areas "…and people do perceive free access as a right." (Campos, et al. (2007: 61)) These authors used the same type of dichotomous choice CVM as was used in the 2012 and 2018 Landsat studies. Campos, et al.'s results indicated that the willingness to pay higher trip expenditures for access to the forest preserve and national park was two to three times higher than the willingness to pay an entrance fee (Campos, et al. (2007: 81)).

Loomis, et al. (2000) used a different method to quantify strategic behavior by hunters, who the authors hypothesized would understate their willingness to pay for a higher hunting license fee. A dichotomous choice CVM was used to estimate the increase in hunting license fee hunters would pay for an improved hunting experience. Specifically, the survey indicated the rationale for the increase in license fees was to reduce crowding and improve chances of harvesting a trophy deer or elk. To estimate actual WTP, a demand curve was statistically estimated using the inflation-adjusted actual price of deer and elk licenses over a 30-year period. The WTP derived for a hunting license from the demand curve was twice the value that hunters' responses to the dichotomous choice CVM estimate was for deer and elk hunting licenses. It is likely hunters were purposefully understating their WTP in response to the CVM WTP question in hopes of keeping any increase in license fees to a minimum.

We view the incentive for strategic response within the 2018 survey as powerful. Some of the responses to the 2018 survey regarding the prospect of charging for Landsat were pointed and strongly worded. Given the CVM survey response incentives of Landsat users to understate WTP in the 2018 survey is similar to the response incentives in Campos, et al., and Loomis, et al., it seems reasonable to use the findings of those two articles to adjust the 2018 CVM WTP of direct Landsat users upwards by a factor of two. This adjustment essentially doubles the 2018 WTP value per scene. Hence, our best estimate of what the mean/average value of a scene to direct Landsat users in 2023 would be $378 for U.S. users and $418 for international users. These values are about 40 percent of what the 2012 value would be in 2023. Nonetheless, we think this lower value of Landsat imagery reasonably accounts for the presence of Sentinel-2 as a substitute relative to the 2012 survey before Sentinel, and the entry of new Landsat users who often value Landsat imagery less than longtime users.

J. Direct Landsat User Total Benefits in 2023

In both surveys, a scene was the quantity that registered users were asked to value. The EROS Center now provides a wider range of Landsat products (e.g., tiles). However, according to USGS EROS, many users still access imagery. Thus, to arrive at an estimated number of scene-equivalents accessed by registered Landsat users in 2023, two steps were taken. First, obtaining data from EROS on terabytes accessed. The volume of Landsat accessed from the USGS in FY2023 includes all publicly available datasets directly used in the cloud and downloaded from the cloud and on premise. Second, applying information on the size (e.g., megabytes) of typical scenes from Landsat Collection 2, Levels 1 and 2. Using this information, we divided the aggregated terabytes by scene size to calculate the estimated 65.65 million scene-equivalents accessed in 2023. We verified the accuracy of this procedure by comparing the estimated number of scenes we calculated using this procedure for 2017 (22 million) against the number of scenes EROS provided us in 2017 when that survey was completed (22.1 million). (EROS extracted information characterizing Landsat products and demand from their Tracking, Reporting, and Metrics system and provided for analysis.)

Since the data from EROS does not distinguish between U.S. and international users, we calculated a weighted average value per scene from the two groups using the 2018 survey data. That survey indicated that U.S. users reported downloading 69 percent of the scenes and international users downloaded 31 percent of the scenes from the EROS website. Thus, the overall weighted average value to the registered Landsat users is the product of the average value per scene multiplied by the percent of scenes each of the two groups accessed. Using \$378 for U.S. users and \$418 for international users, the weighted average value is \$390.41 per scene-equivalent in 2023 dollars.

Multiplying the weighted average value per scene-equivalents (\$390.41) times the number of direct user scene-equivalents accessed, the value to registered Landsat users is \$25.63 billion annually in 2023.

This estimate by no means represents the entire societal benefit from Landsat imagery since it accounts only for the benefits received by direct users (i.e., those that are registered with the EROS Center). Because there are no restrictions on distributing the imagery once a scene is accessed from EROS, it can be used by multiple people for a variety of projects. This figure also does not reflect the benefits which users of derived or value-added products that include Landsat imagery receive because users of those products are not included in this direct user population. A partial estimate of the hundreds of millions of dollars of benefits to these indirect users is detailed in Chapter 2. Further, the millions of scenes-equivalents can now be accessed by unregistered users through commercial platforms such as Google Earth Engine, Microsoft Planetary Computer, and ESRI, among others, are not accounted for. Thus, it is noteworthy that the economic value to direct users should be treated as just one part of the total benefit generated by Landsat imagery. In other words, a more complete survey of the multitude of end users of satellite imagery would result in a valuation that is likely some multiple of the value to just the direct users.

1.5. Economic Losses Associated with Charging for Landsat

In this section, we discuss the issue of potentially charging direct Landsat users for imagery. As was mentioned earlier in this chapter, charging for imagery during the 1980s and 1990s greatly reduced the number of scenes accessed. Charging today would also significantly reduce the benefits to direct Landsat users, quantified in the previous section. Charging would also have a domino effect, creating large losses to society by reducing imagery available to indirect users of Landsat information.

Scientific data and information sources are generally considered to be public goods due to specific characteristics that prevent them from being efficiently allocated in private markets (National Research Council (2003)). They are also not allocated efficiently under administrative pricing. Once an image is downloaded from the Landsat satellite to a computer at the EROS Center or a similar facility, it has the two key characteristics of a public good: First, accessing that image by one person does not "use up" the image (Nicholson (1992)); that is, the image is still there for other people to access. This characteristic indicates that use of an image is non-rival. Second, with a public good such as digital images, the incremental or marginal cost of another person accessing the image is close to zero. Economic efficiency requires the price to be equal to the incremental or marginal cost of supplying another unit of the good. Because the incremental cost of allowing another person to access the same image is zero, the economically efficient price should be zero. Charging a price that is greater than zero reduces the number of images accessed, hence the benefits to the direct users. However, reducing the number of scenes accessed saves no money for the government or resources to society. A common example of other public goods is provision of improved air quality or national defense. Both of these have these two characteristics of being non-rival in consumption and the marginal cost of providing another unit of the good to another citizen is zero.

Charging a price for Landsat imagery would in fact generate administrative costs to the government in one form or another. The agency or its contractor must go through the process of determining prices, keeping track of how many scenes or gigabytes of imagery each user accesses, invoice each user, process payments, monitor who has and has not paid, and reinvoice. Thus, a significant percentage of any revenue from pricing will be expended on the administrative side, reducing revenue received by the government. Such a pricing scheme also imposes costs on the users to pay the invoices. In essence, costs are being generated with pricing when, in fact, without pricing there are no costs of allowing another user to access another image.

Thus, charging results in economic inefficiency: Some users whose budgets make it infeasible to purchase all the images needed for a project are deprived of the benefits of imagery, and there are no incremental cost savings to the government or society. There is a loss to one group without a corresponding gain to another. Economists call this inefficiency a “deadweight loss” to the economy and society (Gramlich (1990: 50-51); Zerbe & Dively (1994: 126)). Therefore, making the users of imagery pay to access imagery is not consistent with economic principles of public goods.

The high prices charged in the 1980s and 1990s for Landsat imagery (Table 1-1) priced out many direct users and prevented the indirect user from accessing Landsat imagery for research on a variety of topics, as described in Chapter 2. How much economic activity was lost during the 1980s and 1990s is difficult to measure after the fact. However, Chapter 2 can provide the reader some examples of the hundreds of millions of dollars of value that may have been lost by the users priced out of Landsat imagery during those two decades.

A. Economic Efficiency Losses and Deadweight Losses from Priced Landsat Imagery

Economic analysis can be used to calculate the amount of the deadweight loss to direct users of Landsat imagery. The relationship between the economic benefits society receives from the use of the imagery at different price points can be shown graphically. An illustrative demand curve for Landsat imagery was previously shown in Figures 1-1 and 1-2, with the probability of paying for a Landsat image on the horizontal axis and the price per scene on the vertical axis. The demand curve for Landsat imagery slopes downward, following the law of demand. As the price per scene increases, the probability of purchasing a scene decreases and vice versa.

Economic benefits, or consumer surplus, can be illustrated graphically as the area under the demand curve and above the price paid for a particular good. When accessing scenes is free, the entire area under the demand curve reflects the economic benefits received from the use of Landsat imagery, as shown in Figure 1-3. Figure 1-4 shows the effects of charging a positive price, $400, for the use of Landsat imagery. The positive price cuts off low-value users and decreases the amount of imagery accessed from 65 million scenes to 10 million scenes. It is clear that charging user fees creates an economic loss to society and has the greatest impact on the potentially large number of low-value users.

Figure 1-3 Full Benefits Realized to Direct Users of Landsat Imagery at Current Price of Zero per Scene

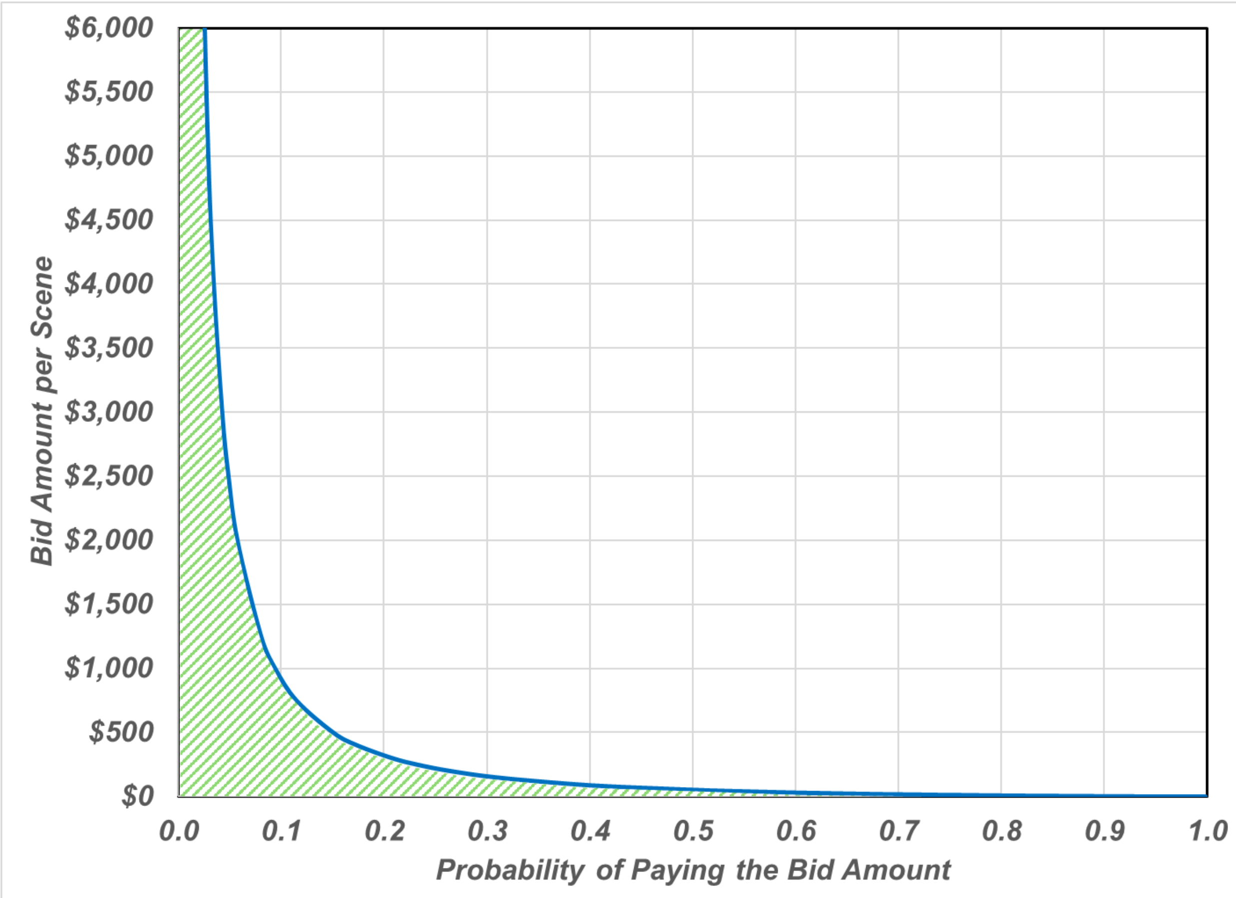
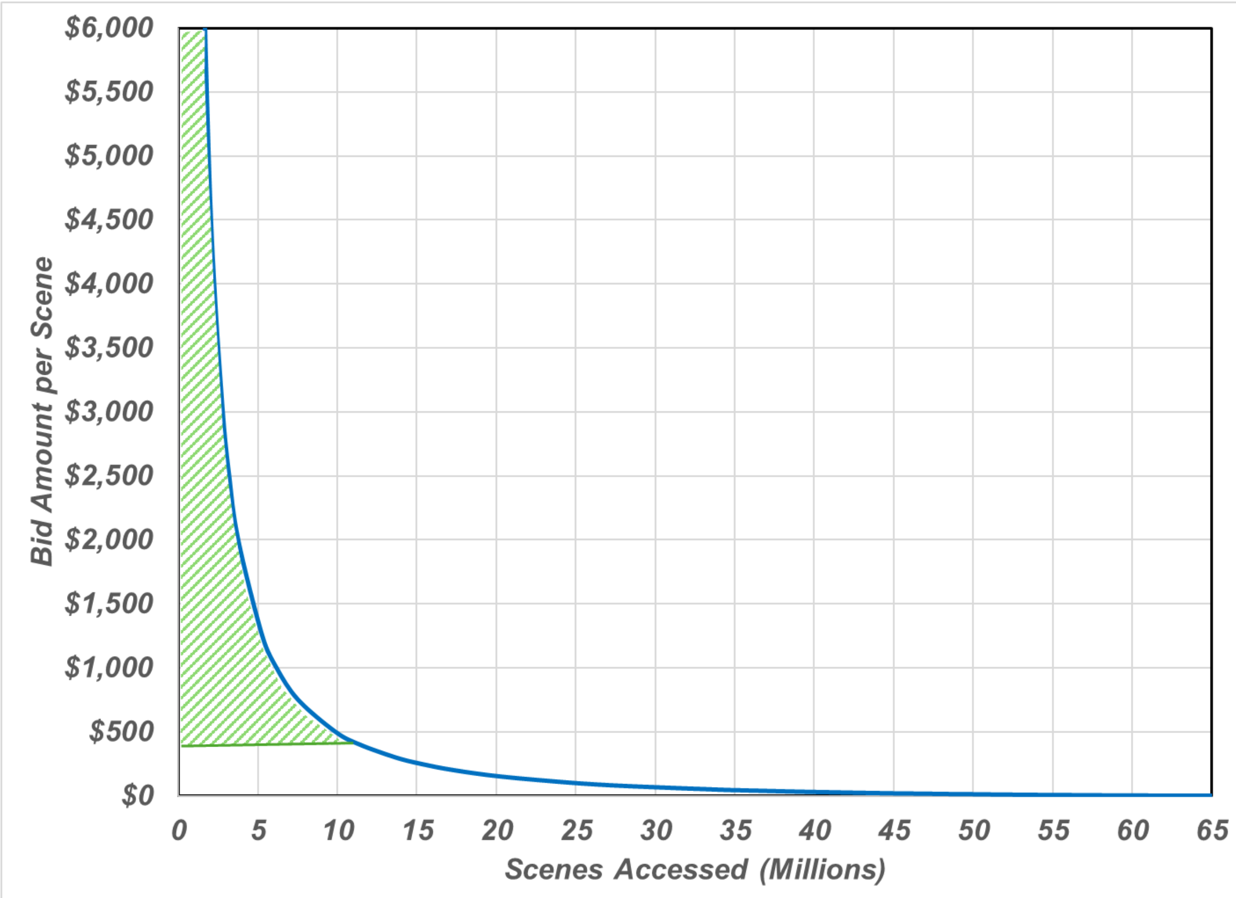


Figure 1-4 Effect of Charging $400 per Scene Reducing the Benefits to Direct Landsat Users



This economic loss can be empirically measured. The average value (labeled as bid amounts on the graphs' vertical axes) is different if there is a cost. The average value net of the cost charged can be calculated by the integral as follows:

$$\text{Average of Cost Charged} = \int_{cost}^{highbid} [1 - F(\alpha + \beta\ln(\text{bid}) + \textstyle\sum_{k=1}^{K} \theta_k d_k)]\, d(bid)$$

The bottom of the shaded area, the consumer surplus, in Figure 1-3 is cut off in Figure 1-4 at the price charged. All surplus below the price charged is lost to the direct users of imagery. We examine costs of $10 per scene, $100 per scene, and $400 per scene in Figure 1-5 and in Table 1-6.

The loss to society per scene is the difference between the average bid amount without charging and the average bid minus the costs per scene. This difference in value per scene is aggregated over the reduced number of scenes obtained. Using our data, the reduced dollar amount per scene can be calculated and an aggregate loss can be measured.

Further, dividing the amount from the net cost calculation by the average bid calculation allows assessment of the percentage of loss to society of consumer surplus from charging for imagery. This percentage loss provides a relative perspective to the impact of the billions of dollars of lost benefit to direct users.

Based on the same demand curve as in Figure 1-3, Figure 1-5 graphically illustrates the effect of increasing the price of Landsat imagery from no cost per scene to $100 per scene. At $100 per scene, it is estimated that more than 60 percent of the imagery acquisitions would be lost (users only access 23 million scenes now instead of 65 million prior to charging). Under this scenario, the upper triangle hatched area represents the remaining consumer surplus to those direct users who continue to use Landsat imagery.

The black rectangle in Figure 1-5 represents the loss in consumer surplus to these same users who continue to use Landsat imagery but now have to pay $100 per scene to do so. This loss in consumer surplus is transferred to the federal government as revenue, and, therefore, represents a transfer of consumer surplus from imagery users to government. But while the transfer is lost to Landsat imagery users, it is not lost to the economy. However, the red hatched region in Figure 1-5 represents the deadweight loss in consumer surplus that arises due to users who are not willing to pay $100 per scene no longer using Landsat imagery and is not transferred to the government. Thus, the loss in value direct users of the 42 million scenes no longer accessed represents a net loss to society as a reduction in consumer surplus or benefits to direct users that accrues to no one as a gain (Krugman & Wells (2013 p. 131)).

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, $100, and $400 is calculated for the 2018 survey and is displayed in Table 1-6.

Figure 1-5 Consumer Surplus Value, Revenue to the Federal Government, and Deadweight Loss Resulting from $100/Scene Charges

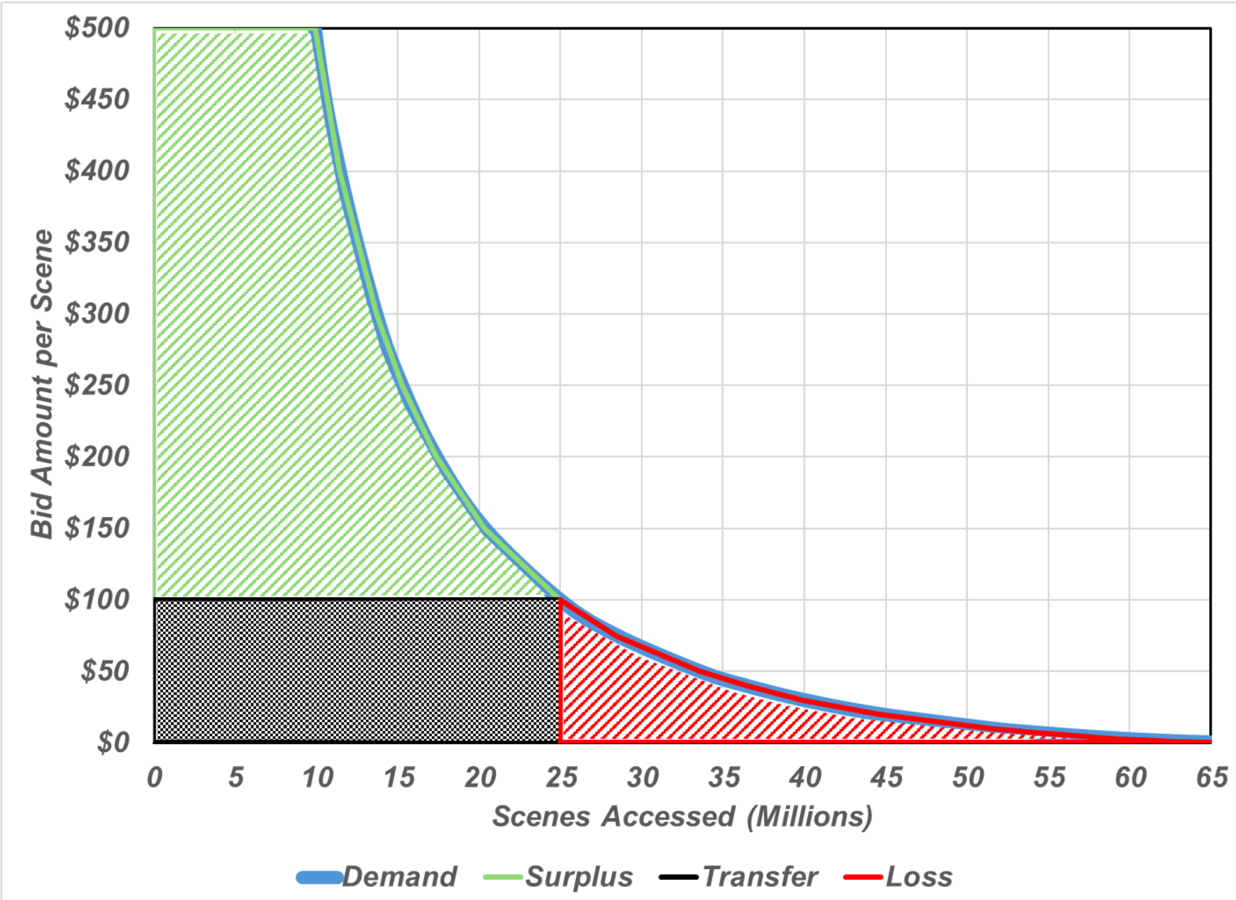


Table 1-6 Losses in Consumer Surplus to Direct Users & Deadweight Loss to Economy/Society from Landsat Imagery Charges at Three Example Prices

Cost	Value	Consumer Surplus or Value			Deadweight Loss	
$/Scene	**$/Scene**	**$ Billion**	**$ Billion Change**	**% Change**	**$ Billion**	**% Change**
$0 (current)	$390.41	$25.630	–	–	$0	–
$10	$381.72	$19.626	-$6.005	-23%	$5.491	-21%
$100	$335.04	$8.361	-$17.269	-67%	$14.773	-58%
$400	$261.27	$2.988	-$22.643	-88%	$18.069	-70%

Continuing with the current policy of free access results in an average value per scene of $390.41. With 65.65 million scene-equivalents accessed in 2023, the total value to the economy to direct Landsat users and the associated benefit to society is conservatively estimated at $25.63 billion.

Charging $10 per scene eliminates about 23 percent of the imagery accessed. The average value per scene decreases to $381.72. The total benefit to Landsat users is reduced to $19.63 billion. This is a loss of benefits to direct Landsat users of $6 billion, or about 23 percent of the imagery's underlying value. The deadweight loss associated with charging $10 per scene is $5.49 billion, and this is 21 percent of the imagery's underlying value. Charging even small amounts for imagery causes nearly all the $6 billion loss in direct user benefits and is also a deadweight loss ($5.49 billion) to society. The 23 percent reduction in scenes accessed could potentially lead to compounding large losses to indirect users for their applications.

Charging $100 per scene eliminates about 62 percent of the imagery accessed. After all, the median value per scene is $53. Thus, charging more than $53 eliminates more than half the scenes accessed. The average value net of this $100 cost decreases to $335.04 per scene. The total benefit to direct Landsat users is reduced to $8.36 billion. This is a loss to the direct Landsat users of $17.27 billion, or about 67 percent of the imagery's underlying value. The deadweight loss associated with charging $100 is $14.77 billion and this is 58 percent of Landsat imagery's underlying value. These substantial losses arise even when charging roughly one-quarter of the value of the underlying scene of $390 per scene.

Charging $400 per scene eliminates about 83 percent of the imagery accessed. The average value per remaining scenes decreases to $261.27 once the user pays $400. The total benefit to Landsat users is reduced to $2.99 billion. This is a loss to the Landsat direct users of $22.64 billion, or about 88 percent of the imagery's underlying value. The deadweight loss associated with charging $400 is $18.07 billion. This is 70 percent of the imagery's underlying value that is lost to society.

It is also important to note that Landsat imagery has been available at no cost since 2008, and the losses calculated are based on the number of scenes accessed for free from EROS. The losses 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 indirect users of Landsat imagery and imagery-derived products. Further, it is important to note that because the starting aggregate benefits to direct Landsat users are conservatively estimated, then the negative impacts of charging are also.

From Table 1-6, it is apparent that the negative impacts on the economy of charging fees results in large losses in economic efficiency, as measured by billions of dollars in deadweight losses to direct users. Within a short period of time, these will result in losses in the indirect user values described in Chapter 2. Charging higher and higher amounts results in only the very-high-valuing users remaining (those that value the imagery in excess of the higher charge) and fewer users, with the remaining users cutting the number of scenes each of them accesses. The billions of dollars in economic efficiency losses to direct users calculated in Table 1-6, plus the likelihood of losses in the hundreds of millions of dollars in indirect user benefits presented in Chapter 2, would have substantial negative impacts on the economy and likely stifle new applications of Landsat imagery. For example, Chapter 2 demonstrates that the application of Landsat imagery has saved hundreds of millions of dollars for federal and state governments, as well as nongovernmental users. High prices for Landsat imagery would make it difficult for many direct and indirect users to afford to keep Landsat imagery up to date and could substantially diminish the cost savings arising from using Landsat imagery.

As noted earlier, Landsat imagery has the characteristics of a public good in that there is no incremental cost to the government of allowing a user to access an additional image. Equivalently, there are no cost savings realized by the government when charging for imagery causes a user to access one less image. But one less image accessed results in a loss in benefits to the direct user, likely losses to indirect users, and a deadweight loss to society as a whole. Thus, if the incremental cost to provide one more copy of a Landsat image is zero, the economically efficient price to charge users for a public good such as Landsat imagery is zero.

CHAPTER 2: LANDSAT BENEFITS TO INDIRECT USERS

2.1. Chapter Synopsis

This chapter* examines Landsat's value for agencies or teams of researchers that are not likely direct (registered) users, as measured in the previous chapter. There are several types of benefits to indirect users, but one of largest and most widespread benefits is cost savings for government agencies, companies, and others around the world that use Landsat-derived imagery in one form or another.

The indirect use benefits arise from the application of Landsat imagery that may have originally been accessed by registered users in an organization for others in the same organization or by other organizations from other platforms that provide access to Landsat imagery, such as Google Earth Engine, among others. In both cases, the benefits of Landsat imagery reviewed in this chapter reflects primarily applied purposes and occasionally commercial purposes, e.g., patent applications. While the indirect user benefits estimated may have some overlap with what the direct users would pay for the imagery, our review of the author disciplines in the articles, summarized in this chapter, suggest the overlap may be minimal. Further, we do not expect much, if any, overlap with the economic benefits generated as a result of using Landsat imagery in commercially derived products. The final section of Chapter 2 describes many other applications of Landsat that, while not quantifiable in specific units, add significant benefits to the society.

A. Tabular Presentation

Table 2-1 reports a summary of the results of literature reviews on topics requested by the USGS in its scope of work and our own analyses of relevant literature. The table provides a concise overview of the values, cost savings, quantities, and topics covered in the literature to illustrate the broad benefits that Landsat provides to the United States and internationally in a world interconnected by climate, trade, and migration. Detailed synopses in Table 2-1 provide short descriptions on each topic. The remainder of the chapter provides details of our analysis of individual topics in Table 2-1.

** The thoroughness of this chapter would not have been possible without the valuable research assistance of Madeline Boyle, Brandon Dodd, and Mia Morones. Any errors or omissions in this chapter are the responsibility of the report's authors.*

Table 2-1 Types of Benefits of Landsat Imagery

Value to Indirect Users	Results (Annual, 2023 Dollars)
Economic Value of Publications Using Landsat[11]	$583 million
Economic Value of Increased Discovery of Gold Reserves and Estimated Production	$255 million
Value of Patents Granted That Cite Landsat in Their Applications[12]	$41 million

Cost Savings to Indirect Users	Results (Annual, 2023 Dollars)
Identifying Wildfire Restoration Priority Areas and Needs[13]	$2 million to $9 million
USDA Avoidance of Paying Fraudulent Crop Insurance Claims Identified Using Landsat	$100 million
Farmers' Reduced Flood Insurance Premiums from USDA's Better Landsat Mapping of Flood Zones	$300 million
Lab Savings from Using Landsat to Monitor Chlorophyll-a (Precursor to Harmful Algal Blooms) in U.S. Lakes and Reservoirs[14]	$51 million
State of Idaho Savings from Estimating Irrigation Water Use by Relying on Landsat Imagery[15]	$20 million
Cost Savings to U.S. Government in Updating Global Maps Using Landsat	$100 million
Improved Accuracy and Cost Savings in Developing Global Shoreline Mapping by Using Landsat	$90 million
Eucalyptus Plantation Owner Potential Savings from Expanding Landsat Monitoring of Tree Growth to One Region of Brazil[16]	$4 million

[11] The current annual value of the estimated 36,750 Landsat publications to the scientific community in 2023.

[12] Average annual value over the 2022–2023 period.

[13] Savings are from using Landsat imagery to develop post-wildfire watershed remediation priorities on federal lands.

[14] Estimated lab cost savings from using imagery of 170,000 lakes and reservoirs nationwide.

[15] Idaho Department of Water Resources reaped cost savings in estimating water use at unmetered agricultural irrigation wells.

[16] Imagery of 2.24 million hectares of planted eucalyptus in Brazil's Minas Gerais state.

The following list presents some applications of Landsat that are not quantifiable and not included in the Table 2-1. The final section of this chapter describes them in detail.

- Carbon emissions and sequestration: Several authors have used Landsat remote sensing and imagery to better measure carbon sequestration or losses in carbon from land use changes around the world.
- Deforestation: Landsat's worldwide coverage has helped the governments of Indonesia, Republic of Congo, Peru, and Brazil to quickly discover illegal logging, to act, and – when appropriate – alert companies that have pledged to only use sustainable forest products about potential issues with their supply chain.
- Water quantity: Authors of several papers have used Landsat to measure evapotranspiration and to monitor fallowing of farm fields involved in temporary water transfers to cities.
- Wildlife:
    - Landsat was used to count penguins in Antarctica. This had previously been a long-term difficulty for wildlife biologists[17].
    - Ducks Unlimited has used Landsat imagery to help map, monitor, and prioritize wetland and upland habitat for waterfowl in Canada, the United States, and Mexico.
- Biodiversity:
    - Landsat imagery is listed as one of the cost-effective approaches to monitoring biodiversity by the United Nations Environment Program.
    - Tracking of invasive species distribution using Landsat helps identify potential threats to native species and biodiversity.
- Monitoring Significant Changes in Ecosystems Worldwide:
    - California's kelp forest ecosystem
    - Greening in the Arctic
- Oceanographic:
    - Landsat imagery helped to identify 650 previously unmapped barrier islands.
    - Landsat imagery was used in the first global inventory of coral reefs.
- Urban Planning:
    - Land values in the continental United States were estimated by pairing Landsat imagery with data on home values from Zillow.
    - Landsat imagery was used to determine urban expansion from 1985 to 2015.
    - Heat island effects of major urban areas worldwide were estimated using Landsat.
- Artificial Intelligence: Landsat data is a fundamental component of artificial intelligence foundational models that have cross-sectoral downstream applications.
- Private Sector Applications: Landsat is considered the gold standard for satellite imagery and is used for cross-sensor calibration by commercial satellite companies.

[17] Peter T. Fretwell, Philip N. Trathan, 2009. "Penguins from space: faecal stains reveal the location of emperor penguin colonies." Global Ecology and Biogeography. 18, 543–552.

Quantitative Examples of Landsat Imagery Accessed by Unregistered Users

- Accessing images from Google Earth Engine in one month of 2024 totaled 1.4 million.
- Environmental Systems Research Institute (ESRI) accessed 50,000 Landsat images a year for users of ESRI's ArcGIS Online version. These users are not likely registered Landsat users.
- There are 136 GIS classes that use ESRI's ArcGIS at the 25 largest U.S. universities. This suggests that thousands of students learn about Landsat EarthExplorer via their GIS classes each year.
- Xie and Lark (2021) created a Landsat-based Irrigation Dataset, which comprises annual 30-meter-resolution irrigation maps, derivative products, and ground reference locations for the United States from 1997–2017. (The data can be downloaded at LANID-US: Landsat-based Irrigation Dataset for the United States (zenodo.org). As of June 20, 2024, there were 4,596 views and 3,280 accessed (366.1 gigabytes) of all versions. This equates to an average of approximately 1,093 accessed a year since the dataset's release.)

2.2. Details of Economic Values Generated by Imagery

A. Value of Publications Utilizing Landsat to the Scientific Community

The annual value of the estimated 36,750 publications using Landsat in one form or another in 2023 was $583 million.[18]

There have been a voluminous number of journal articles and other publications that either focus on Landsat imagery or use Landsat imagery as a tool in conducting studies on a wide range of topics. Wulder, et al. (2022: 5) estimate as many as 767,000 publications referenced Landsat in their articles. As detailed in this section, to estimate the value of these publications to the scientific community it is important to know the timing of when the articles appeared in the published literature. Using Google Scholar and searching by years, we calculated 600,160 publications. That is still a sizable number, and as Wulder, et al. found, a larger use of Landsat rather than other Earth observation satellites.

Morretta, et al. (2022) provides a conceptual framework, an implementable empirical approach, and a case study for Italian satellites on the value of Earth observation satellites in scientific publications.

The core of their model can be thought of as a production function where scientists' time, journal editors' time, and publishers' costs are inputs to producing new scientific knowledge. We adapt their empirical approach to publications that involve Landsat in one dimension or another of the publication. The core of their model is (a) labor costs to scientists in conceiving the study, conducting

[18] From our review of the literature for this report, we found that there were numerous ways in which Landsat imagery was used in journal article publications. This included using one or more images of the same area over time, or different areas along with spatial statistics, to arrive at a conclusion or test a hypothesis. Landsat imagery could also be used as one component of a larger overall model used in the article. The properties of Landsat imagery could be compared to other remote-sensing satellites to evaluate which satellite imagery is best suited for various applications. Lastly, several papers performed comparisons of the differences in accuracy or precision of alternative machine learning algorithms that could be applied to Landsat imagery.

the study, authoring the paper, responding to reviewer comments, and finalizing the manuscript for publication,[19] (b) labor costs of editors, and (c) operating costs to publish the journals.

Researcher costs: We estimated the salary costs of researchers in the primary subject-matter fields of Landsat publications from Wulder, et al. (2022: 6) from the U.S. Bureau of Labor Statistics.[20] Morretta, et al. (2022) assume that a typical researcher spends half their annual time performing research. This seems reasonable for academics, since most also teach, advise students, serve on numerous committees, and occasionally travel to conferences. Personal experience from being a former government employee (Loomis) and working with many government employees performing research projects suggests this assumption of 50 percent of time devoted to research may be reasonable for them, as well. Time spent in agency meetings and travel to get to conferences takes time away from research.

A key element in Morretta, et al.'s model is the productivity of researchers, which in this case is how many journal articles, working papers, or conference proceedings papers they publish per year. They estimate that an author produces four of any of these publications a year, whether as the lead author or co-author (Morretta, et al. (2022: 7)). In their model, there are three costs of producing an article: (a) the upfront time cost of reading the relevant literature that guides the production of the article[21], represented as CIT in their model, and (b) the time cost to conduct the research, write it up, go through the review process, and finalize the paper, represented as marginal production cost (MPC) in their model. Given the salaries, 50 percent of time spent on research, and four articles per year, the marginal production cost per article is about $10,200, which leads to (c) the marginal cost of the editor's time and the production cost of publishing each article, which over their study period was $400[22]. Thus, the total cost of a single journal publication is $10,600.

Morretta, et al. provides the following equation to calculate the present value of what a flow of publications over an extended period of time is worth today.

$$PV_{Land,\tau} = \sum_{t=1}^{T} Land_t * \frac{MPC_t}{(1+SDR)^{t-\tau}} + \sum_{t=1}^{T} CIT_t * \frac{ValueCIT_t}{(1+SDR)^{t-\tau}}$$

[19] In nearly all scientific journals, peer reviewers donate their time to critically review the soundness of submitted manuscripts. From an economic perspective, this time clearly has an opportunity cost of that input as well. As such, this is an element of Morretta, et al.'s model that make the estimates of the value of the publications to the scientific community a conservative one.

[20] See https://www.bls.gov/oes/current/oes_nat.htm

[21] This time includes reading articles to decide whether they are of direct relevance to designing their study, comparing their results to that of past studies, etc.

[22] The reader needs to keep in mind that the time period of Landsat publications starts in the mid-1970s and stretches to 2023. From the 1970s into the late 1990s, most journals were paper copies only, and even today, while journals post PDFs, most prestigious journals still produce printed copies of the journal, as well.

It starts in 1976 and goes to T in 2023. The SDR is the social discount rate. We obtained that from the OMB (2023), which sets the discount rate (long-term inflation-adjusted), interest rate, or time value of money, for use by federal agencies. The SDR rate is 2 percent.

Conducting these calculations for publications that involve Landsat in one form or another in each year from 1976 to 2023 (MPC), including the references cited in each of the publications (CIT), plus the $400 per article editor and journal publication costs**,** yields a present value over the 48-year period of $11.46 billion. Where possible we are putting values adjusted for inflation to the year 2023, the annual value of the estimated 36,750 Landsat publications in 2023 is $583 million.

It is important to point out the conservative nature of this benefit estimate. Morretta, et al. note that the benefits estimated by their method are just the benefits to the scientific community that either involves a particular satellite (in our case, Landsat or the use of Landsat as one of the methods in the study), and therefore, " . . . are just a portion of the vast benefits to a large community of stakeholders, such as firms, people, and society in general." (Morretta, et al. (2022: 12)).

In economic terms, there are substantial positive external benefits to other indirect users of Landsat imagery that are addressed in subsequent sections of this chapter. We use "other indirect users" as many of the co-authors of the papers, including many lead authors, may not be registered Landsat users, i.e., not the direct users surveyed in the prior chapter. Interdisciplinary research teams listed in more than 100 Landsat articles our team reviewed for this project included numerous non-geographers or non-spatial analysts across an entire range of natural scientists (e.g., wildfire specialists, biologists, ecologists, hydrologists) and social scientists (e.g., economists), many of which may not be registered Landsat users.

B. Economic Value of Patents Granted Citing Landsat in Their Applications

Using an annual average of 42 patents during the 2022–2023 time period and the median social value of a patent that Landsat contributed to, the annual social value of U.S. patents during that period was $40.8 million. Over the last 46 years, some dimension of Landsat data was cited in 454 patent applications.

Within six years of the initial Landsat satellite launch, patent applications were citing Landsat. The annual number of such Landsat-related patent applications has been averaging 25 per year from 2018 to 2021, then increasing to nearly 50 in 2023. The U.S. Patent Office classifies the most common fields using Landsat-supplemented patents as involving physics (which includes computing), electricity, and, increasingly, a category called "human necessities." This category includes agriculture, food processing, furniture, medical devices, and firefighting. By mid-2024, there were a cumulative total of 545 patent applications that relied upon Landsat imagery or other aspects of Landsat satellites (e.g., sensors).

To estimate the value, we focused on registered patents that reference Landsat. Following a model developed by Florio, et al. (2016), the social value of a patent is the sum of the private return to the inventor (or the inventor's company), plus the public value of additional knowledge the patent application makes known. This additional knowledge is conveyed in the citations made in publicly available patent applications and is then available to others to build upon, further spurring innovation. The private return from patents is based on market transactions for patents (Lu (2020)). Using the Florio, et al. model and the data for the private return on the patents, along with the number of citations in the patent applications, we calculated the social value of registered patents that referenced Landsat as part of their application. This averages $1.5 million of social value per patent, with a median value of $970,990. To provide the social value of patents associated with Landsat in the current time period, we used the average number of patents granted in the 2022–2023 time period. We did this because 2023 had an unusual spike of 49 patents granted. In the previous year, 34 were granted and that was about eight patents above the average for the last five years. Using an annual average of 42 patents in 2022–2023, and the median social value of a patent, the annual social value of U.S. patents during the time frame was $40.8 million.

This is a conservative estimate, as it leaves out any value of international patents that have referenced Landsat in their applications. However, not all the $40.8 million in annual value is attributable to Landsat. In fact, it would be a difficult empirical task to parse out how much of that value is specifically contributed by Landsat. For example, if just Landsat imagery would be relied upon when using the patent, and since Landsat imagery is free, a method called residual imputation would be required to estimate the value Landsat contributed (Young and Loomis, (2014)). This method requires that the prices/wages and quantities/hours of labor of all the other inputs be subtracted from the total value of the patent to arrive at the remainder that would be due to the free Landsat imagery. To do this would require, at least, examining a large sample of the 454 patents – a task well beyond the three months allotted for this study. In addition, much of the data on wages, quantities of labor, and other inputs to utilize the patent may very well be proprietary. Thus, the $40.8 million value is the total value of patents in which Landsat played a significant enough role that it was referred to and cited in the application, but not solely the value contributed to the patent from Landsat.

C. Value of Mineral Discovery to Companies

Potential revenues from additional gold production due to the information contained in Landsat mapping is estimated to be $277.6 million a year.

Landsat imagery provides valuable geological information through its mapping program that reduces uncertainty in exploring for minerals for existing mining firms. As a result, Landsat imagery also makes the entry of new firms into the mineral industry easier (Nagaraj (2021: 564)). Nagaraj uses the example of Landsat mapping reducing uncertainty in the exploration for gold in the continental United States (Nagaraj (2021: 571)). Nagaraj tests for the effect of Landsat imagery on gold discoveries using a multiple-regression time series model that compares areas that were mapped before Landsat, after Landsat, and those that were never mapped at all.

Nagaraj summarizes his findings as follows: "The main result is that . . . there is a positive impact of Landsat images on gold discovery, suggesting that public data can increase private performance . . . This means the rate of discovery in imaged regions is almost doubled . . ." (Nagaraj (2022: 574)). According to Nagaraj (2024: 13), "The Landsat program led to a gain of approximately $17 million for every mapped block over a 15-year time period. For a country the size of the United States, this translates to additional gold reserves worth about $10 billion USD that can be attributed to the information from the Landsat program."

To translate the value of gold reserves into the value of annual gold production, three steps are required. First, total reserves would need to be adjusted to an annual basis by dividing by the 15-year period used by Nagaraj (2024). The result of this first step ($10 billion divided by 15 years) is $666.67 million per year of reserves on average discovered over the 15-year period. Second, we used USGS "Mineral Commodity Summaries" (Data Series 140) that indicates on average from 1991 to 2023, the yearly average production from recoverable reserves was 0.066 percent. The $666.67 million in the value of reserves translates into about $43.7 million annually in gold production revenue. The third step is to reflect the current (2024) price of gold (roughly $2,333 per ounce at the time of publication) as compared to the price of gold in 1990 ($400), which was the end of Nagaraj's 2022 time period. The ratio of the 2024 price to the 1990 price is 5.83. Thus, the $43.7 million valuation in 1990 is $255 million in today's gold prices. Therefore, the potential revenue from additional gold production due to the information contained in Landsat mapping would be $255 million a year. Of course, the substantial cost of the mining and processing would need to be subtracted out to arrive at the net value of the gold to the nation and society.

2.3. Cost Savings to Society from Use of Landsat Imagery

A. Reliance on Landsat Imagery Saves U.S. Forest Service and Bureau of Land Management $2 Million to $9 Million Annually

Due to decades of wildfire suppression, many forests have a high density of trees. In addition, insect damage, such as bark beetles, and drought have often left these forests with many standing dead trees. When wildfires occur, the combination of these three factors results in high-intensity wildfires. In some cases, the resulting wildfire-generated temperatures can be so high that they mineralize portions of the soil, making them "hydrophobic," whereby any thunderstorms will cause downstream flooding, stripping away portions of the remaining downstream soil. There are actions land management agencies such as the U.S. Forest Service and Bureau of Land Management can take to lessen the damage. However, these measures, such as aerial reseeding, dropping straw, building berms with straw wattles or fiber rolls, are expensive. Since large fires can burn tens of thousands of acres, the issue is whether to employ these mitigation measures and, if so, where to target them.

Two articles have investigated using Landsat satellite imagery as a way to identify soil burn severity as compared to helicopter overflights or on-the-ground field work. Traditionally, agencies used these latter two approaches to develop their Burn Area Emergency Response (BAER) plans. Recently, two evaluations calculated the cost savings from using Landsat imagery to reduce these costs.

The first paper, by Bernknopf, et al. (2021), used Landsat imagery to provide information on two critical elements of the BAER: (a) Burned Area Reflectance Classification maps and (b) Soil Burn Severity maps to measure the loss of organic matter. Based on these two elements, plus other factors, such as slope and proximity to water or infrastructure, BAER plans recommend mitigation strategies. Bernknopf, et al. compared the use of Landsat imagery with minimal helicopter use to commercial imagery with greater helicopter use. They also compared reliance on Landsat imagery versus helicopter-only reconnaissance. The savings attributable to using Landsat imagery versus commercial imagery to the U.S. Forest Service was $11,157 on their case-study fire, the Elk Complex Fire. Since Bernknopf, et al. (2021: 27) indicated that there were an average of 150 BAER requests a year, and " . . . there were no significant economies of scale from savings in aggregating from an individual incident request to an annual rate of 150 requests," they proceeded to scale up the Elk Complex BAER cost savings to the annual cost savings. In the case of Landsat imagery and limited helicopter versus commercial imagery and helicopter reconnaissance, the estimated savings were $2 million a year. In the case of relying solely on Landsat imagery versus helicopter reconnaissance only, the cost savings were $9 million a year.

Another study, Miller, et al. (2022), utilized Landsat imagery by the BAER teams to develop extremely specific erosion risk maps after a wildfire to target erosion control measures before any significant rainfall was expected to occur in the burn area. Miller, et al. indicated that information from Landsat 8 on vegetation, soil, and elevation layers was used to identify which locations were most susceptible to flooding and landslides. Not only is the speed of Landsat to identify these priority areas for response an advantage, but it also results in a significant labor savings during most fire seasons when BAER response teams are often stretched thin over as much as 10 million acres some years (National Interagency Fire Center[23]). Miller, et al. estimated the cost savings using Landsat on five wildfires over a 2.6-year time period. We put this on an annual basis and updated it to 2024. The resulting value was $300,000 in annual cost savings for their five case-study wildfires, a savings of $60,000 per wildfire. As noted by Bernknopf, et al. (2021), there are 150,000 of these BAER analyses that are usually done each year. As such, the cost savings would be $9 million a year.

B. Landsat Imagery Saves the USDA $100 Million Per Year in Crop Insurance Fraud

Landsat imagery has been used to detect fraud by farmers in the U.S. Department of Agriculture's (USDA) Federal Crop Insurance Program (Rocchio (2006)). The USDA's Risk Management Agency, or its contractors, has used Landsat imagery to validate the claim of crop damage due to drought or weather. The USDA uses about 600 Landsat scenes a year.

Landsat imagery often does validate what looks like a questionable claim for damages. However, one of the main contractors that was a remote sensing and GIS advisor to the USDA found that fraud occurred in about 1 percent of the cases, including cases where the farmer had not even planted the field. The 30-meter resolution in Landsat can detect fraud down to as small as five acres across the entire continental United States and Hawaii (Rocchio (2006)). In part due to the success of detecting fraud and success in using Landsat imagery as evidence in the courtroom, the USDA has trained some of its crop insurance compliance investigators in using Landsat imagery. Rocchio's article quotes Dr. John Brown of the Agricultural Investigation and Research Corp. that "a conservative estimate would be that Landsat saves the U.S. government $100 million per year." (Rocchio (2006))

[23] https://www.nifc.gov/fire-information/statistics/wildfires

C. Using Landsat to Monitor Water Quality for Chlorophyll-a Saves $51 Million Annually in Lab Costs

Chlorophyll-a is a contributor to harmful algal blooms (HABs). The algal blooms pose health threats to aquatic vegetation, fish, humans, and pets. HABs are found along beaches and in freshwater lakes, including the Great Lakes. Given the key role that chlorophyll-a plays in algal biomass, chlorophyll-a is a useful indicator of the algal content of lakes and reservoirs.

Given the detrimental effects of certain algal blooms, one might expect that every state would have HABs monitoring programs, but 18 states do not (Papenfus, et al. (2020: Figure 2)). While the Environmental Protection Agency's National Lakes Assessment program monitors chlorophyll-a in 1,269 lakes nationwide, including in states that do not perform their own monitoring, this national assessment happens only once every five years.

In contrast, Landsat satellite imagery covers 170,000 lakes, many of which are relatively smaller water bodies that are more prone to eutrophication and HABs (Papenfus, et al. (2020)). Actual on-site sampling of these many lakes would be quite expensive, in part due to travel cost and travel time (Papenfus, et al. (2020)). Thus, Landsat provides the most complete spatial coverage at a fraction of the cost.

Papenfus, et al. performed a "what if" analysis of what the cost savings would be if states were to attempt to sample chlorophyll-a at the 170,000 lakes. Their "what if" analysis is quite conservative in omitting the largest cost of an on-site monitoring program, which is the travel and personnel costs to collect the samples. Rather, they focus on cost savings of the lab analysis[24] for chlorophyll-a. Given that Landsat would collect nearly 2 million observations per year, the estimated savings is $51 million in 2024 dollars. The authors acknowledged that there would be more data that could be collected with on-site sampling than just on chlorophyll-a, but that assumes the 18 states with no monitoring programs started to conduct on-site water quality sampling.

Thus, as noted by Papenfus, et al., (2020: 808) " . . . there are large potential cost savings associated with using the [Landsat] satellite data" to monitor HABs and their detrimental effects on aquatic and human health.

D. USDA's Use of Landsat Saves Farmers in Potential Flood Zones an Estimated $300 Million in Crop Insurance Premiums Annually

Relying on Landsat imagery, the USDA undertook a program to create much more accurate maps of the potential risk of flood damage to farmers enrolled in the USDA's crop insurance program. This allowed many growers to have a lower flood insurance rate. These flood maps are constantly being updated based on new Landsat observations reflecting changes in water course, levee protection, and other mitigating factors. The provision of more detailed zones reduced premium costs by more

[24] The authors' estimate of the lab cost of $20 a sample is consistent with Louisiana State University's price list in 2018.

than $300 million annually (Landsat Advisory Group (2014)). Without Landsat, it is conservatively estimated that the USDA would have to raise premiums for more than 200,000 farmers' policies equal to $300 million annually.

E. Idaho Department of Water Resource's Monitoring of Unmetered Irrigation Wells Saves Nearly $20 Million a Year

The Idaho Department of Water Resources achieves substantial cost savings from utilizing Landsat's thermal infrared sensor data instead of using their existing power consumption coefficient method to estimate groundwater pumping and associated water use (Landsat Advisory Group (2014)). The thermal infrared sensing data, along with mapping evapotranspiration with high resolution and internalized calibration data, measured actual crop evapotranspiration on a field-by-field basis. The department's annual costs of monitoring unmetered groundwater wells dropped from $100 to less than $11 per well using Landsat. Given more than 219,013 unmetered wells, the department's cost savings is $19.5 million annually.

F. U.S. Government Updating of Its Global Maps Using Landsat Saves $100 Million Annually

Keeping U.S. government maps of nearly all areas of the globe up to date, especially those of strategic military purposes, such as important domestic infrastructure and foreign military sites, is a substantial task. Past efforts have involved such high costs that the average age of these maps is 10 years old. Using Landsat, it is expected that the average age of the maps would be cut to one year and maintained there. The annual cost savings would be more than $100 million annually (Landsat Advisory Group (2014)).

G. Landsat Global Shoreline Mapping Saves $90 Million

Using Landsat to map global shoreline has improved accuracy while saving $90 million over other approaches to identify the high-water line at low tide for more than half the world's shoreline (Landsat Advisory Group (2014)).

Landsat GeoCover imagery was able to attain 50-meter accuracy on shorelines, which was substantially more precise than prior digitized maps. The Landsat short-wave infrared detector was able to identify the high-water line at low tide across 50 percent of the global shoreline for $10 million, whereas digitizing the same area would cost more than $100 million. Thus, reliance on Landsat saves the National Oceanic and Atmospheric Administration shoreline mapping group $90 million.

H. Eucalyptus Plantation Growth Monitoring Using Landsat Could Potentially Save $3.37 Million Annually

Santos, et al. (2023) demonstrate a methodology that used the Landsat 7 Enhanced Thematic Mapper Plus sensor to project forest growth and the yield of eucalyptus to estimate the potential cost savings by using satellite sampling in place of on-site sampling. The authors calculated the cost savings of using Landsat 7 on sample plots representing 833 hectares in the Minas Gerais state of Brazil at $1,252 a year. If plantation owners applied Landsat to their entire 2.24 million hectares of planted eucalyptus in the region, this would yield an estimated annual cost savings in measuring plantation growth of $3.37 million.

I. Savings Using Landsat in Measuring Forest Growing Stock Volume in Italy

The D'Amico, et al. (2022) paper focuses on the estimation of the forest growth parameter, which is a key part of forest management. Specifically, the growing stock volume estimate is the volume of all living trees within a specified region of a forest and is also a key component in measuring forest health. The authors' study area was Italian forests. While airborne laser scanning data has been shown to be a useful tool, it is often not available for the entire forest area. Landsat images proved to be useful for large-scale forest surveys. The cost savings attributable to using Landsat Enhanced Thematic Mapper Plus sensor data was estimated to be $250,000 annually compared to airborne laser scanning.

2.4. Description of Other Applications of Landsat Imagery

A. Carbon Emissions and Sequestration

Landsat remote sensing and imagery has been used by several authors to better measure carbon emissions from forest losses:

- Harris, et al. (2021) used Landsat imagery, which they consider to be the backbone of their research, to build global maps of 21st century forest carbon fluxes, which is consequential for the evolution of carbon markets. In addition to forests, Landsat data is also a significant tool for monitoring coastal and marine ecosystems, which store about five times more carbon than forests and are part of the so-called blue carbon market, a $190 billion per year opportunity[25].
- Goldberg, et al. (2020) used Landsat imagery to create a map of changes to global mangrove habitats between 2000 and 2016, resulting from land-use change, primarily through conversion to aquaculture and agriculture. The data are crucial for conservation efforts and carbon projects[26].
- Boisvenue, et al. (2016) used Landsat to monitor Canadian forests and integrate that into Canada's greenhouse gas reporting system.
- Tang, et al. (2020) utilized Landsat data to develop a spatially explicit model of aboveground biomass of forests in a carbon bookkeeping model for the Amazon. Using Landsat imagery, they were able to estimate total emissions from forest clearing and the burning of ground for grazing, as well as carbon uptake.
- Liu, et al. (2024) used Landsat imagery to measure global forest losses and associated carbon emissions from 2015 through 2020. The lengthy period of consistent Landsat imagery allowed the authors to quantify that the rate of forest loss and associated emissions in 2015 through 2020 was double that from 1985 through 2020.

[25] https://www.worldbank.org/en/news/feature/2023/11/21/what-you-need-to-know-about-blue-carbon

[26] https://onlinelibrary.wiley.com/doi/10.1111/gcb.15275

- In a similar fashion to Tang, et al., Arevalo, et al. (2023) developed a temporal and spatial method to map aboveground biomass (AGB) in the Brazilian Amazon basin using parameters from 20 years of Landsat Time Series data. This method was successful in mapping AGB for 1999–2019 with minimal error and can continue to be used as a fine-scale AGB mapping tool for areas with variable biomass ranges.
- Pascual, et al. (2021) combined various types of remote sensing imagery in several different measurement methods to create a spatial carbon sequestration potential index measuring forest carbon density in Hawaii. The near-infrared reflectance gross primary productivity measurement method, developed from Landsat imagery, was determined to be the most reliable at the finest resolution.
- Shen, et al. (2020) used Landsat Enhanced Thematic Mapper Plus data to quantify the changes in total AGB in Shanghai and in calculating the changes in carbon stocks between 2005 and 2015. These data are invaluable for the management of Shanghai's urban forest stand.
- Uniyal, et al. (2022) used environmental parameters from Landsat data as the foundation of four machine-learning models, making it a critical element of determining the spatial distribution of biomass and carbon in Jodhpur, India.

Due to time constraints for this study, our review of the literature on the use of Landsat to monitor or measure the changes in carbon emissions and sequestration was not exhaustive. These articles give the reader a sense of the breadth of the application of Landsat in this policy-relevant topic.

B. Carbon Markets

Carbon markets are dependent on the value of carbon from the natural ecosystems, such as forests, coastal, and marine ecosystems, and represent a potential market size of almost $1 trillion[27]. Monitoring and estimating the changes to emitted and sequestered carbon requires having access to long-term datasets, such as from the Landsat missions. The availability of Landsat's open dataset has not only significant applications in research, but the long-term nature of the data means that research is capable of being translated to commercial applications. For instance, Haddad, et al. (2015) used Landsat data to build a global tree cover map that was not only used to identify deforestation, but also to detect changes in biodiversity ecosystems due to deforestation[28]. The results of these scientific projects leveraging Landsat eventually led to the formation of a company that offers commercial services, including carbon credits valuation, supporting reforestation efforts, and wildfire risk modeling[29]. The formation of new businesses that leverage Landsat-based research leads to increased tax revenues and jobs.

[27] https://www.reuters.com/markets/commodities/global-carbon-markets-value-hit-record-949-bln-last-year-lseg-2024-02-12

[28] https://www.science.org/doi/full/10.1126/sciadv.1500052

[29] https://landsat.gsfc.nasa.gov/article/taking-the-pulse-of-earth

C. Ecosystem Service Value in the Continental United States

Landsat's finer level of resolution compared to other satellite imagery in 1998 allowed for a more accurate and much larger estimate of the acreage of wetlands in the continental United States. The net result was that the estimated value of the ecosystem service values from wetlands increased by $80 billion.

Konarska, et al. (2002) was one of the first to apply Landsat data to quantify the amount of land and water that provides ecosystem services. Ecosystem services are the benefits that nature provides to people (Loomis, et al. (2000); Boyd and Banzhaff (2006); Brown, et al. (2007)). Konarska, et al. compared Landsat's 30-meter resolution with another remote sensing imagery satellite available in 1998, but with much coarser resolution. With Landsat's finer resolution (Thematic Mapper imagery), the National Land Cover Database (NLCD) identified small features more precisely, such as lakes, towns, and most importantly, wetlands. There are thousands of small wetlands, and coarser mapping will often misclassify them with the larger landscapes. In the case of wetlands, the finer Landsat imagery identified 5,155 percent more wetland acreage (Konarska, et al. (2002: 496; Figure 2-2)). Since wetlands provide some of the highest valued ecosystem services, prior estimates of the value of ecosystem services in the continental United States were substantially underestimated. However, the Konarska, et al. (2002) estimate of the value of the gain in wetland area relied on one of the few global estimates of ecosystem service values, which in many ways greatly overestimated the value of ecosystem services from wetlands (Costanza, et al. (1997)).

For our calculation of the value of the ecosystem services of the additional wetland acreage identified by Landsat, we started with one of the reviews of ecosystem service values of wetlands in the continental United States (Woodward and Wui (2002)). We then calculated a geographically weighted average of that study's per acre values. This continental average U.S. value was then converted to hectares and then updated to 2023 dollars ($1,831 per hectare). Since Konarska, et al. only provided the percentage gain (5,155 percent) in wetland area with Landsat, not the acreage, we then applied Konarska, et al.'s percentage to the U.S. Fish and Wildlife Service status and trends estimate of wetland acreage in the continental United States for the year closest (Dahl (2011); Konarska, et al. (2002)). The hectare gains from using Landsat's more precise 30-meter resolution compared to the coarser remote sensing imagery was 43.67 million hectares of wetlands. With a value of $1,831/ha, this amounts to Landsat indicating that the amount of ecosystem service values of wetlands as $80 billion more.

D. Water Quantity

Unlike water consumption in municipal and industrial uses, water use in agriculture is often difficult to measure. One of the primary reasons is that many irrigation ditches, or even irrigation groundwater pumps, do not have meters. However, a variety of estimates indicate that agricultural water use, especially if measured by diversions, is by far the largest water use, especially in the Western United States (Shaw (2005)). For example, irrigated agriculture can account for nearly 90 percent of water use in states such as Idaho and Wyoming (Shaw (2005: 137)). Even in heavily urban states like California, irrigated agriculture uses most of the water supply due to the state's vast Central Valley cultivation, as well as the large Imperial Irrigation District that draws roughly 4 million acre-feet of water from the Colorado River.

During periods of drought, a relatively inexpensive method of preserving water for cities is to pay farmers to fallow their fields. But ensuring they fallow the fields and do not pump groundwater often requires monitoring, and Landsat imagery is useful for this. In the long term, understanding agricultural water use and trends can be difficult due to a lack of record keeping at the farm level.

The OpenET project, led by NASA and other collaborators, uses data primarily from the Landsat missions to create satellite-based evapotranspiration (ET) data for improved water management across the western United States[30]. Landsat is currently the only operational satellite that combines thermal and optical data at a relatively high spatial resolution, allowing the analysis of water use at the agricultural field level. Landsat-derived ET data has been used to simplify regulatory compliance assessments in California, forest restoration efforts of the Salt River Project in Arizona, groundwater use management in Oregon and Nevada, among other examples[31]. As a result of the use of ET data, farmers and water managers can improve their irrigation practices and save costs associated with both water use and indirect electricity use.

Senay, et al. (2017) overcame the lack of agricultural water metering for a large irrigation district in California by relying on Landsat imagery from 1984–2014. They used Landsat-based, field-scale evapotranspiration maps to look at the relative importance of water management, including field fallowing, and climate variables. Their analysis showed the fallowing that occurred in 2011 saved 107,200 acre-feet of water. "The water saved from agricultural use is redirected for municipal water use through the Metropolitan Water District of Southern California. Assuming all water is used for domestic purposes, the estimated number of beneficiary households is . . . reaching up to 362,700, or nearly 1 million individuals in 2011." (Senay, et al. (2017: 110)) This transfer of water yielded a payout of $20.5 million to farmers that year. The authors noted: "Our main objective was to quantify and characterize the spatiotemporal dynamics of historical (1984–2014) [evapotranspiration] using Landsat images over the Palo Verde Irrigation District and irrigated sub-basins in parts of the Central Valley in California, along with six other agroclimatic/hydrologic variables. A total of 3,396 Landsat images were processed and analyzed to produce monthly and annual evapotranspiration . . ." The authors felt their objectives were met, concluding their study demonstrated the usefulness of Landsat-derived information to monitor and assess the impact of management decisions on water use. (Senay, et al. (2017: 110, 111))

- The Gallo Winery in California uses Landsat's thermal band capability to monitor evapotranspiration of vineyards to attain higher wine quality (Landsat Advisory Group (2014)).
- The Federal Emergency Management Agency uses Landsat imagery as an input to its updating of floodplain maps. This allows more accurate floodplain mapping in terms of areas within 100-year

[30] https://etdata.org

[31] https://etdata.org/openet-use-cases

floodplains, which is an important decision variable to government agencies from the federal level (e.g., the U.S. Army Corps of Engineers) to local cities and towns.

- Nadeem, et al. (2023) evaluated the issue of excessive groundwater pumping in Pakistan during the dry season. They used Landsat 8 with the application of Gravity Recovery and Climate Experiment observations to estimate total water storage anomalies and to estimate crop water demand and consumption. The authors' findings showed that most of the districts they observed had been over-irrigating with their groundwater supply. In fact, using Landsat 8 data in combination with the experiment's observations and total water storage anomalies, they estimated the possibility to enhance operational efficiency could lead to a potential water savings of 81 percent. This translates to approximately 155 million cubic meters of groundwater during the dry season from April to June.

E. Biodiversity & Wildlife

- Ducks Unlimited has used Landsat imagery to help map, monitor, and prioritize wetland and upland waterfowl habitat in Canada, the United States, and Mexico.
- Landsat Image Mosaic of Antarctica and supporting Landsat imagery is used to count emperor penguin colonies in Antarctica through fecal staining detection on coastal sea ice (Fretwell and Trathan (2009: 546-549)). At the end of this study, and paired with past literature, 38 colonies had been detected with confirmed breeding status using remote sensor imagery. Of these, 28 were found with Landsat in combination with other remote sensing satellites and 10 were discovered using Landsat exclusively in this study.
- According to Secades, et al. (2013), the United Nations Environment Program lists Landsat imagery as one of its cost-effective approaches to monitoring biodiversity.
- Tracking of invasive species distribution using Landsat helps identify potential threats to native species and biodiversity.
    - Significant changes in ecosystems worldwide
    - California's kelp forest ecosystem
    - Greening in the Arctic
- Oceanographic
    - Landsat imagery helped to identify 650 previously unmapped barrier islands.
    - Using Landsat imagery, the first global inventory of coral reefs was performed.

F. Deforestation

- The Landsat Science website indicated that the use of Landsat 7 and 8 in combination – coupled with Landsat's 30-meter resolution – allows frequent-enough Earth observation for land managers in multiple countries to know where deforestation (often illegal) is happening and to respond to it. Landsat has particularly helped Indonesia, Republic of Congo, Peru, and Brazil. The quick discovery of deforestation makes possible government and environmental-group action and alerts companies that have pledged to only use sustainable forest products about potential issues with their supply chain of forest products. (Landsat Science (2016))

- The Global Forest Watch initiative led by the World Resources Institute provides an online platform with data and tools for monitoring forests. This project offers global tree cover change data products of 30-meter resolution for the years 2000 through 2012, as well as a deforestation alarm system, both based on Landsat imagery and implemented by the Global Land Analysis and Discovery laboratory at the University of Maryland[32]. As the only publicly available medium-resolution global satellite data source before 2016, data from the Landsat missions enable spatiotemporally consistent analysis of long-term land use and land cover changes[33]. Agriculture enterprises in the United States, such as REDD+, SilvaCarbon, and the North American Carbon Program, and international organizations such as the UN Forest and Agriculture Organization use the tool to identify and report agriculture-driven deforestation. Governments also use it to implement deforestation policies.

G. Urban Planning

- Wentland, et al. (2020) calculated monetary valuations for land types across the United States using fine-grain microdata from Zillow, the National Land Use Database, and the NLCD, which uses Landsat's Thematic Mapper. This study developed an index that provides a simple and comprehensive way to visualize change that occurs across all NLCD land cover. Urban imperviousness measurements indicate urban impervious surfaces, such as roads and rooftops, as a percentage of developed surface over every 30-meter pixel in the conterminous United States.
- Xuecao, et al. (2018) used the NLCD to map urban expansion from 1985–2015 in intervals from 1985–2001, 2001–2011, and 2011–2015. The study area for this research was the cities of Des Moines and Ames in Iowa. The authors used a temporal segmentation approach to measure changes in land cover from vegetation and water to bare and urban land. The authors found years in which the start and end of a land cover change was identified using a change vector analysis approach. Overall, the paper found that temporal segmentation was successful in capturing and accurately identifying changes due to urban growth with an accuracy of 90 percent. The work from this paper shows that the NLCD from Landsat, along with their proposed framework, is promising for mapping long-term urban extent and for urban growth modeling.
- Tetali, et al. (2021) investigated the literature surrounding Landsat usage in identifying the severity of urban heat islands, which is the phenomenon where urban areas experience higher temperatures compared to nearby rural areas due to the absorption and release of heat from urban roads, buildings, and other infrastructure. Urban areas with a greater amount of greenery often have fewer urban heat islands. The authors studied 42 cities in India and 32 cities in the United States using Landsat 8 thermal bands 10, 5, and 4 to calculate a normalized difference vegetation index to identify urban-rural mean land surface temperature differences in the summer and winter months of 2016. The authors found the expected phenomenon of surface

[32] https://glad.umd.edu/projects/global-forest-watch

[33] https://www.frontiersin.org/journals/remote-sensing/articles/10.3389/frsen.2022.856903/full

urban heat islands in the United States in the summer and winter; however, they found a slightly less expected phenomenon in the Indian cities where there was not a significant difference between a change in land surface temperature between urban and rural areas. They hypothesized that this is due to India keeping cropland dry and sparser compared to the United States, where rural areas tend to be greener. Their findings from this research show that urban planning can be complex and differ considerably from country to country. Although there are no monetary gains tied explicitly to this research, it does show how Landsat can be used effectively to measure land temperature phenomena.

H. Economic Development

Satellite imagery is used as a proxy for economic development, especially in countries which lack actual data at the regional or municipal levels or historical data at the national levels. Landsat, with availability dating back to 1984, offers a method to analyze historical economic developments. Lehnert, et al. (2023) used Landsat data to fill gaps across space and time to analyze economic activity in east Germany and pointed to the high spatial resolution, spectral resolution, and historical archives as fundamental to their approach[34]. Chen, et al. (2020) used evidence of land use and land cover change derived from Landsat imagery to analyze the evolution of regional economic development in China[35].

I. Artificial Intelligence and Foundational Models

Data collected by Landsat 8 and 9 satellites, together with the Sentinel-2A and Sentinel-2B satellites, are a fundamental component of artificial intelligence foundational models, which are essentially deep learning models that are pre-trained using a broad set of data with several applications. NASA's Harmonized Landsat Sentinel-2 project combines data from both the missions to enable global observations of the planet every two to three days[36]. This broad global dataset is a crucial part of the "Geospatial AI Foundational Model," which NASA and IBM are currently developing as an exclusive foundational model using satellite imagery[37]. The combined use of data from the Landsat and Sentinel missions means that the model has applications across domains such as crop detection, flooding, wildfire monitoring, and other environmental applications. The use of the foundational model that is built on top of the Harmonized Landsat Sentinel-2 project has led to significant improvement in mapping floods and fire burn scars compared to deep learning models.

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[34] https://academic.oup.com/pnasnexus/article/2/4/pgad099/7092933

[35] https://www.nature.com/articles/s41598-020-69716-2

[36] https://hls.gsfc.nasa.gov

[37] https://www.earthdata.nasa.gov/news/impact-ibm-hls-foundation-model

J. Calibration of Private Sector Satellites

Landsat is a longstanding remote sensing system that is widely considered as a gold-standard benchmark for other instruments. As such, data from the Landsat missions are used by public and private organizations worldwide for calibration and validation of their own systems. A number of private-sector satellite firms use Landsat data for calibration and validation of the imagery captured by their shoebox-sized CubeSats. One example is Planet Labs Inc. (Planet), a publicly traded Earth observation firm, which operates a constellation of over 200 satellites, of which the majority are CubeSats. To make sure the data is readable and analysis-ready for users, Planet scientists used Landsat data for cross-calibration, a process that enhances the possibility of fusing both the datasets[38]. This has downstream applications in agriculture, urbanization, deforestation, disaster management, and other fields of study.

K. Transformation of Scientific Research to Commercial Operational Services

The availability of an open dataset like Landsat has not only significant applications in research, but the long-term nature of the data means that it is possible to translate scientific research into commercial, operational services. The formation of new businesses that leverage Landsat-based research leads to increase in tax revenues and jobs.

[38] https://landsat.gsfc.nasa.gov/article/landsat-adds-value-reliability-to-cubesat-imagery

CHAPTER 3: LANDSAT NEXT'S VALUE

3.1. Synopsis of Landsat Next's Value

A multiple regression analysis was used to estimate the value of improvements provided by Landsat Next, such as increased spatial resolution, added number of bands, and more frequent revisit time. Our analysis shows a gain in value per scene of $117-$139 over Landsat 8/9. When we add these increases in value per scene to the average $390 value of a Landsat scene from Chapter 1, then the value of a scene generated by Landsat Next would be between $507 and $529 per scene. To arrive at the annual amount of the increase in value of Landsat Next scenes, we multiply the $117-$139 by the estimated 65.65 million scene-equivalents accessed in 2023. This results in an annual gain of $7.69-$9.15 billion more than Landsat 8/9. Adding these annual gains in value from Landsat Next to the estimate of the direct registered Landsat user value reported in Chapter 1 of $25.63 billion and holding the number of scene-equivalents accessed constant at 2023 levels, the total value just to direct registered users of Landsat Next would be between $33.32 billion to $34.78 billion in 2023. This represents a 30 percent to 35.7 percent increase in value, respectively. It important to recognize this value represents the value only to those direct users that access through USGS EarthExplorer and does not reflect benefits to other users who access Landsat imagery through commercial cloud providers. Therefore, these dollar values are a lower bound of the total direct benefits to users of Landsat Next. The volume of Landsat accessed from the USGS in FY2023 includes all publicly available datasets directly used in the cloud and downloaded from the cloud and on premise.

3.2. Introduction to Landsat Next

Before evaluating the applications and benefits of Landsat Next, it is important to describe how this satellite is different than its predecessors, Landsat 8 and 9. Landsat Next is actually a constellation of three satellites providing a collection of land observations with higher spatial, spectral, and temporal resolution than Landsat 8 and 9. This mission has been designed to meet emerging Landsat remote sensing needs for multiple disciplines. These unique features make it an all-around significant improvement as a remote sensing tool with its quick revisit rate, high spatial resolution, and increased spectral bands (Wu (2024)).[39]

The USGS Fact Sheet on Landsat Next[40] indicates the following:

- Landsat Next will collect 2,200 scenes, or land observations, per day, almost tripling Landsat 9's current scene collection rate of 740 scenes per day.
- Landsat Next has a six-day revisit cycle, which is significantly faster than the 16-day revisit cycle of Landsat 8 and Landsat 9. A revisit cycle is the number of days between two land observations

[39] Wu, Z. Landsat Next "Superspectral Triplets" Mission. PowerPoint." Slide 1, USGS, June 3, 2024.

[40] Landsat Next: Satellites offer improved data to Earth science." Fact Sheet 2024-3005, Version 1.1, March 2024, USGS.

over the same area on Earth's surface. This shortened revisit cycle can better support research fields that need weekly clear views, such as agriculture, water quality, natural disasters, and snowpack measurement[41].

- Each observation with Landsat Next images will range in spatial resolution from 10 to 60 meters, an improvement over Landsat 9's 15- to 100-meter resolution. Spatial resolution is the size of the smallest ground area or feature that can be detected on a land observation.
- Landsat Next will include 26 bands of spectral information, an increase from Landsat 9's 11. These include more spectral bands with specific purposes, such as bands for water vapor, liquid water, and snow/ice.
- Spectral resolution of Landsat Next provides more specific spectral data for bands that have been collected by older Landsat imagery.
    - Landsat Next has a similar increase in spectral richness as the Thermal Infrared (TIR) bands for the Red, Near Infrared Radiation (NIR), and Short-Wave Infrared Radiation (SWIR).
    - Nonetheless, the ranges of these new bands continue to make possible one of the strong features of the continuum of Landsat satellites: the ability of the users to conduct longitudinal analyses over past decades.

This increased spectral coverage and richness will greatly further research and monitoring in land cover change, natural disaster relief, ecology and ecosystems, urban development, agriculture, and others with reductions in error and limitations[42]. While Landsat Next has additional and finer resolution TIR bands, it still is backwards compatible with earlier versions of Landsat imagery. Thus, the important ability to do long-term longitudinal studies is preserved.

The demand for increased spatial resolution, spectral resolution, revisit rate, and the frequency of cloud-free imagery collection for Landsat Next was determined through interviews with more than 150 remote-sensing experts in a wide range of fields, including agriculture, ecology, forestry, glaciers, minerals, and natural hazards (Wu, et al. (2019: 2)).

Based on these interviews, Wu, et al. classified user requirements into minimum, breakthrough, and ideal. Minimum needs represent simple continuity of current Landsat mission attributes; breakthrough needs represent the next step up in the level of improvement desired from users; while ideal needs represent the optimal attributes users would like for their respective disciplines (Wu, et al. (2019: 2)). The user needs identified in this study are summarized in our adaptation of Wu, et al.'s. table to more closely relate to the current Landsat program and Landsat Next. We have dropped the column on ideal, since with the exception of three of the seven attributes, the ideal was the same or very similar to Table 3-1. (Wu, et al. (2019: 6-7)).

[41] Wu, Z. Landsat Next "Superspectral Triplets" Mission. PowerPoint." Slide 1, USGS, June 3, 2024.

[42] Wu, Z. Landsat Next "Superspectral Triplets" Mission PowerPoint." Slide 3, USGS, June 3, 2024.

Table 3-1 Comparison of Current Landsat 8/9 to Landsat Next

Landsat Satellite Attribute	Continuity with Landsat 8/9	Landsat Next
Spatial Resolution: Reflective Bands	30 meters (m) or coarser	10 m to 30 m
Spatial Resolution: Thermal Infrared Radiation (TIR) Bands	100 m or coarser	30 m to 100 m
Cloud-Free Observation Frequency	Monthly	Weekly
General Spectral Characteristics	Continuity of current spectral bands on Landsat 8/9, especially Red and Near Infrared Radiation (NIR) bands	Red edge bands, additional visible light bands, and increased Near Infrared Radiation (NIR) and Short-Wave Infrared Radiation (SWIR) spectral coverage
Atmospheric Correction Bands: Water Vapor	One water vapor band	Two water vapor bands
Atmospheric Correction Bands: Aerosols	Preserving Landsat 8/9 Coastal Aerosol band	All existing bands and an additional Deep Blue aerosol band and Red Edge/NIR
Atmospheric Correction Bands: Ozone	Preserving Landsat 8/9 Green and Red bands	All minimum bands and an additional ozone band
Cloud Mask Band	The continuation of current TIR bands on Landsat 8/9	N/A

3.3. Synergistic Applications of Landsat Next

A. Current Use of Landsat in the Commercial Sector

Imagery from Landsat and commercial satellites have a degree of what economists call complementarity. For example, as detailed in the previous chapter, due to the quality of imagery as well as the availability over a long timeframe, Landsat is generally considered the gold standard data in the satellite remote-sensing sector and is used for cross-calibrations of a number of commercial satellites. But this is just one of many applications.

Commercial satellite companies use Landsat data to build proof-of-concepts of their potential products and services to evaluate market demand and gain customer feedback, which serves as a validation for their proprietary satellites. Hydrosat, a U.S.-based satellite company, uses data from Landsat and Sentinel-2 to build a surface temperature product, which will be complemented with data from their proprietary satellite constellation[43]. Similarly, EarthDaily Analytics, a Canadian satellite company, used data from Landsat among other sensors to build a realistic simulation of what their proposed satellite constellation with a daily revisit time would enable for their customers[44]. The complementarity of Landsat enables commercial satellite companies to demonstrate their potential value in the market.

In addition to enabling commercial satellite companies, Landsat acts as a fundamental component of several downstream remote-sensing application firms across industries such as agriculture, forestry, carbon monitoring, disaster management, and bathymetry. These companies generally begin developing their applications using open data programs, such as Landsat and Sentinel, for economic reasons before leveraging their commercial satellites. Due to its longevity, Landsat is generally considered a fundamental data source for a number of commercial environmental-service solutions. OroraTech, a German wildfire monitoring firm, uses data from Landsat among other sources for its burnt area mapping product[45]. Chloris Geospatial, a U.S.-based forest carbon monitoring company, uses Landsat data among several other sources for building its data products. Perennial, a U.S.-based regenerative agriculture solution provider. uses Landsat data for its soil carbon estimation product.

B. Landsat Next: Synergies with Public Satellites

Landsat Next includes about 11 bands with similar spatial and spectral characteristics as Sentinel-2 data to support data synergy. These include Coastal/Aerosol (433-453 nanometers (nm), Blue (457.5-522.5 nm), Green (542.5-577.5 nm), Red 2 (650-680 nm), Red Edge 1 (697.5-712.5 nm), Red

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[43] https://breakingdefense.com/2023/02/air-force-to-evaluate-intel-value-of-hydrosats-hot-spot-data/

[44] https://www.spiedigitallibrary.org/conference-proceedings-of-spie/12729/127291F/Introducing-the-EarthDaily-Constellation-a-scientific-grade-earth-observation-mission/10.1117/12.2678313.short

[45] https://ororatech.com/ororatechs-high-resolution-burnt-area-feature/

Edge 2 (732.5-747.5 nm), NIR Broad (784.5-899.5 nm), NIR 1 (855-875 nm), Water Vapor (935-955 nm), Cirrus (1360-1390 nm), and SWIR 1 (1565-1655 nm).

Combining data from existing Sentinel-2 and Landsat satellites to improve the observations over an area is common. There have been several applications leveraging the synergy between the two missions. Wang, et al. (2017) published methodologies to fuse data from Sentinel-2 and Landsat[46]. Pahlevan, et al. (2019) used the combined datasets to build a global water quality monitoring system[47]. Roy, et al. (2019) introduced a combined sensor, multi-temporal change detection approach for burned area mapping[48]. In addition to this, the Harmonized Landsat-8 and Sentinel-2 project (described in Chapter 2) produces a seamless, harmonized surface reflectance record, which is used for a variety of applications, including land monitoring, water management, and crop monitoring, among others[49,50,51].

With the data continuity for Sentinel-2 expected to last at least until 2035, the improved synergies of Landsat Next and Sentinel-2 are expected to lead to more applications. Furthermore, the Copernicus program of the European Union (of which Sentinel-2 is a part) is expanding, with the expected launches of six missions to take place over the next five years, adding instruments such as high-resolution hyperspectral imagers and thermal infrared sensors[52]. By the time Landsat Next will be in orbit in the 2030/2031 timeframe, further synergies with the Copernicus missions will be possible. For example, the Land Surface Temperature Monitoring mission will have five new thermal infrared bands, with possible synergies with Landsat Next, leading to increased harmonization of the data, which in turn can lead to further applications in evapotranspiration, coastal monitoring, and weather forecasting.

C. Landsat Next's Synergies with Commercial Satellites and Other Applications

Landsat Next will benefit commercial satellite companies and commercial firms that will use Landsat Next data to build applications and services.

For the commercial satellite companies, the synergies will only multiply with Landsat Next, especially as more companies launch their satellites in the coming years. Given that Landsat Next will provide data with a much higher spatial, temporal, and spectral resolution, emerging and existing satellite firms will be able to leverage Landsat Next to build their proof-of-concepts and validate their business case before launching their satellites. Similarly, companies will have the potential to

[46] https://ieeexplore.ieee.org/abstract/document/7894218

[47] https://www.sciencedirect.com/science/article/pii/S0034425718304814

[48] https://www.sciencedirect.com/science/article/pii/S0034425719302731

[49] https://ieeexplore.ieee.org/abstract/document/8517760

[50] https://www.sciencedirect.com/science/article/pii/S0034425718304139

[51] https://www.mdpi.com/2072-4292/12/8/1275

[52] https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Copernicus_Sentinel_Expansion_missions

develop and deliver products that are interoperable with Landsat Next. This will create a much broader level of standardization for remote sensing products, which will help the adoption of remote sensing technologies in general.

3.4. Enhanced Applications Expected with Landsat Next

The Wu, et al. study supplemented its interviews with a comprehensive literature review on the research or scientific benefits achievable with Landsat Next. We reviewed these benefits and identified the major ones that were likely the most economically valuable improvements based on our economic analysis in Chapter 2 on the indirect use of Landsat imagery, as well as the magnitude of economic activity associated with the application. We highlight the new or significantly improved capabilities with Landsat Next to contrast it with current applications using Landsat 7/8/9.

A. Increased Spatial Resolution and Thermal Infrared Sensing

The increase in spatial resolution from 30 meters to 10 meters and TIR sensing improvements provide benefits such as the following:

- Improvements to the accuracy of crop mapping and yield numbers (Wu, et al. (2019: 7)), by crop type and geographical area, has value for farmers in decision making, for instance, to help decide whether to store recently harvested crops or to sell to food processing companies. This is also useful for providing early warning on famines and floods for relief agencies such as the UN (World Food Program).
- More frequent measurement of changes to glaciers, coastlines, and snow/ice coverage of land (the cryosphere), along with the rate of permafrost melting (Wu, et al. (2019: 8-10)). This is useful to gain more knowledge of the changes in glacier retreat and associated permafrost melting. Timely knowledge is important for alerting coastal cities such as New York City or Miami to better prepare for near-term sea level rise and to minimize damages with storm surges and flooding of low-lying areas. Having more accurate estimates of changes in coastlines is critical to navigation, as well as for adapting port infrastructure. More accurate monitoring of snow/ice coverage and the extent of droughts aids state and federal water agencies and local irrigation districts and municipalities to assess potential water supplies.

B. Increased Frequency of Observations

The increase in cloud-free observation frequency from monthly to weekly with Landsat Next enables benefits such as the following:

- More frequent estimates of evapotranspiration dynamics (Wu, et al. (2019: 8)), which is useful for measuring unmetered irrigation water usage in many agricultural areas in the western United States, particularly where irrigation diverts the majority of water in the state, e.g., Idaho.
- Increases in the accuracy of natural hazard mapping for wildfires, floods, oil spills, and volcanic activity, for which timely information is crucial. For example, tracing the spread of smoke from extremely large fires across urban areas allows advanced warning of unhealthy air that may affect large urban areas. Being able to observe the eruption activity of remote volcanoes may allow

volcanologists to predict the likelihood of ash and the path of ash that can seriously disrupt commercial airline and cargo plane activity.

C. Increased in Number of Spectral Bands

As noted previously, Landsat Next has more than double the spectral bands than Landsat 8/9. Table 3-2 outlines the benefits of the specific bands. As discussed below, many of these benefits arise from bands currently on Landsat 8/9. The applications specifically made possible by the new bands in Landsat Next are highlighted in Table 3-2.

Table 3-2 Likely Important Types of Benefits from Bands in Landsat Next

Spectral Band(s)	Benefits
Red Edge and Near Infrared (NIR) Bands	Crop Mapping Plant Health Biomass Vegetation and Ecosystem Stress Forest Canopy Components Coral Reef Mapping Mineral Differentiation Snow vs. Cloud Differentiation
Narrower Blue and Green Bands	Algal Bloom Mapping
Increased Number of Short-Wave Infrared (SWIR) Bands	Tilled vs. Non-Tilled Crops Cryosphere (Snow/Ice) Features Algal Blooms Burn Scars
Increased Number of Thermal Infrared (TIR) Bands	Mineral Chemical Variation Cryosphere Conditions Land Surface Temperature Aquatic Surface Temperatures Volcanic Hazard Assessment Below-Ground Coal and Gas Fire Detection
1030 nm Band	Albedo Estimation Snow Grain Size Calculation
8500 to 8600 nm TIR Band	Atmospheric Sulfur Dioxide Detection

The application of bands in Landsat Next related to snow and ice is a significant improvement over Landsat 8/9, with important implications for forecasting water supply and water runoff, including when too much water threatens potential flooding in river basins.

The detection of atmospheric sulfur dioxide is important due to it being a criteria air pollutant listed in the federal Clean Air Act, with significant health hazards. In addition, sulfur dioxide in combination with nitric oxides can contribute to acid rain. Since emissions of sulfur dioxide occurs from many sources, the ability to provide widespread geographic monitoring of sulfur dioxide is valuable to society.

D. Detailed Examples of Potential Applications of Landsat Next Imagery

Agriculture

Crop Residue Monitoring/Soil Conversion:

Landsat Next is expected to improve crop residue monitoring with the additions and amplifications of the SWIR sensors. A study by Hively, et al. (2021) tested the ability of narrow SWIR reflectance bands to measure lignocellulose absorption features centered near 2100 and 2300 nm, as well as measuring/mapping non-photosynthetic vegetation (NPV). The authors found that the top performer for prediction of NPV over full-range vegetation cover were bands 2040, 2100, and 2210, but the 2040 nm band was needed to avoid interference from atmospheric carbon dioxide absorption. Landsat 8 bands are centered at 1610 and 2200 nm (as are Landsat 9) and they performed poorly in the experiment, as they experience more interference from green vegetation. It is important to note that Landsat Next's added band 19 (SWIR 2a) will have a range from 2025.5-2050.5, centered at 2038, which is near exact to the ideal number of 2040 for measuring NPV found in the study.

A similar study that set forth to optimize Landsat Next's SWIR bands to estimate fractional crop residue found that a generalized ratio-based index with a 2031–2085–2216 nm band combination was the top performer (Lamb, et al. (2022)). This ratio is a considerably close match to Hively, et al.'s combination of 2040-2100-2210 nm, giving increased confidence to Landsat Next's future array of SWIR bands.

U.S. and Global Agricultural Monitoring:

The Rangeland Condition Monitoring Assessment Projection project provides historical maps of fractional vegetation cover across the Western United States using Landsat and artificial intelligence over the years 1985–2023. A 2024 study based in southern Montana ran a series of tests to observe the accuracy of the Landsat-base-model (base), as well as a test that had the base + emulation of Landsat Next (base + LNEXT) (Rigge, et al. (2024). To replicate the addition of using Landsat Next to the Rangeland Condition Monitoring Assessment Projection creation, the authors used a tool called the Earth Surface Mineral Dust Source Investigation. They were able to nearly re-create 20 of the 26 proposed Landsat Next bands with five thermal infrared bands and a cirrus band unable to be replicated by the Earth Surface Mineral Dust Source Investigation tool. Historically, rangelands have been difficult to map using satellite imagery, as vegetation tends to have more bare ground and complex mineralogy. The study ultimately found that legacy (previous) Landsat bands missed large portions of the electromagnetic spectrum where rangeland fractional component classification was necessary. Ultimately, the addition of the Landsat Next replication to the legacy Landsat bands improved efficiency an average of 18.25 percent.

Forestry

Landsat heritage satellites have proven effective in many aspects of forest monitoring, from beetle and insect outbreaks to change detection of overall plant canopy and biomass within forests. Bryk, et al. (2020) used bands 1–7 from the Landsat 8 Operational Land Imager (OLI), as well as the Normalized Difference Vegetation Index (NDVI) derived from the Red and NIR bands (Landsat 8 bands 4 and 5). The Green and SWIR bands were also important components utilized in the detection of the deterioration in spruce trees in the Białowieza Forest District in Poland from 2013 to 2019. The study results confirmed the applicability of NDVI images available from the Landsat archives in monitoring the modifications of spruce stands (a contiguous group of spruce trees) undergoing a bark beetle infestation (Bryk, et al. (2020: p. 14)).

Another study across a similar time span of 2016–2018 observed a gypsy moth outbreak and defoliation in Southern New England (Pasquarella, et al. (2021)). Insect defoliation refers to insects consuming leaves or needles and consequently causing damage to a plant or tree canopy. The researchers utilized Landsat 8 to observe the breakout period, while Landsat 5 and 7 images of the same region were used as a pre-outbreak baseline comparison. The study found compelling evidence of strong correlations between Landsat-based condition scores and ground-based field data to predict canopy cover changes and gypsy moth populations across different life stages. It also found that the Landsat-based condition scores better explained larval abundance more so than egg mass counts. (Pasquarella, et al. (2021: pp. 605, 600))

Changes in forest canopy cover can be attributable to many reasons beyond pest outbreaks, including timber harvest, urban development, storms, drought, disease, etc. Mulverhill, et al. (2023) used seven-day Harmonized Landsat Sentinel-2 image composites in addition to a Bayesian Estimator of Abrupt Change, Seasonality, and Trend algorithm to monitor forest cover change across two large managed forests in Canada. The study demonstrated that the framework presented ultimately performed well, with disturbance to forest cover being accurately accounted for with 88.7 percent and 92 percent, respectively, among the two forests. The framework had the potential to detect cover change in near-real time (Mulverhill, et al., (2023: pp. 315, 318)). A separate study investigating forest cover canopy used Landsat 8 and Sentinel-2A and -2B to track intra-year biomass dynamics twice weekly in Canada's forested ecozones in 2019. It resulted determining that the tracking of intra- and inter-year change can accurately monitor stand-replacing forest changes every 10 days, aiding forest change assessment through the growing season (Pelletier, et al. (2024: p. 16)).

Many studies using Earth observation to examine forest health and other natural Earth phenomena use a combination of Landsat and Sentinel satellites for data collection, as data can often be integrated so that issues with cloud cover can be ameliorated and revisit time can be shortened. Beyond the additional 15 bands included in Landsat Next, many of the persisting bands of Landsat

Next are tailored so that they can continue to be used in conjunction with present Sentinel satellites for overall data synergy.

Cryosphere

Surface ice/snow monitoring will become critical since the snowpack is heavily affected by climate change and acts as timed water storage for municipal, agricultural, and energy production use across the world. Stored water held in snowpacks is also known as the snow water equivalent (SWE). In the Western United States alone, snowmelt is estimated to be the originator for more than half of the West's runoff (Li, et al. (2017)).

In-situ SWE data does not give a complete picture of the present condition of snowpack in the Western United States, as there are often limitations to where snow stations can be mounted. Present in-situ snow stations are typically located in forest clearings, mid-elevations, and flat terrain that does not include the full heterogeneity of the SWE (Fang (2022)). One of the current leaders for in-situ snow monitoring is Snowpack Telemetry. There are approximately 900 sites located across the Western United States, and they are used to calculate estimates on snow depth and snowpack, temperatures, and other climatic conditions (USDA, n.d.). The Snow Data Assimilation System is a product created by the National Snow and Ice Data Center, which also provides snow depth and SWE measurements with full coverage of the contiguous United States at 1x1 kilometer (km) spatial resolution and a one-day temporal resolution. Although the revisit time is convenient for data collection, a 1x1 km spatial resolution is low compared to other open-source and market products.

At present, the Normalized Difference Snow Index (NDSI) is widely used for large-scale surface ice/snow identification. The calculation for NDSI takes the normalized difference of Green and SWIR bands.

Currently, the NDSI is widely used for large-scale surface ice/snow identification. The NDSI can effectively enhance the ice/snow information and suppress background information. However, to some extent, using the NDSI derived from legacy Landsat images to delineate snow-covered areas has some limitations due to "heterogeneous false signals caused by the complexity of natural features" (Wang, et al. (2020)). This creates a space for Landsat Next to improve existing snowpack monitoring. With the future fulfillment of bands 15 and 16 (Snow/Ice 1 and 2) at a 20-meter resolution and band 18 (SWIR 1) and band 4 (Green) increasing in resolution from Landsat 8/9's 30-meter resolution to the anticipated 10-meter resolution of Landsat Next, there is much opportunity for increased accuracy in snowpack measurements.

Recent literature has found success in using Landsat 8/9 for snow cover mapping to an extent, but there still exists limitations with resolution, revisit time, and cloud cover that could be significantly improved by modifications of Landsat Next. Donmez, et al. (2021) noted, "Landsat images offered a suitable spatial resolution for the snow cover mapping. They produced the snow cover maps with reasonable accuracy for the regional studies based on Water-Resistant Snow Index approach. However, the Landsat images still have a remarkable disadvantage to monitor the snow changes periodically due to their limited cloud-free availability." Another researcher states, "Landsat 8 Operational Land Imager provides 30 m spatial resolution images, which is sufficient to monitor land cover changes, but its 16-day temporal resolution is generally not suitable for monitoring snow cover in mountainous regions due to its high variability during the hydrological year." (Bousbaa, et al. (2022)). The desires for improved Landsat products, specifically increased cloud-free revisit frequency, improved resolution, and greater spectral characteristics are also highlighted in a user needs collection process administered by the USGS to gain insights on federal civil user needs.

Many of these impediments on previous research are likely to be addressed with the added elements of Landsat Next. The anticipated six-day revisit time, additional 15 spectral bands, and improved resolution will likely help fill the data gap of previous Landsat missions.

Public Health

Landsat Next's improvements are expected to increase remote sensing monitoring of land surface temperature and aerosol pollutants in urban areas, which are both indicators of overall public health (Bilal & Qiu (2018: 7560)). Landsat imagery is currently used to monitor both urban air quality and heat islands, and Landsat Next will address the challenges and inaccuracies of current methods.

To monitor air quality in urban areas, data is collected on aerosol properties, such as dust, particulate pollution, ash, and smoke by using specific bands (Bilal & Qiu (2018: 7560)). In Bilal and Qui's study on aerosol retrievals over urban surfaces, the Blue, Green, and Red bands of Landsat 8 were listed as necessary for this type of data collection. Similarly, George, et al. used Landsat 8's thermal, short-wave infrared, near infrared, Cirrus, Red, Green, and Blue bands to detect atmospheric pollution content in Tamil Nadu, India (George (2017: 186)).

High urban temperatures are also directly correlated to public health. In Buscail, et al.'s study on heatwave mapping in local communities in France to address public health and climate change concerns, Landsat Enhanced Thematic Mapper+ imagery was used in two separate methods. The first was the use of the images' thermal band – spanning 10.4 to 12.5 micrometers (μm) at 60 m of spatial resolution – to calculate and spatially average surface temperatures per census block group (Buscail, et al. (2012: 3)). The second method used the Red and NIR bands – 630 to 690 nm and 750 and 900 nm, respectively – to calculate NDVI and, therefore, land cover proportions of vegetation, water, and developed land (Buscail, et al. (2012: 3)). White-Newsome, et al. (2017: 2386) collected land-surface temperature values using Landsat 5 imagery, national land cover datasets, and field temperature measurements and compared the results (White-Newsome (2013, 925)). Slightly different from these first two papers, a Sagris and Sepp (2017) paper assessing urban heat island effects and heatwave impacts on public health utilized Landsat 8's thermal band imagery for a split-window land-surface temperature algorithm.

While current Landsat imagery provides all the spectral information necessary to analyze public health impacts, the slow revisit rate and lack of thermal bands cause major issues with current air quality and heatwave monitoring. The six-day revisit rate on Landsat Next creates the opportunity for sub-weekly cloud-free imagery, a necessary part of monitoring urban areas. Specifically, Bilal and Qiu, White-Newsome, et al., and Buscail, et al. all cite a lack of freely available cloud-free imagery as a major limitation to their methods, a problem that will be addressed by Landsat Next (2018: 7562); (2013: 928); (2012: 6)). Buscail, et al. also cites a major disadvantage of current Landsat imagery, which is a decreased thermal spectral range, which is addressed by Landsat Next's three additional thermal bands (2012, 6).

Water Resources

Evapotranspiration is an important indicator of water availability and is measured by various researchers, organizations, and governments. Current Landsat imagery is utilized to measure evapotranspiration and the increased spectral, temporal, and spatial resolution of Landsat Next will improve this research application significantly. In a study on using Landsat-derived evapotranspiration in water rights policy in the Western United States, Allen, et al. (2005: 254) utilized Landsat 5 and 7 imageries in a Mapping Evapotranspiration at High Resolution with Internalized Calibration model and used the surface energy equation to calculate evapotranspiration values. A continuation of the Landsat program through Landsat Next is important to ensure the proper use of models that rely on Landsat imagery for large time periods, allowing for the comparison of results over time. A second study on water resources in the western United States, specifically mapping water use in the Colorado River Basin, addressed the challenges of using Landsat 8 imagery in various methods of evapotranspiration measurements (Senay, et al. (2016: 172)). A main challenge of using Landsat 8 is the limited revisit rate and the resulting lack of freely available cloud-free imagery (Senay, et al. (2016: 182)). Landsat Next has a revisit rate of six days compared to the 16-day revisit rate of Landsat 8, which will increase the ability of Landsat to provide cloud-free imagery to measure evapotranspiration (USGS Infographic).

Another important evapotranspiration study looked at the importance of moderate resolution thermal imagery in water resources research. Anderson, et al. (2012: 51) stressed the importance of multiple thermal bands at 60 meters of spatial resolution or less, because these specs allow for calculations to be performed for small agricultural plots and wild plant communities. The study also found using thermal bands to be an effective way to map evapotranspiration (Anderson, et al. (2012: 52)). Landsat Next meets these requirements with five thermal bands, all at 60 m of spatial resolution (USGS Infographic).

Water Quality

Water quality, more specifically the detection of algal blooms in water bodies, is an application of Landsat Next that is incredibly beneficial to science. Several studies list the benefits of current Landsat data for algal bloom detection. Alarcon, et al., (2018: 9293) in their study on the characterization of algal blooms, utilized the Blue, NIR, and Red bands of Landsat 8-OLI imagery to detect the presence of chlorophyll through surface reflection of natural water sources. Keith, et al. furthered the depth of Alarcon's analysis by using Landsat 8-OLI imagery to identify algal blooms in drinking water reservoirs by combining the Coastal Aerosol (CA), Green, and NIR bands to estimate chlorophyll-a concentrations in lakes, rather than depending on surface reflectance (2018: 9292); (2018: 2830). The study also conducted a literature review to determine the spectral bands best used for detecting "light absorption by phytoplankton, colored dissolved organic matter, non-algal particles, and water from optical data" (Keith, et al. (2018, 2833). Phytoplankton and dissolved organic matter are most important when calculating water quality, and the most useful bands for these purposes were found to be CA and Blue bands, while minimum absorption is found from Green and Red bands (Keith, et al. (2018: 2833)). Landsat Next will further the ability of remote sensing research to estimate chlorophyll and phytoplankton concentrations in smaller water bodies through the decreased spatial resolution (10 m) of the CA and Blue bands (USGS Infographic).

Wildfire

Landsat has been a critical tool for pre- and post-fire assessment, with more than 50 years of land surface monitoring records. There already exists the Landsat Burned Area products that are designed to identify burned areas across all ecosystems with raster files that discern burn classification and burn probability. These Burned Area products have shown up regularly in the fire management literature, as they provide a comprehensive fire history of the past couple of decades.

Just a few examples of the Landsat Burned Area products being employed include the following:

- Teske, et al. (2021) tracked the spatial extents of fires and derived the fire history metrics of Florida. The researchers applied a 90 percent threshold to the Landsat burn probability product with supplementary aids from existing fire datasets in Florida and found that the output matched patterns recorded by fire managers in three pilot areas. This study was the first time wall-to-wall fire extents were mapped for a U.S. state and provided a replicable method to produce more maps and supplement future fire management plans. (Teske, et al. (2021: p. 17))
- Hawbaker, et al. (2020) developed a Landsat Burned Area algorithm based upon and updated from the Landsat Burned Area Essential Climate Variable algorithm to dispense spatial and temporal patterns of burned areas across the conterminous United States. The Burned Area products are routinely updated as more data is collected from Landsat imagery. The study found that the utilization of the updated Landsat Burned Area algorithm was proficient at consistently mapping burned areas that were larger than two hectares across time and over the continental United States (Hawbaker, et al. (2020: p. 21)).
- Storey, et al. (2021) evaluated the accuracy of Landsat Burned Area maps of 19 fires ranging from 65,000 to 86,776 hectares in southern California from the years 1996–2018. Optimized classifications of the pre-fire to post-fire differences in the Landsat-based Normalized Burn Ratio had the greatest overall accuracy of 94 percent (Storey, et al. (2021: p. 500)). The study implemented pre-fire NDVI statistical data for empirical inference of Normalized Burn Ratio thresholds, which resulted in median accuracies of 90 to 91 percent for the relevant study areas.

While Landsat Burned Area maps have been valuable for fire management in the United States, current Landsat imagery still has limitations in fully capturing pre- and post-fire conditions. Hawbaker, et al. (2020: p. 1)) communicated that, “The amount of Burned Area detected varies not only in response to climate but also with the number of operational sensors and scenes collected.” Vegetation cover can also impact the accuracy of Burned Area mapping. Storey, et al. (2021: p. 500) reported that there were some minor discrepancies in correlation among the normalized burn ratio metrics compared to previous studies. It is hypothesized to be because of the almost entirely shrub vegetation present in the California study areas. The future gain of data from Landsat Next will undoubtedly increase the scenes and revisit rates of Burned Areas not only in the United States, but the world, as well. The new SWIR 2b band is set to accompany Landsat Next and will be particularly useful for fire scar detection for post-burn analysis (Landsat Missions, n.d).

3.5. 2018 Registered Landsat User Preference Survey Methodology

To estimate the relative values of different characteristics or attributes of any "product" to consumers, whether marketed or non-marketed, market researchers design surveys that require consumers to choose among alternative product designs portrayed in a survey. This type of method was originally referred to as conjoint (Louviere (1988)) but is now referred to as stated choice (Louviere, et al. (2000)). The options or alternative product profiles contain differing levels of attributes, including a monetary attribute (the "price" of the option). The exercise presented to survey respondents most closely mimics the act of purchasing a market good, where consumers choose from among several options of a particular good, such as a car (e.g., horsepower vs. mpg), weighing the various models' attributes (one of which is the cost) to estimate what are the most preferred features (Freeman (2003); Hensher, et al. (2005)).

There is an enormous literature in the marketing field – and specifically regarding new product development that makes use of stated choice methods. There is a smaller but still relatively large and relevant literature that employs stated choice methods to value and choose goods provided that are not traded in any market, i.e., non-market goods (Holmes, et al. 2017).

The stated choice survey method was used to elicit responses that reveal preferences, priorities, and the relative importance of individual features associated with Landsat satellites. There are several different features, or attributes, of Landsat imagery and several different ways the imagery might be enhanced with the varying levels of Landsat attributes. We developed different Landsat profiles that included multiple attributes and the various levels of those attributes. The choices among sets of alternative profiles are motivated by differences in the levels of the attributes that define the profiles. By controlling the attribute levels experimentally and asking respondents to make choices among sets of profiles in a series of choice questions, the stated choice method allows us to effectively reverse-develop choice to quantify the impact of changes in attribute levels on choice. The estimates of these impacts reflect the strength of preference for changes in attribute levels. As the number of Landsat profiles used in the survey increases, the number of combinations of surveys needed rises exponentially. To keep the survey manageable and to provide the most useful insights, we consulted with the USGS National Land Imaging Program. Nonetheless, we wished to cover the potential range of technically feasible options, as well as have sufficient variation in the levels to allow for the estimation of coefficients on each attribute.

Statistical Analysis Methods

Stated-choice models summarize survey respondent choices across sets of attributes associated with new Landsat profiles as compared to the current attributes associated with Landsat 8. These models make use of rank-ordered responses. Survey respondents are offered three separate combinations of imagery. One of the combinations is the set of attributes associated with Landsat 8 – what was the latest Landsat satellite at the time of the survey. This set is the base for comparison in the rank-ordered modeling. Two alternatives are also offered to each respondent. The attributes are improvements in Spatial Resolution (2 levels), Frequency of Cloud-Free Usable Imagery/Frequency of Cloud-Free Days (4 levels), Spectral Band (3 levels), and Thermal Band Spatial Resolution (3 levels). The attributes of Landsat 8 imagery and possible levels of enhancements surveyed are shown in Table 3-3, which bolds the levels of the attributes that now correspond to Landsat Next. Since the purpose of the survey was to provide information to the USGS on relative preferences for improvements, it was not known at the time which of these levels would end up being chosen for Landsat Next.

Respondents were first asked to rank two alternative satellite imagery profiles relative to Landsat 8, without cost being an attribute. In a separate choice matrix, they were given the same set of attributes but with the addition of a cost attribute and different levels of other attributes. Combinations of attributes are randomized across choice sets, and no dominated choices were offered. For example, no combinations of attributes are offered where there cost and attributes are the same as Landsat 8, which had a default of zero dollars in all choice sets.

Respondents are offered two alternative profiles of satellite imagery, Option A and Option B, in addition to the current version of Landsat. Respondents were asked to rank the best of the three alternatives and the worst of the alternatives. The alternative profile not ranked is the middle preference. The attributes associated with the alternative profiles were used in a rank-ordered logit model to determine the preferred satellite imagery attributes. Rank-order logit modeling describes the preference of alternative Landsat profiles relative to the base choice. For this analysis, the base choice employed is always Landsat 8. All the alternative Landsat profiles are not offered to all respondents. The survey was designed to measure main effects, and a relatively orthogonal design was constructed.

Table 3-3 provides the full set of alternative levels of all the attributes from which we drew the choice sets for Option A and B.

Table 3-3 Satellite Attributes and Levels Used in the 2018 Survey Inflated to $2023[a]

Potential Attributes	Landsat 8 Level	Possible Levels for Option A & Option B
Spatial resolution	30 meters	5 meters **10 meters** 30 meters
Cloud-free, usable imagery	32 days	2 days 4 days **7 days** 14 days 32 days
Spectral bands	Landsat 8 bands	**Landsat 8 bands & Red Edge (680-730 nm)** **Landsat 8 bands & additional SWIR bands (1.5-2.5 μm)** **Landsat 8 bands plus additional TIR bands (8-14 μm)** Landsat 8 bands
Thermal band spatial resolution	100 meters	10 meters **30 meters** 60 meters 100 meters
Cost to download an image (for the with-cost version of the survey)	$0 per scene	$34 per scene $68 per scene $137 per scene $242 per scene $373 per scene $684 per scene $1,119 per scene $2,238 per scene $4,724 per scene

a. Bolded levels of each attribute are the levels in the proposed Landsat Next satellite constellation, shown for information only, and not known at the time of this survey in 2018.

Rank-ordered logit parametric results are used to calculate odds ratios for the attribute level the respondent received in their assigned Landsat profile relative to the base attribute. For example, if the odds ratio for an attribute level relative to the Landsat 8 base is 1.00, that attribute level is preferred equally to the level of the Landsat 8 base attribute. If the odds ratio for that attribute level is greater than 1.00, then it is more preferred than the base attribute level in Landsat 8. Likewise, if the odds ratio is less than 1.00, then the attribute is less preferred than the base attribute level in Landsat 8. For example, if the odds ratio for spatial resolution of 5 m is 3.00. Landsat imagery has a current spatial resolution of 30 m. Thus, 5 m is preferred 300 percent relative to 30 m – or 5 m is preferred 3:1 relative to 30 m. If the odds ratio for spatial resolution of 10 m is 2.00, then, 10 m is preferred 200 percent relative to 30 m – or 10 m is preferred 2:1 relative to 30 m. Odds ratios have probabilistic interpretations, so 5 m is preferred over 10 m by 100 percent = (300 percent–200 percent), or is preferred 2:1. If an attribute has an odds ratio of 50 percent, then it is less preferred than the base attribute level. The base attribute is preferred 2:1. These are powerful and straightforward ways to present and interpret results. Further, the significance of each of the alternative attribute level is testable. This will determine if the alternative is a significant improvement on the base feature. Each alternative can be pairwise tested to see if it is different from each of the other alternatives within the set of improvements to the Landsat 8 base attribute. For example, is the odds ratio of spatial resolution 10 m and 5 m statistically different from the Landsat 8 base of 30 m? If so, are the two parameters on the odds ratio associated with 10 m and 5 m statistically different from each other?

However, one limitation of the rank-order approach is the difficulty in including individual specific explanatory variables. This is because the likelihood function of rank-ordered models is calculated within each single individual and summed across all individuals for a sample average. The model represents average preferences. Because the likelihood function is calculated within the individual as the reference, then no exogenous explanatory variables can be included in the model. For example, there is no variation in the number of scenes downloaded for a given individual, so this results in the parameter for number of scenes being unidentified. Only the alternative attribute levels offered to respondents vary in this specification, and no variation in preferences across individuals are assumed important in this model. This limitation can be relaxed by incorporating interaction effects between some exogenous explanatory variable and the attribute dummy variables. For example, the dummy variables for each attribute different from the Landsat 8 base can be included and then a product of each dummy and numbers of unique scenes downloaded can also be included. The limitation can be relaxed but the number of variables in each model is 2x for each single potential source of this heterogeneity. Exceptionally large sample sizes are required to relax the limitation. The rank-ordered preferences are examined for numbers of scenes downloaded and years the respondent has been using Landsat imagery. These were both important variables in the willingness to pay (WTP) models. However, we do estimate separate stated choice models for domestic users and international users, as they may have different preferences for improvements in imagery.

Table 3-4 provides an example of what one of the with cost, choice sets that a single respondent would be given and asked to choose their "most preferred" and their "least preferred."

Table 3-4 Example Choice Set with Cost

Features of Imagery	Landsat 8	Option A	Option B
Spatial Resolution	30 meters	5 meters	30 meters
Cloud-Free Usable Imagery	32 days	32 days	4 days
Spectral Bands	Landsat 8 Bands	Landsat 8 Bands plus additional TIR bands (8-14 micrometers)	Landsat 8 Bands plus additional Red Edge bands (680-730 nanometers)
Thermal Band Resolution	100 meters	100 meters	30 meters
Cost per Image Download	$0	$137	$684
Select Most Preferred Option	O	O	O
Select Least Preferred Option	O	O	O

Sample Frame and Sample Design

The population used for this study comprised all individuals that accessed Landsat images through the EROS Center within the calendar year prior to the survey release (2017). The population did not include downstream and secondary users that did not obtain imagery from EROS – only direct users of Landsat images. We are aware that there may be millions of subsequent indirect users of the images produced by the initial users. Some of the indirect uses of Landsat imagery were presented in Chapter 2. Nonetheless, the results of this survey are informative as to relative preferences of a large sample of registered Landsat users as of 2018[53]. We first conducted a U.S. federal user survey. EROS provided a list of 914 email addresses. After duplicate and nonworking email addresses were removed, 895 addresses remained. We then conducted a non-federal U.S. user survey in combination with an international user survey; EROS provided another list of 125,565 relevant email addresses. Of those, 80,055 were international users with a specific, self-identified country outside of the United States and its territories. There were 13,962 users that self-identified a from the United States or U.S. territories. We conducted a census of the U.S. users. We then used a random sample of the international users to equal the number of U.S. users (13,962). After duplicate and nonworking email addresses were removed, 27,313 addresses remained. A variety of questions were asked of the respondents in addition to the stated choice attribute questions, including questions related to the specific use and qualitative value of satellite imagery. We also incorporated contingent valuation modeling to gain new insight into user value of Landsat imagery. See Chapter 1 for the results of that portion of this survey.

Again, a census of U.S. users was attempted. It is only limited by response rates that were beyond our control, and a sample of international users was selected to be of equivalent size to the U.S. sample. Further, we believe that the economic interpretation of changes in imagery attributes generalizes to future imagery use and is relevant to understanding the value of Landsat Next.

Survey Implementation

The U.S. federal users survey was launched in February 2018. The non-federal U.S. user plus international user survey was launched August 2018. The implementation for both survey launches followed the Dillman (2017) repeat contact method (~10 repeat contacts) to obtain the highest survey response rate feasible. For the U.S. federal user survey, a total of 251 individuals responded, for a response rate of 28 percent. This number includes both completed surveys (n = 205) and partially completed surveys (n = 46). For the non-federal U.S. user plus international user survey, a total of 4,454 individuals responded to the survey, for a response rate of 16 percent. This number includes both completed surveys (n = 3,310) and partially completed surveys (n = 1,144). This response rate is comparable to recent email/web survey responses (Dillman (2017); Dillman, et al. (2014); National Research Council (2013); Petchenik and Watermolen (2011)).

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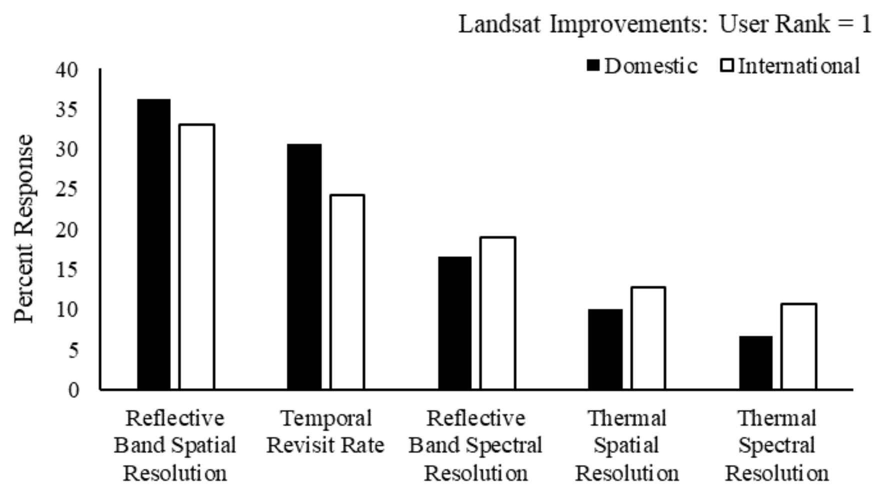
[53] Given costs totaling hundreds of millions of dollars to build and launch each new version of Landsat, it would be quite prudent to repeat these surveys in the year prior to making decisions on major modifications to Landsat satellites and associated imagery improvements.

Results

Before respondents viewed the stated choice questions, they answered a general ranking question related to their preference for future Landsat improvements. We added this question early in the survey (sixth question) to gain as much information as possible about Landsat improvements from users just in case some of them may have dropped out of this rather lengthy survey. The question was phrased, "Please rank future Landsat improvements in order of importance to you. Based on your preference, rank from 1 to 5 where 1 is most important to you and 5 is least important to you." Figure 3-1 shows that Reflective Band Spatial Resolution (Domestic=36 percent; International=33 percent) and Temporal Revisit Rate (Domestic=31 percent; International=24 percent) ranked most important to the respondents. These results are similar to the stated choice analysis reported in the next section with both Reflective Band Spatial Resolution (Figure 3-2) and Temporal Revisit Rate (Figure 3-3) ranked most important to the respondents. Although both questions indicate similar responses for attribute preference, the stated choice analysis provides additional detail on the magnitude of respondent preferences.

Figure 3-1 Landsat Users' Percent Response Based on the Landsat Attribute Improvements that are Most Important to the User (N = 3,752)



No-Dollar Cost Stated Choice Rank-Ordered Results

This section discusses respondent preferences for satellite imagery when there are no dollar cost trade-offs associated with alternatives being considered. The models perform well and provide clear insights for preferences of several of the imagery attributes.

We chose to show the respondents two questions as follows: one without cost included and a second with cost. This was due to concerns regarding whether responses to the survey would influence a possible decision by the federal government to charge for downloading images, and, if charging, the amount that all users would have to pay. Respondents were potentially aware of and concerned about the prospect of a policy change of charging for Landsat. Respondents may have read articles such as Popkin (2018) in the highly regarded journal *Nature* about these issues before and during survey release. This induces "strategic behavior" on the part of the respondents to understate the amount they would pay, or simply refuse to pay, so as to send a signal they were opposed to charging for Landsat, especially when the good has been previously free for a decade (Campos, et al. (2007)). As discussed earlier in this report in Chapter 1, economic valuations may be biased downward by half due to strategic behavior.

Thus, the first stated choice question without cost allowed respondents to focus solely on the relative importance to them of different Landsat imagery attributes and how much of one attribute level they would give up to gain an improvement in a separate attribute level. This approach avoided respondents heavily focusing on cost as the primary attribute. We report the respondent results for responses to both the without-cost stated choice matrix and the with-cost stated choice matrix (Table 3-4).

Spatial Resolution – Domestic; No Dollar Cost[54]

Alternative levels of the spatial resolution attribute have clear results. The odds ratio for a resolution of 10 m compared to 30 m is 2.8228; this resolution is preferred almost 3:1 relative to Landsat 8. The odds ratio for a resolution of 5 m compared to 30 m is 3.89; this resolution is preferred almost 4:1 relative to Landsat 8. The resolution of 5 m is preferred over 10 m by 107.20 percent (389.48 percent – 282.28 percent), or double. This difference is statistically significant. Improved spatial resolution is the most desirable feature or attribute for new imagery.

Spatial Resolution – International; No Dollar Cost[55]

Alternative spatial resolution levels for international users also have clear results. The odds ratio for a resolution of 10 m compared to 30 m is 1.6812; this resolution is preferred almost 2:1 relative to Landsat 8. The odds ratio for a resolution of 5 m compared to 30 m is 2.90; this resolution is preferred almost 3:1 relative to Landsat 8. The resolution of 5 m is preferred over 10 m by 122.38 percent (290.50 percent – 168.12 percent), or double, and this difference is statistically significant. Improved spatial resolution is the most desirable attribute for new imagery.

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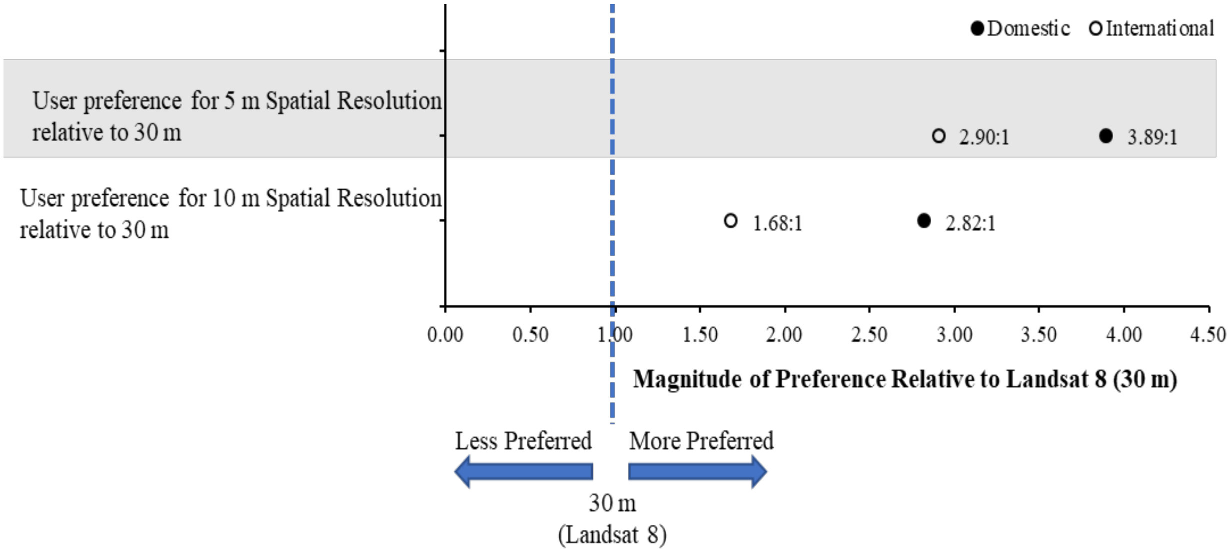
[54] Represented as solid dots in Figure 3-2.
[55] Represented as open dots in Figure 3-3.

Figure 3-2 Domestic/International Preferences for Increased Spatial Resolution; No Dollar Cost[a]



a. Landsat user preference for spatial resolution enhancements of Landsat imagery. An odds ratio > 1.0 (dotted line) for an attribute level indicate that Landsat users prefer an attribute level to Landsat 8's 30 m resolution (OR = 1.0). All comparisons are statistically significant ($p < 0.001$).

An important conclusion from the spatial resolution results is that users are interested in increased detail. The finer resolution has not exhausted the users' interest and does not show declining returns. More detail is simply better, even at the expense of giving up some improvements in other attributes to achieve higher resolution – at least without dollar costs.

Cloud-Free, Usable Imagery (Temporal Revisit Rate) – Domestic; No Dollar Cost[56]

Improved frequency of imagery with cloud-free days is also highly preferred in the no-cost models. The odds ratio for 14 days, as opposed to the Landsat 8 base of 32 days, is 1.73 or 173 percent; for seven days as opposed to the Landsat 8 base 32 days, it is 2.76 or 276 percent; for four days as opposed to the Landsat 8 base 32 days, it is 2.77 or 277 percent; for two days, it is 3.08 or 308 percent. More frequent cloud-free days are preferred. However, note that the difference in the odds ratio for four and seven days is only 1 percent. All of the four different levels (2, 4, 7, 14 days) are significantly different from Landsat 8. Although 14 days is different from the three more-frequent days (2, 4, 7 days), seven days is not significantly different from four days or two days. Cloud-free, usable imagery every two days is preferred about 30 percent to every four days and every seven days, but this difference is not significant. Thus, the preferences reveal that cloud-free, usable imagery every seven days is sufficient, and that while there is a preference for even more frequent cloud-free imagery, that strength of preference is not statistically different between four and seven days. This suggests that the weekly revisit rate in Landsat Next is likely an optimal level of improvement for domestic users.

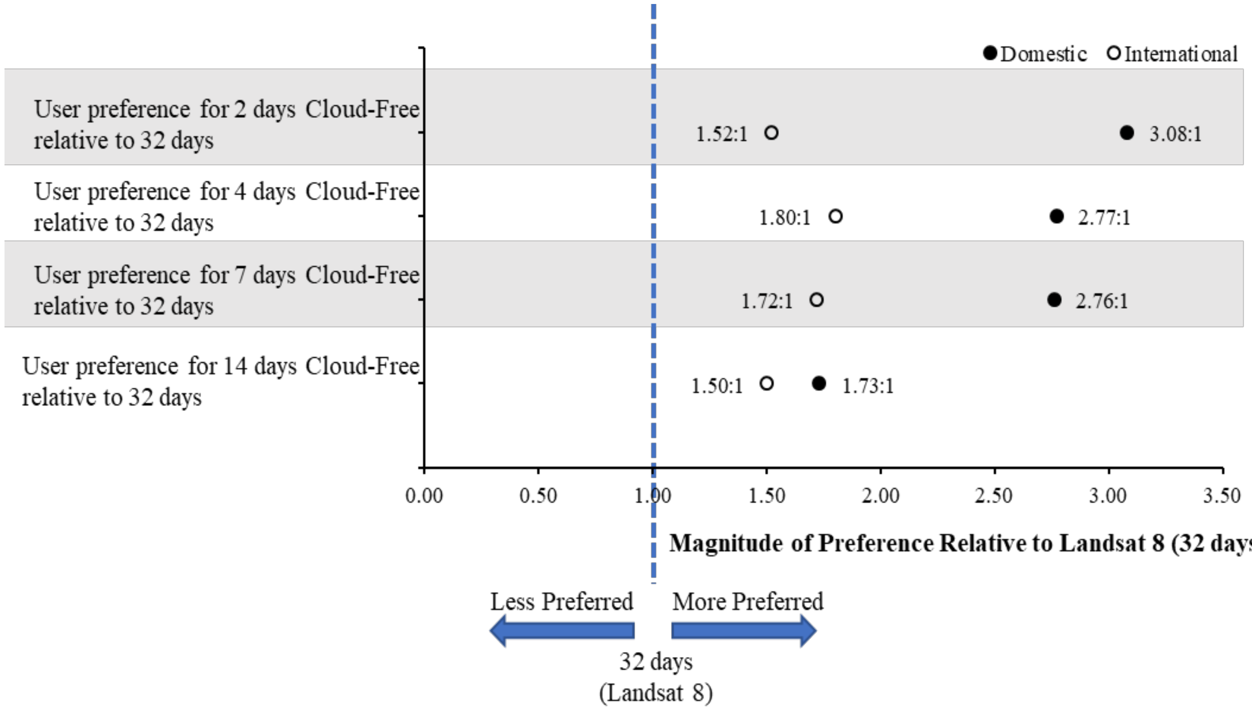
Cloud-Free, Usable Imagery (Temporal Revisit Rate) – International; No Dollar Cost[57]

Improved frequency of imagery with cloud-free days is also highly preferred in the no-cost models. The odds ratio for 14 days as opposed to the Landsat 8 base of 32 days is 1.50 or 150 percent; for seven days as opposed to the Landsat 8 base of 32 days, it is 1.72 or 172 percent; for four days as opposed to the Landsat 8 base of 32 days, it is 1.80 or 180 percent; and for two days, it is 1.52 or 152 percent. Respondents prefer the more frequent cloud-free, usable imagery days (2, 4, 7 days). However, preferences reveal that cloud-free, usable imagery every 14 days is sufficient and that there is no statistically significant preference for more frequent imagery.

Figure 3-2. Domestic/International; No Cost: Landsat user preference for cloud-free, usable imagery days enhancements of Landsat imagery. An odds ratio > 1.0 (dotted line) for an attribute level indicate that Landsat users prefer an attribute level to Landsat 8's 32 days (OR = 1.0). All comparisons are statistically significant ($p < 0.001$).

[56] Solid dots in Figure 3-3.
[57] Open dots in Figure 3-3.

Figure 3-3 Domestic/International Preferences for Cloud-Free Days; No Dollar Cost



Thermal Band Spatial Resolution – Domestic; No Dollar Cost[58]

Increased thermal band resolution is also preferred, but the preference for thermal band spatial resolution attribute improvement levels is not as strong as it is for spatial resolution and cloud-free days. The odds ratio for 60 m as opposed to the Landsat 8 base of 100 m is 1.35 or 135 percent relative to this base; for 30 m as opposed to the Landsat 8 base of 100 m, it is 1.47 or 147 percent; and for 10 m, it is 1.91, or about twice as preferred as the Landsat 8 base (100 m). The stopping point for selecting the attribute level based on user preference is less clear in the results. All three improvements are significantly preferred to Landsat 8. However, 60 m is similar to 30 m, whereas it is different from 10 m. And 30 m is also different from 10 m. Improving the resolution to 60 m or all the way to 10 m appears to be the two thermal band spatial resolution attribute levels users prefer. Nonetheless, the improvement to 30 meters in Landsat Next is a statistically significant improvement for domestic users.

Thermal Band Spatial Resolution – International; No Dollar Cost[59]

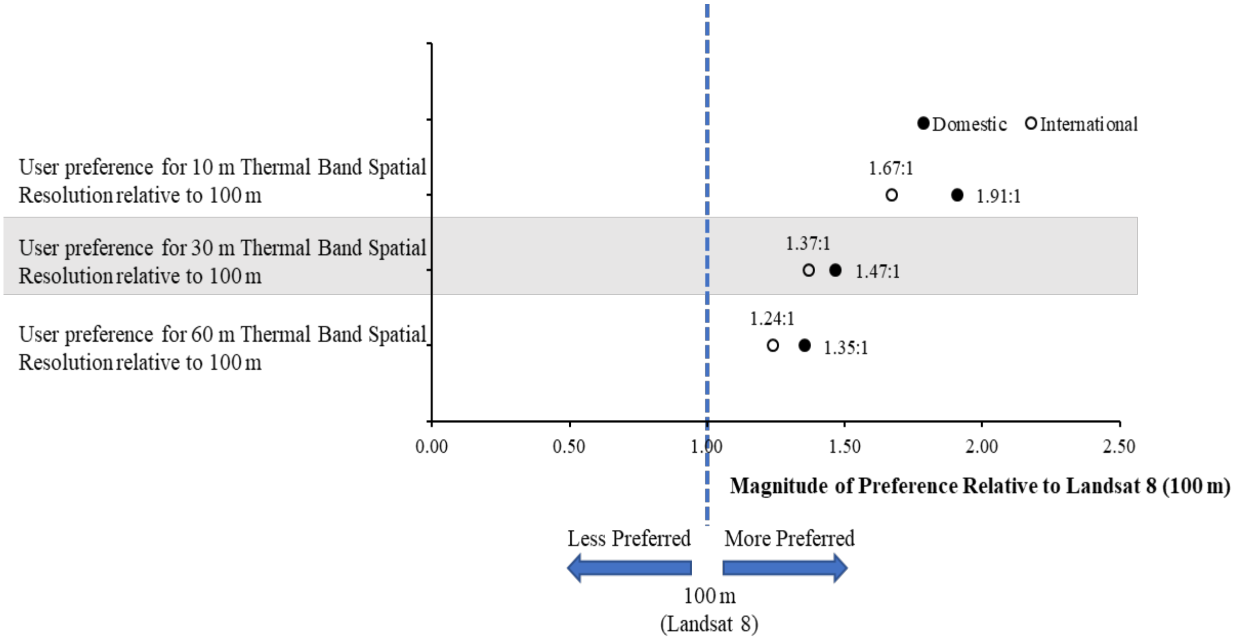
Improved thermal band resolution is also preferred, but the preference for these attributes is also less important than spatial resolution or cloud-free days. The odds ratio for 60 m as opposed to the Landsat 8 base of 100 m is 1.24 or 124 percent relative to this base; for 30 m as opposed to 100 m, it is 1.37, or 137 percent; and for 10 m, it is 1.67, or 167 percent relative to the Landsat base. The stopping point for providing this attribute is less clear in these results. All three are significantly preferred to Landsat 8. But 60 m is similar to 30 m, whereas it is different from 10 m. And 30 m is also different from 10 m. Improving the resolution to 60 m or all the way to 10 m appears to be what is wanted by international users, as well. Nonetheless, the preferences of international users are similar to domestic users, and the improvement to 30 m in Landsat Next is a statistically significant improvement for international users.

Thermal band spatial resolution does show declining returns to additional improvements. More detail is more important but at a declining rate. Apparently, larger increases are needed before the users see them as a significant improvement. This declining incremental contribution of an input is not unusual economic behavior in the use of inputs for the production of outputs.

Figure 3-4, No Cost, illustrates Landsat user preference for thermal band spatial resolution enhancements of next generation Landsat satellites. An odds ratio > 1.0 for an attribute level indicates that Landsat users prefer an attribute level to Landsat 8's 100 m resolution (OR = 1.0). All comparisons are statistically significant ($p < 0.001$).

[58] Solid dots in Figure 3-3.
[59] Solid dots in Figure 3-4.

Figure 3-4 Domestic and International Preferences for Thermal Band Spatial Resolution; No Dollar Cost



Spectral Bands – Domestic/International Preference; No Dollar Cost

For domestic respondents, none of the strength of preferences for alternative spectral bands beyond Landsat 8 were viewed as significant improvements. One of the available levels – Landsat 8 bands plus Red Edge (RE) (680–730 nm) had an odds ratio of 1.05, so this level is preferred 5.25 percent relative to only Landsat 8 spectral bands. However, the p-value on this parameter is 0.59, or it is significant at the 59 percent level – this is highly insignificant. Similarly, the odds ratio for the other two available levels: Landsat 8 bands plus additional SWIR bands (1.5–2.5 μm) and Landsat 8 bands plus additional TIR bands (8–14 μm) were 1.11 and 1.14, respectively. Therefore, each is preferred 10 percent relative to only Landsat 8, but neither is statistically significant at the 5 percent or 10 percent significance levels. Further, testing to see if these three parameters are pairwise different from each other reveals that none are different. All of the parameters for alternative spectral bands are statistically insignificant from the Landsat 8 base and each is statistically insignificant from each other. Responses were similar for international respondents.

While these additional bands may be important to some users, they are generally not of overall importance enough to most users that these users are willing to trade off other improvements in such features as spatial resolution or revisit rate to gain these bands. This is likely to be the case in many imagery enhancements – at least in the short run. Immediately, there may be little overall interest or use of enhancements by a majority of registered Landsat users as of 2018. Like other technological advances, it may take many users a few years to envision potential applications for some of the additional bands offered in the survey or more bands that they currently have, and for which they have few applications for now.

The final effort with the no-cost results was to examine the sensitivity of results to other respondent attributes, specifically, numbers of scenes downloaded and years using imagery. Results indicate that both of these can be somewhat important, but not in terms of changes in all the parameters of the attributes. There are some parameters that vary with the number of scenes that users downloaded, and some parameters that vary with the number of years that users have been using imagery. Users that download more scenes want frequent cloud-free, usable imagery days. Cloud-free, usable imagery days are not more or less important to longtime users. Further, users that have been using imagery longer want improved thermal band spatial resolution. Thermal band resolution is not more or less important to high-volume users. The number of scenes and years a user has made use of imagery does not impact preferences for either spatial resolution or spectral band. Details of these results are not provided here to conserve space but can be provided as needed.

With-Dollar Cost Stated Choice Rank-Ordered Results

The next portion of discussion turns to the rank-ordered model results where the dollar cost of downloading imagery is included as an attribute, along with improvements in imagery quality. The original purpose of this question, and one which stated choice methods are commonly used for, is to estimate the dollar value of incremental improvements. As with the no-cost model results, the base choice within the set of three alternatives that each respondent evaluates is the current Landsat imagery, Landsat 8. All comparisons can be evaluated relative to the current set of Landsat 8 features. As in the “no dollar cost” choice sets, respondents are given three alternative Landsat profiles, of which the current Landsat 8 is one of them. Landsat 8 imagery has zero cost to download an image. The two alternatives have improvements in one or more attributes *and* have different positive dollar cost per scene associated with the bundle of attribute improvements.

We find that once cost to download a scene is included, then the dollar cost is the main attribute evaluated in the minds of the respondents. Any level of cost makes Alternative A or B strongly not preferred, and there are only a few Landsat attribute improvement combinations that are preferred to Landsat 8 when these attribute profiles come with a substantial dollar cost of downloading imagery. As discussed in more detail two sub-sections from now, this resistance to the dollar cost may not have to do with a low value of improvements in Landsat imagery, such as Landsat Next, but rather due to users’ awareness that the U.S. Department of the Interior was considering charging for downloading imagery for the first time in decades (Popkin (2018)). Thus, responses may have likely reflected a strategic bias toward the default zero cost for Landsat 8 to send a message to the USGS that users strongly opposed pricing of Landsat imagery.

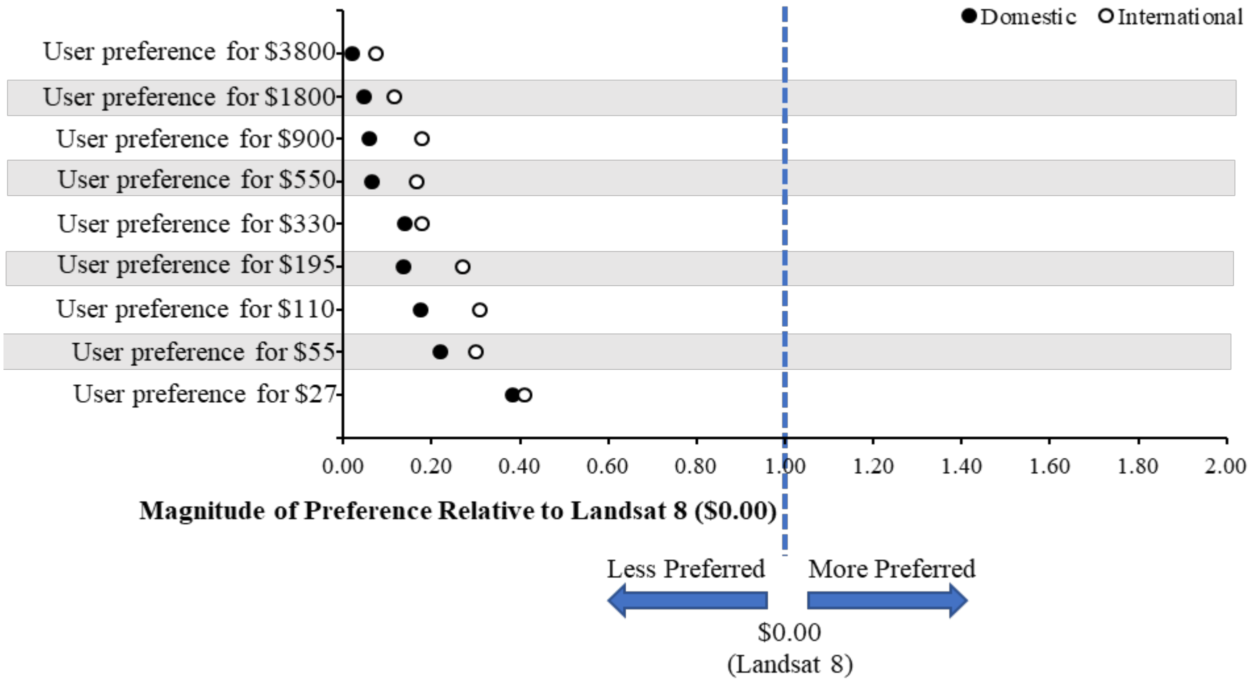
Cost Model with Cost Level Variables

In this model specification, different dollar cost levels for downloading imagery were entered as separate variables to allow for non-linearity in the response to cost. Cost is included as a set of dummy variables – or zero-one variables – as follows: Landsat 8 imagery is zero cost and it is the base of comparison. There are 9 costs, or price per scene, one of which was randomly assigned in each of the two imagery improvement alternatives shown to respondents in the survey. The dollar levels that were included in the survey were $34, $68, $137, $242, $373, $684, $1,119, $2,238, and $4,724. Nine dummy variables were included in the model, with eight equal to zero for dollar amounts that were not included in the respondent’s choice set, and one for the cost dummy variable for the one dollar cost that was in the attribute in the choice set displayed to the respondent. Pooling the data across all respondents, the statistical model indicates that all nine of the cost dummy variables are highly significant. When the odds ratio is calculated for each of the amounts, then all are far less than 1.0, indicating that at no time is an attribute with-cost preferred (Figure 3-5). Cost level variables are the most statistically significant in the model. The odds ratio is 0.38 for the cost amount of $34 per scene and all ratios decline almost uniformly to 0.02 for the cost amount of $4,724 per scene. Interpreting the odds ratio from the perspective of impact on the population of users suggests that charging $34 per scene for imagery would result in the loss of more than two-thirds of the users. Charging $4,724 per scene would result in the loss of almost 98 percent of the users. Similarly, charging between $68 and $137 per scene for imagery would result in the loss of somewhere between just-under and just-over 80 percent of the users, respectively. Any cost substantially reduces Landsat imagery use. This result is consistent with the results of the contingent valuation method survey conducted at the same time and reported in detail in Chapter 1.

Many of the imagery improvements of Landsat are no longer important or as important when a cost for downloading imagery is included. For example, when cost is included in the model as a set of dummy variables, then the alternative spectral bands are no longer statistically significant and improvements in thermal band spatial resolution are no longer important. In the case of thermal band spatial resolution, this may be an artifact of the strategic bias against pricing overwhelming the incremental benefits of increased thermal band resolution.

Figure 3-5, Landsat user preference regarding cost of improvements to Landsat imagery, showed an odds ratio < 1.0 for an attribute level indicated that Landsat users do not prefer the cost attribute level to Landsat 8 with a cost of \$0 (OR = 1.0). All comparisons are statistically significant ($p < 0.001$).

Figure 3-5 Landsat User Preference Regarding Cost of Improvements to Landsat Imagery

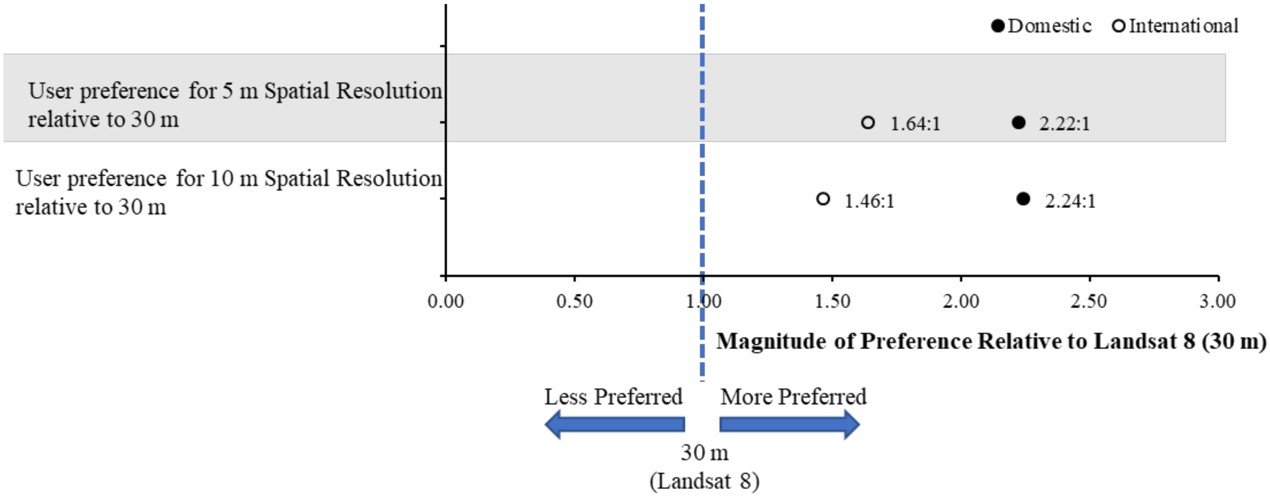


Spatial Resolution – Domestic Users Preferences with Dollar Cost

In the with-cost models, improved spatial resolution continues to be the most highly valued attribute for domestic users, as judged by the fairly large odds ratio (Figure 3-6). Improving the number of cloud-free, usable imagery days is the second most important improvement in imagery (Figure 3-7). All the spatial resolution and cloud-free, usable imagery days variables, as compared to Landsat 8 defaults, are highly statistically significant. The odds ratio for spatial resolution of 10 m compared to 30 m is 2.24 and this communicates that this improved resolution is preferred 124 percent to current Landsat imagery. The odds ratio for spatial resolution of 5 m compared to 30 m is 2.22 and this communicates that this improved resolution is preferred 122 percent to current Landsat imagery. The parameters on the two spatial resolutions are not significantly different from each other, so a resolution of 5 m compared to 10 m is not significantly preferred. Specifically, 2.2221–2.2426 = –0.0205, and this amount is statistically insignificant from zero. Recall in the no-dollar cost model, spatial resolution of 5 m was preferred 4x relative to Landsat 8, the spatial resolution of 10 m was preferred 3x relative to Landsat 8, so that 5 m is preferred about 1x relative to 10 m where the base is Landsat 8. In the no-dollar cost model, the preference of 5 m to 10 m was also statistically significant. Comparing the strength of preference of the no-dollar cost model and with the dollar cost model clearly shows the overwhelming influence of adding a dollar cost of imagery improvements to the strength of preference for improvements in imagery.

Figure 3-6, Dollar Cost Included: Landsat User Preference for Spatial Resolution Enhancements of Landsat Imagery, shows an odds ratio > 1.0 for an attribute level, indicating that Landsat users prefer attribute improvement levels to Landsat 8's 30 m resolution (OR = 1.0). All comparisons are statistically significant ($p < 0.001$).

Figure 3-6 Dollar Cost Included: Landsat User Preference for Spatial Resolution Enhancements of Landsat Imagery



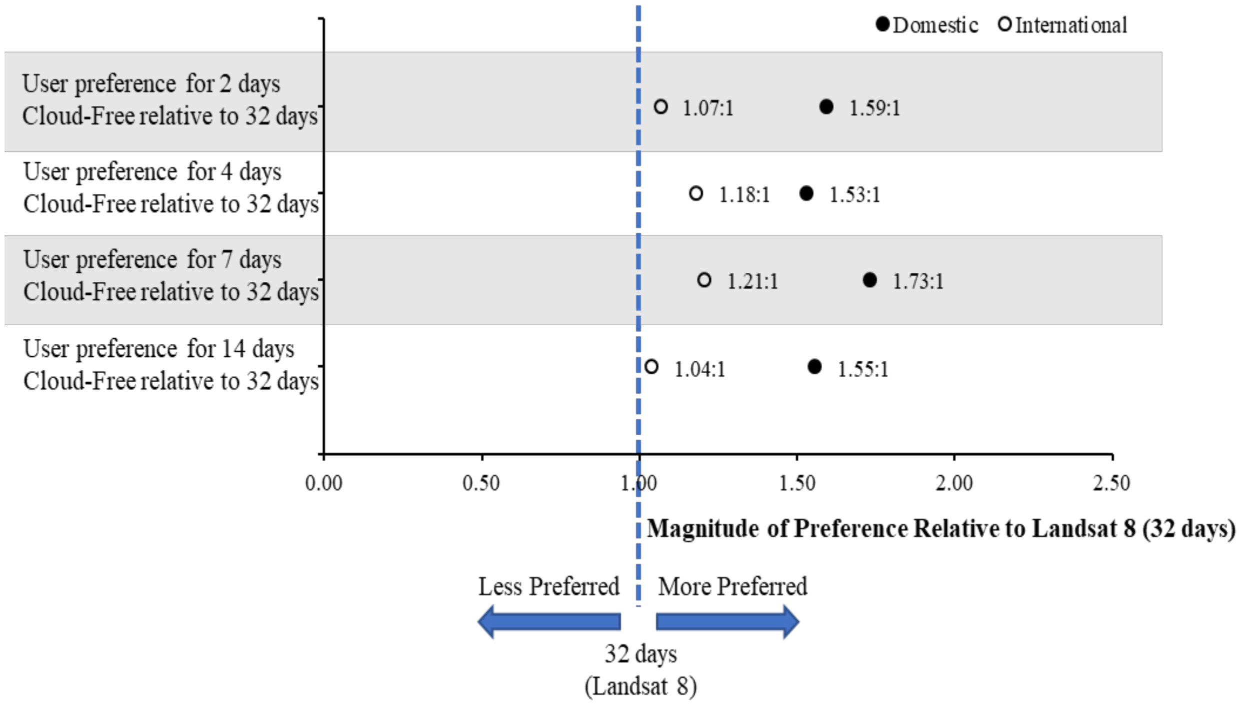
Cloud-Free Usable Days – Domestic Users Preferences with Dollar Costs

In the with-cost models, improved cloud-free, usable imagery days is the second most preferred attribute (Figure 3-7). The odds ratio for cloud-free, usable imagery days of 14 days compared to 32 days is 1.55 and this communicates that this attribute is preferred 55 percent to current Landsat imagery. The odds ratio for cloud-free, usable imagery days of seven days compared to 32 days is 1.73 and this communicates that this attribute is preferred 73 percent to current Landsat imagery. The improvements in cloud-free imagery represent a statistically significant improvement over Landsat 8. However, none of the improvements in cloud-free, usable imagery day dummies are statistically significantly different from each other. So, seven days is preferred to 14 days, but the difference of 17.6 percent is not statistically significantly different from zero. Similarly, more frequent cloud-free, usable imagery days all have odds ratios close to the odds ratio for 14 cloud-free, usable imagery days and these measures are similar to each other. Thus with-cost to download imagery in the model, seven days is the preferred improvement in cloud-free, usable days.

These results are important and informative, although strongly influenced by the strategic bias of strongly negative responses to any cost for Landsat imagery. There are a multitude of attributes that have minor value. Thus, for example, doubling the number of attributes in the Landsat system will not double its value to users.

Figure 3-7, Dollar Cost Included: Landsat User Preference for Cloud-Free, Usable Imagery Days Enhancements of Landsat Imagery, shows an odds ratio > 1.0 for an attribute level and indicates that Landsat users prefer an attribute level to Landsat 8's days (OR = 1.0). All comparisons are statistically significant ($p < 0.001$).

Figure 3-7 Dollar Cost Included: Landsat User Preference for Cloud-Free, Usable Imagery Days Enhancements of Landsat Imagery



International Users Preferences for Improvements with Dollar Costs

The results between the domestic users and international users are rather similar for the with-dollar cost models where costs are captured in dummy variables. For international users, improved spatial resolution is still the most preferred improvement. While these are the most-preferred attributes for international users, there are smaller odds ratios than domestic users for these improvements. For international users, the odds ratios are 1.46 and 1.64, for resolutions of 10 m and 5 m where both are compared to Landsat 8 of 30 m (Figure 3-7). Increased frequency of cloud-free, usable imagery days is the second most preferred for international users, but none of the odds ratios are statistically different than Landsat 8 levels.

Cost Model with Cost as a Single Continuous Variable and Valuation of Significant Improvements in Imagery

Instead of using dummy variables for cost amounts, the cost variable can be included as a continuous variable within the rank-ordered model. The parameter estimate is –0.0007066. Using the formula $100\times(\exp(\beta_{cost})-1)$, then this result can be interpreted as the change in the odds ratio given a one dollar change in cost. The formula converts the parameter to an odds ratio and then to percentage change in those odds given a change in the continuous variable. The result of the formula is –0.0706. Thus, a one dollar increase in the cost per scene results in a 7.06 percent decline in odds ratio while holding all other attributes constant. This is an extremely large impact. Increasing costs per scene from $0 to $34 results in the odds ratio declining to a magnitude of –1.9072. Thus, if the original odds ratio for an attribute was 2.0000 (twice as preferred or 100 percent preferred to the base), then the resulting odds ratio is close to zero (2.0000-1.9072). Cost is the overwhelming attribute. And like the behavior in the contingent value method survey conducted as part of the same survey as the stated choice survey in this chapter, this may be indicative of the timing of the survey with the revelation that U.S. federal government was considering charging for Landsat imagery. But it may also be due to the overwhelming importance of cost per scene, especially for a portion of high-volume downloaders of scenes.

The strength of using a continuous cost coefficient on the cost variable compared to using individual coefficients on the different cost level dummy variables is that the continuous cost coefficient can be used to calculate the incremental or marginal dollar value of the improvement in an attribute. Calculus can be used with this specification to show the incremental or marginal value of the dummy variable attribute is the ratio of the attribute dummy variable coefficient divided by the cost variable coefficient. The shortcoming of this approach, for this specific application to valuing improvements of Landsat imagery, is that the magnitude of the strength of preference changes somewhat from the no-dollar cost model due to influence of dollar cost on users anchoring on the zero-cost Landsat 8. These results are discussed but not presented in detail. The details that are presented are those that communicate results most clearly and in this alternative model are informative. However, for reasons discussed more in detail below, the dollar values are highly likely an underestimate of the dollar value potential improvements in imagery.

The only attributes that are significant in the with-dollar cost stated choice model where dollar cost is included as a continuous variable is spatial resolution. This is similar to the dollar cost as a dummy variables model. In that model, it is spatial resolution that is the most important set of attributes. In the model with the continuous dollar cost variable, all the other attribute sets are not significant or have negative valuations. Negative valuations imply the attributes are not valuable to the respondents, which is unlikely, but no doubt reflect the strategic behavior of opposing any cost of downloading imagery.

The incremental or marginal valuation of improved spatial resolution is $664.48 per scene for a resolution of 10 meters and $647.76 per scene for a resolution of 5 meters compared to Landsat 8's 30-meter resolution. The higher resolution has a slightly lower value, but these two results are from dummy variable coefficients on improvements in resolution that are not statistically different from each other.

The results that change when charging for imagery is introduced are that the improvements in cloud-free, usable imagery days attributes are no longer statistically different than Landsat 8. The issue may be that the relationship between dollar cost and ranking is nonlinear, as seen in the cost dummy variable results (Figure 3-5). The odds ratios decline geometrically at higher costs. But calculating the marginal value requires a linear cost coefficient, so making use of a logarithm of cost is not an option.

The results between the domestic users and international users are rather similar in their respective cost-as-a-continuous-variable models. International users' most preferred improved attribute is spatial resolution. The marginal valuation of improved spatial resolution is $205.14 per scene for a resolution of 10 meters and $447.32 per scene for a resolution of 5 meters. The higher resolution is double the dollar value of the lower resolution, and these two results are from dummy variable coefficients that *are* statistically different, i.e., 5-meter resolution is statistically greater than 10-meter resolution. As with domestic users, the marginal value of all other attributes is statistically insignificant or not valued, as ranked by survey respondents.

Finally, like the no-dollar cost model, we examine a rank-ordered model with interaction terms between the different dummy variables for attributes and the continuous cost variable. This specification allows the results of the parameter estimates for the different attributes to change as the costs change. The specification also allows the cost parameter to be different for different attributes. The results are mostly insignificant, and the interpretation does not clarify, simplify, or improve communication of the relationship between attributes and cost. We also included interactions between all of the dummy variables and numbers of scenes downloaded by the respondent and the number of years the respondent had been using Landsat imagery. Neither the number of scenes nor the number of years downloading were significant. The interactions of these variables with dollar costs were significant variables. Thus, once dollar costs are included, the responses are uniform across high-volume and low-volume downloading users and longtime versus new users.

Regardless of the model specifications, models that contain a dollar cost variable continue to communicate that any dollar cost is strongly not preferred to the status quo of Landsat 8. Different spectral bands are most strongly not preferred in the with- dollar cost model. However, cloud-free, usable imagery days and spatial resolution show little changes in users' relative preference for improvements in these two attributes compared to improvements in most other attributes. Nonetheless, the magnitude of strength of preference does decrease in the with- dollar cost model. The unique result from this specification is that with higher dollar costs, the higher thermal band spatial resolutions are more preferred than the no- dollar cost model. Improvements to this attribute is one that users would be willing to pay for.

Reasons Why the Preferences Between No-Doller Cost and With-Dollar Cost are So Different

Two specific events have important ramifications for our stated choice effort: (1) A new supply of free imagery that became available from the European Space Agency's Sentinel-2A and -2B satellites; and (2) discussions that had been widely circulated within the remote sensing community regarding the USGS charging for Landsat imagery (Popkin (2018)).

1) The introduction of Sentinel-2 as a no cost substitute for Landsat: Before this 2015 event, there had been no free satellite imagery comparable to Landsat 8. Thus, the 2018 stated choice with-cost question likely became a question about how much more or how much of a premium would a user pay for improved Landsat imagery compared to Sentinel-2 imagery. For some users, Landsat did offer some advantages and improvements in Landsat images were worth paying an additional cost. Although Sentinel-2 satellites have spectral bands similar to Landsat 8's, Landsat 8 has thermal bands. In addition, many of the analysts are familiar with using Landsat and have developed applications and software around the program. Thus, to some Landsat users (e.g., longtime users downloading a few images) these advantages of Landsat over Sentinel-2 are important, and they would pay a significant premium for certain improvements. For some users, however, Sentinel-2's shorter revisit time of one week and greater spatial resolution (down to 10 meters) made it an attractive substitute for projects benefiting from these two attributes. For many other users, features of Sentinel-2 worked just as well for their projects.
2) Landsat has been free since 2008 – a long time span for many users. These users now view this free access as the normal state of affairs. The prospect of charging for Landsat imagery brings up issues for the survey respondents, such as uncertainty on how to incorporate Landsat's unknown levels of fees into current project budgets that were developed without fees, and how the fees would affect future budgets. Landsat did have a fee at one time. Concern about returning to a payment system for Landsat while answering "with dollar cost" stated choice questions can impact users' responses, i.e., strategic behavior may have affected choice values. Respondents are potentially aware of and concerned about the potential policy change of charging for downloading Landsat imagery. Respondents may have read articles (Popkin (2018)) about these issues before and during survey release. Their strategic behavior may have led them to refuse to pay anything other than the lowest dollar amounts, regardless of the improvement levels, and others to simply refuse to pay any amount and choose the free Landsat 8 alternative. Both of these response behaviors were likely intended by users to send a signal they were opposed to

charging, especially when the good has been previously free for a decade (Campos, et al. (2007)). In these cases, respondents are worried that indicating an amount they would pay would result in future charges. This phenomenon has been found in other willingness-to-pay surveys (Campos, et al. (2007)). Even when the good has a current price, such as a hunting license, respondents tend to provide valuation responses to survey questions that are statistically lower than what they actually paid in the past, when those prices are adjusted for inflation (Loomis, et al. (2000)). The users make this understatement of their values so as to send a message in the survey to the agency, hoping to avoid or at least minimize future fee increases.

Resistance to paying for improvements to Landsat imagery among users who were willing to use or were already using Sentinel-2 makes economic sense. However, the effect of strategic bias in refusing to pay for improvements to Landsat 8 imagery or exhibiting extreme sensitivity to anything other than a nominal price increase to discourage USGS from charging, results in a distorted picture of the underlying value of imagery improvements. The timeline for the present study did not allow for repeating this stated choice survey now that it has been six years since the 2018 survey and the threat of the USGS charging has passed. Therefore, we undertook an alternative approach to gain insights on the value improvements in Landsat imagery similar to Landsat Next in the following major section of this chapter.

Conclusions from Stated Choice Survey and Results

A stated preference survey was conducted to quantify the relative values that registered Landsat users have for improvements to four different attributes of Landsat profiles: spatial resolution; cloud-free, usable imagery; spectral bands; and thermal band spatial resolution. The stated choice survey forced Landsat users to choose among different bundles of Landsat profiles that included one or more improvements in the current Landsat imagery. This choice format implicitly made the user face the reality that it is not realistic to simultaneously improve every dimension of Landsat imagery.

Users were asked two trade-off questions: the first included one or more improved imagery attributes, and the second with the same mix of imagery improvements but with a dollar cost to download a scene. Each question simply required them to choose between two alternative improvements versus the current Landsat 8 imagery.

Consistent Findings of the Stated Choice Survey

The initial stated choice survey questions required Landsat users to trade off among improvements in imagery and provided strength of preferences for improvements. These results were not comingled with the strategic behavior of sending a signal to the USGS about reinstating pricing for downloading imagery. The strength of preferences showed:

- The most important improvement is increased spatial resolution. This is true in the model without dollar costs and is true in the model when users must pay for improvements in imagery.
- In the without dollar cost model, users preferred improvements in spatial resolution all the way to 5 m, whereas with dollar costs, 10 m would be just as acceptable as an improvement to 5 m.

- The second most preferred improvement in the models with and without dollar costs was the frequency of cloud-free, usable imagery days per month.
- Even in the without dollar cost choice model, it appears that improving the frequency of cloud-free, usable imagery days to seven days per month is sufficient for most users.
- Increases in thermal bands' spatial resolution prompts a statistically significant increase in value.
- The addition of different types of spectral bands (e.g., Red Edge (680–730 nm) and the SWIR (1.5-2.5 μm) option is an improvement of limited value to most registered Landsat users. However, TIRS bands (8-14 μm) is one attribute, like the thermal band spatial resolution, that appears modestly important to registered users in the survey results.
- When dollar cost was included in the stated choice model, the respondents focused primarily on cost at the exclusion of nearly all the other attributes other than spatial resolution. This nearly single focus on dollar cost to the exclusion of other attributes is unusual in most stated preference surveys (Holmes, et al. (2017)), but may in part be due to Sentinel satellites standing as a free substitute and, in part, to send a message to the USGS about unacceptable new pricing. The results showed that any costs will likely substantially reduce Landsat satellite imagery use. Specifically, even the at the lowest cost per scene of $34, there would be a loss of more than two-thirds of registered Landsat users. With cost, improvements in spatial resolution are the highest valued improvement to both domestic and international users.

These findings from the stated choice survey method clearly communicate the Landsat imagery improvements that are most desired and valued by users: improved resolution, more revisit time to allow for more cloud-free days and increases in thermal band spatial resolution. These three desired improvements match three of the major improvements in Landsat Next, suggesting that direct registered Landsat users will find Landsat Next's imagery a very beneficial improvement for their future research.

3.6. Analysis of Commercial Satellite Pricing for Insights on Landsat Next's Value

The survey of registered Landsat users on the improvements in Landsat 8 imagery reported on in the previous section match many of the proposed improvements in Landsat Next's imagery. However, that survey was done in 2018. Wu, et al.'s (2019) interviews with about 150 subject matter specialists about user needs for the next generation of Landsat satellites was also in 2018.

Since these surveys and interviews are roughly about six years ago, we decided that another more recent perspective on the value of remote sensing imagery improvements could be obtained by analyzing information on commercial satellites and other public satellites[60].

[60] The data collection and summary reflect substantial work by one of our research assistants, Brandon Dodd. However, he bears no responsibility for our interpretation and detailed statistical analysis of the data.

A. Commercial Satellite Data

To investigate factors influencing the current values of satellite imagery features most similar to features in Landsat Next, a review of for-purchase imagery was conducted. In total, 31 different satellites were identified as having prices for imagery. A total of 82 observations of prices obtained for the various different types of imagery offered for sale.[61] Of those 82, three of the observations came from three different governmental satellites. For the purpose of this analysis, these three observations were omitted due to unknown drivers that could influence image pricing. For example, two of the omitted images have very low relative prices, which could be indicative of governmental funds helping to keep rates suppressed to near free levels. The analysis was conducted using the remaining 79 observations from 28 proprietary satellites.

During the data collection process, some aspects that warrant notation are worth pointing out. First, the majority of the initial data came from a combination of five major spectral bands: Panchromatic, Blue, Green, Red, and Near-Infrared. This presents challenges for the analysis because Landsat Next has 26 bands in total, of which the Blue, Green, Red, and Near-Infrared bands constitute only a small portion. This meant that more imagery containing the “extra” spectral information possessed by Landsat Next was required. Existing Landsat Satellites are referred to as multispectral imagers. Multispectral satellites effectively capture images in a few broad wavelength bands and have long been the standard for Earth observations. However, because it was observed that the majority of proprietary imagery sold from multispectral satellites had only a few bands of spectral information, further investigation was required to find more advanced satellites.

In comparison to multispectral imagery, the emerging advancement of hyperspectral imagery captures images in hundreds of narrow, contiguous spectral bands, often spanning the entire sensitivity range of a sensor. Hyperspectral imaging systems can provide more detailed data than multispectral imaging systems, allowing for more precise identification of materials and substances. Given that companies pursuing hyperspectral technologies were observed to have added spectral information, which Landsat Next will also have, they seemed to be an appropriate source for pricing. However, although some information could be documented, it was observed that a large majority of proprietary satellites containing an enhanced spectral range have yet to be launched. This further complicates the valuation attempts, and therefore, these five satellites were dropped from the presentation of bands in Table 3-5.

By the end of the search, four extra bands were identified as having imagery prices: Coastal Aerosol, Yellow, Red Edge, and Shortwave Infrared. While many governmental satellites are starting to pursue or already possess more bands than previously mentioned, a major lack of such information has been observed within the proprietary market. Table 3-5 summarizes the number and percentage of satellites with each of the types of band combinations.

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[61] This data was collected from company websites, and where necessary, calls to a few companies to clarify the pricing or imagery characteristics.

Table 3-5 Summary Statistics of Prices of Commercial Satellite Imagery by Common Features of Imagery[a]

Spectral Information	# of Satellites	Percentage of Satellites	Average Price per km^2	Median Price
Standard Four & Panchromatic	23	32%	$13.67	$16.00
Standard Four	22	30%	$17.37	$17.50
Panchromatic Only	20	28%	$12.53	$14.00
Standard Four, Panchromatic, CA, RE, & Yellow	5	7%	$20.80	$21.00
SWIR Only	2	3%	$18.00	$18.00
Total Observations	72	100%	$16.47	$17.30

a. Prices are reported per square kilometer. Standard four means Blue, Green, Red, and Near-Infrared bands; CA stands for Coastal Aerosol band; RE stands for Red Edge band; and SWIR stands for shortwave infrared band(s).

Collectively, satellites containing any given combination of Panchromatic, Blue, Green, Red, and Near-Infrared bands alone account for over 83 percent of the sample and are also responsible for the lowest relative valued images on average.

With respect to the bands on Landsat Next, there was only a single observation that contained the added spectral information (CA, Yellow, RE, and SWIR) in addition to the standard four bands. Its price was by far the highest at $34 per square kilometer and is omitted from Table 3-6 but included in our statistical analysis. **This means a near 96 percent average premium is being charged for an image containing the four added bands over the average image with only the standard four. This indicates that increased spectral bands provide higher values owing to the added information**. **This certainly indicates the added value of these bands in Landsat Next.** Additionally, our summary statistics also indicate that images with Panchromatic bands have relatively lower values. While not crucial to the valuation of Landsat Next, Panchromatic bands have been installed on prior Landsat satellites and to this day remain particularly important in proprietary imagery.

In Table 3-6, the average price of all recorded images was $16.47 per square kilometer. But the average, as always, hides a great deal of variability. Even trimming for what is considered an outlier (see the econometric analysis below), the next highest price is $34 per image, and several are over $20 a scene. Thus, something might not be accounted for in the reporting of these prices on company websites. Think about the automobile manufacturer's suggested retail price, or MSRP. The actual price paid was higher immediately after the pandemic but often lower than the manufacturer’s price. Some of this may be true of imagery, as well. Firms will oftentimes enhance their imagery to create more value-added products suitable to some types of users. For example, our data indicates that some firms have many more bands than they sell but may be using these additional bands to “sharpen” or enhance the image. Without a detailed interview by persons knowledgeable regarding the intricacies of the pricing of remote sensing imagery it is hard to know this for certain. Therefore, we attempt to include this in our statistical model as an intercept shifter or dummy variable called “suspected sharpening.” Table 3-6 also provides the descriptive statistics of the data for potential inclusion in the regression model.

Table 3-6 Summary Statistics of Private Satellite Imagery Information

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Cost per Image ($/km^2)[a] (Dependent variable)	76	$14.37	6.7512	$1.15	$34
Total Satellite Bands	76	12.3421	43.0717	1	29
Number Bands in Image Sold	76	4.1711	2.6249	1	16
Suspected Sharpening	76	0.4605	0.5018	0	1
Spatial Resolution in Meters	76	1.0884	1.3192	0.3	6.5
Swath Width KM NADIR	76	16.7592	11.9526	5	77
Revisit Time in Days	76	1.5893	1.3703	0.025	6
Panchromatic (Y=1; No=0)	76	0.6579	0.4776	0	1
Coastal Aerosol (Y=1; No=0)	76	0.1053	0.3089	0	1
Blue/Red/Green (Y=1; No=0)	76	0.6974	0.4624	0	1
Yellow (Y=1; No=0)	76	0.0789	0.2714	0	1
Red Edge (Y=1; No=0)	76	0.1316	0.3403	0	1
Near Infrared (Y=1; No=0)	76	0.6842	0.4679	0	1
SWIR (Y=1; No=0)	76	0.0395	0.1960	0	1
TIR 1/2/3	76	0	0	0	0
TIR 4/5	76	0	0	0	0
Water Vapor	76	0	0	0	0
Cirrus	76	0	0	0	0
Liquid Water	76	0	0	0	0
Snow/Ice	76	0	0	0	0
Standard Four Bands (Y=1; No=0)	76	0.6842	0.4679	0	1

a. Landsat image is about 1.85 times larger than the 1km^2 image, so if a reader wanted to convert to a price for an equivalent Landsat image, they would need to multiply by 1.85.

Satellite Imagery Price Modeling

The statistical or econometric method we applied is known as hedonic price modeling (Taylor (2017)). The method uses multiple regression to explain the price of a good and changes in that price across different characteristics of that good. We use statistical regression methods to explain the variation of satellite imagery prices as a function of the characteristics of that image. For example, the method can ascertain if pricing is influenced by spatial resolution, numbers of days per revisit, the number of the bands, and if specific bands are available in the image or not.

Hedonic modeling is useful for three results: First, the regression coefficients on the characteristic variables – the explanatory variables – offer a marginal value interpretation. Specifically, if the explanatory variable increases by one unit, then the coefficient measures the impact on the price of imagery. If the explanatory variable is a dummy or and intercept-shifter variable, then the coefficient measures the impact on price of that characteristic being present in the imagery. Second, the complete regression model can be used with specific levels of the explanatory variables to predict the mean price of the imagery with that bundle of characteristics. Third, hypothesis testing can be conducted on the individual coefficients and the total model. The questions that can be answered are what individual characteristics impact the price charged by imagery producers, and what percentage of the variation in the price charged is explained by the bundle of characteristics.

Further, the coefficients on the independent or explanatory variables in the regression reflect *ceteris paribus* conditions. That is, each incremental or marginal impact is interpreted, holding the other aspects of the imagery constant. For example, the measure of the number of days between revisits is not convoluted with the number of bands or spatial resolution. This is a strength of the multiple regression-based method.

The dependent variable in the regression is the cost per square-kilometer image ($1km^2$) in dollars. We attempt to explain the variation in prices charged as a function of the following imagery characteristics: total number of satellite bands in the image, number of bands in the image sold, spatial resolution in meters, swath width kw nadir, and revisit time in days. In addition, we include the following characteristics as yes=1 if the image has this characteristic, and no=0 if not: Panchromatic, Coastal Aerosol, Blue, Green, Red, Yellow, Red Edge, Near Infrared, SWIR, TIR 1/2/3, TIR 4/5, Water Vapor, Cirrus, Liquid Water, Snow/Ice, and Suspected Sharpening of the image.

For our commercial satellite data, there is no variation across Blue, Red, and Green. If one color is in the satellite image, then all three are present, so the three yes/no measures are combined into a single yes/no variable. Further, for the private satellite imagery in our data, there are no TIR 1/2/3, TIR 4/5, Water Vapor, Liquid Water, Cirrus, and Snow/Ice measures. These aspects of information are only available in free government-owned imagery. Thus, these variables are dropped from the modeling effort as a price of zero for imagery provides no insights as to the value of these imagery characteristics.

Finally, there are a couple of observations that are clearly outliers, in that their values are very far from all the other observation in the data; including these outliers can cause misleading results. Means and conditional means such as regression estimation through ordinary least squares are not robust to outliers. A single outlier observation can have undue influence on a single regression coefficient's size, sign, and significance. Besides simple visual inspection of prices, formal influence statistics are used to determine how to drop some observations. For example, there is one private satellite that offers the Yellow band in images they sell, and that has by far the highest price at $247 an image. If that observation is included in the regression with the other 80 observations, that one observation dominates the outcome. Specifically, the regression results indicate that Yellow is highly significant and naturally highly valued. But dropping that one observation suggests Yellow actually has no value. Images containing Yellow are generally priced lower in the remaining sample. Dropping the highest price imagery results in the loss of the variable measuring the presence of the standard four bands described in Table 3-5. This variable is perfectly collinear with other variables when the three satellites that are highest priced are not included.

Details on Variables Included in the Price Model

A single observation is an image, not a satellite. Images can be packaged in different combinations of spectral information or with different enhancements.

Dependent variables of interest:

- Cost per Image: U.S. dollars per square kilometer ($1km^2$)
  - The cost per image was the universally observed unit of measurement by firms.

Independent variables included in the dataset:

- Intercept Shifter/Dummy Variables:
  - Has Price: Controls for whether or not an image observation includes a price or not.
  - Serves as an alternative to the government/private dummy variable.
  - Government/Private: Controls for whether the observation corresponds to a particular satellite that is either governmental or privately owned. This delineation is made for multiple reasons, one being that most governmental satellites do not charge for their imagery, where proprietary do. Additionally, there are bands that tend to be on governmental satellites that are not on proprietary satellites; among the bands included within the spreadsheet are TIR 1/2/3, TIR 4/5, Water Vapor, Cirrus, Liquid Water, and Snow/Ice.
    - 1 for private
    - 0 for government
  - Suspected Sharpening: accounts for whether an observation, or image, is going through a sharpening/enhancement process that is otherwise unable to be accounted for. This is identified by companies stating they sharpen the image or if sharpening is highly suspected based off of advertisement.
    - 1 for sharpening
    - 0 for basic image

- Band Information: bands that are stated to be on observations of a corresponding satellite are included as dummy variables to account for whether a satellite has or does not have the spectral information.
    - 1 indicates image contains that band
    - 0 indicates it does not

- Numerical Variables:
    - Minimum Order: The number of square kilometers that must be purchased of a specific image type when completing a transaction. This is most often a continuous area.
    - Total Satellite Bands: The total number of spectral bands that are on the satellite in which the image was captured.
    - Number of Bands in Image Sold: The total number of spectral bands that are sold within the image and/or observation.
    - Spatial Resolution (meters): Accounts for the lowest ground sample distance the respective satellite is capable of completing.
        - This is a relatively minimum measure because the spatial resolution of different spectral bands within the image can vary. For example, color bands tend to have a worse (higher meters) resolution than Panchromatic (smaller meters) resolution. Thus, values are reflective of such discrepancies.
    - Swath Width (km): It is a secondary option when considering the resolution. Swath is the width at which the greater imagery can be taken from the satellite. It has a positive correlation to Spatial Resolution because the better the spatial resolution (lower value), the lower the swath width.
    - Revisit Time (days): accounts for how fast another image of the same location, and/or a very similar spot to the original location, can be taken. Considers the frequency with which a location can be monitored and observed, or the time required for an updated image to be taken.

Hypotheses About the Variables

Based on our correlation analysis and the remote sensing literature, we expect certain findings to remain consistent during model estimation.

1) The more spectral bands a satellite possesses, and that are subsequently sold, the higher the price an image will have.
    a. Positive relationship and coefficient
2) Enhancement or any sharpening/processing of an image will bring a higher price to an image.
    a. Positive relationship and coefficient
    b. Also applies to band enhancement potential and suspected sharpening variables.
3) Increased spatial resolution (lower value of either meters or swath width measured in kilometers) will bring higher value.
    a. Negative relationship and coefficient
4) The quicker the revisit rate (fewer days), the higher the price.
    a. Negative relationship and coefficient

Dependent Variable: Cost per image (square kilometer)

Cost per image is universal for all companies, and they report their prices based off a single square kilometer (regardless of minimum order quantity).

Independent Variables:

1) Has Price: Including this dummy variable will control for $0 prices observed with the governmental satellites.
2) Number of Bands in Image Sold: This is the primary effect of spectral information on the price of an image. Total satellite bands do not provide us with that measurement, only what the satellite is capable of.
3) Suspected Sharpening: Some images are sharpened via using a band such as panchromatic to make the original image clearer or appear more in focus. Since only some commercial images were sharpened, it was important to include a variable to distinguish those images sold from images not sharpened when estimating the effect of the other variables such as spatial resolution and revisit time on price. Failing to account for sharpening of images could also add unexplained variation in the statistical analysis of prices of imagery. It is very possible that a portion of the value in an image is related to the sharpening process. By coding this variable as an intercept shifter or "dummy," variable coded as 1 if images being sold are likely sharpened, and 0 if likely not sharpened, is a reasonable way to control for this potential feature of the images sold.
4) Spatial Resolution: Spatial resolution is important for consumers of remote sensing imagery because the clarity of the image dictates how it can be used. Failing to account for resolution could be problematic. While swath width serves as a proxy, it is a physical satellite characteristic, not a sellable image characteristic. Thus, spatial resolution is preferable, and Landsat Next represents an improvement over Landsat 8/9 in this dimension.
5) Revisit Time: Revisit Time, in days, can be important for how quickly someone can get updated imagery. Failing to account for it, similar to resolution, could be problematic; significant or not. Further, Landsat Next represents an improvement over Landsat 8/9 in this dimension.

Spectral Dummies:

These variables are more complicated to include in the regression, but important to include because they may have an impact on the value of an image. Possible dummy variables are:

- Standard Four Bands
- Panchromatic
- Coastal Aerosol
- Yellow
- Red Edge
- SWIR

It is possible to have positive and negative coefficients for each of these bands. A negative coefficient could signify that the bands are commonly included in most imagery and therefore does not add to the value and might even subtract from the average price to reflect the “normality” of the image. Variables of suspect in this are the standard four bands and Panchromatic. If the regression results yield a positive coefficient, this would indicate that the added information could increase the price of the image from the average.

Table 3-6 provided the descriptive statistics of the variables initially considered in the regression. While there were 20 possible explanatory variables in Table 3-6, as previously discussed some variables were found only on public satellites, e.g., TIR, thus having a price of zero making that variable not informative for estimating price effects. Other variables like swath width, had a high correlation with spatial resolution, that we argued was likely to influence the price of the imagery, more than swath width. Thus, there are 13 candidate variables remaining. Including all of the 13 candidate explanatory variables in the price model results in all of the variables but two being statistically insignificant. These results are likely due to a high enough correlation between several variables resulting in multicollinearity, which increases the standard errors, i.e., the variance, of the coefficients yielding insignificant p-values. The two that are significant are spatial resolution in meters and suspected sharpening. This model is provided in Table 3-7. This initial model provides a starting point for model refinements.

Table 3-7 Private Imagery Price and All Candidate Characteristics Variables Results[a]

Variable	Coefficient	Standard Error	P-Value
Intercept	13.5399	3.2027	<.0001
Total Satellite Bands	1.7059	1.3899	0.2243
Number Bands in Image	1.709	1.3807	0.2205
Suspected Sharpening	**4.4181**	**2.3479**	**0.0646**
Spatial Resolution in Meters	**-3.1181**	**1.2135**	**0.0126**
Swath Width KM Nadir	0.0562	0.1021	0.5843
Revisit Time in Days	-0.6603	0.5649	0.2470
Panchromatic	-0.9850	2.8983	0.7351
Coastal Aerosol	3.1824	5.9170	0.5926
Blue/Red/Green	-4.1248	7.3739	0.5779
Yellow	-6.9897	5.5466	0.2123
Red Edge	0.6074	4.1752	0.8848
Near Infrared	-1.6254	6.8943	0.8144
SWIR	-0.5479	11.0088	0.9605
F-Statistic	5.05	–	<.0001
R-Squared	0.5143	–	–

a. Rows in bold have statistically significant coefficients.

Thus, two automated procedures are used to build two alternative models. Forward and backward model fitting methods are used. Forward fitting adds the most significant variable at each step until there is no significant improvement. The explanatory variable that improves R-squared the most is added until there is no additional variable in the candidate set that can be included that are significant at the 50 percent level. This resulting model is provided in Table 3-8. This 50 percent level is a very low significance threshold, and caution is warranted in that any variable added will improve R-squared and an added variable will likely reduce the significance of variables already present.

Table 3-8 Results of the Forward Fitting Private Imagery Price and Imagery Characteristics[a]

Variable	Coefficient	Standard Error	P-Value
Intercept	12.7817	2.2156	<.0001
Number Bands in Image	1.3823	1.1266	0.2243
Suspected Sharpening	**4.7815**	**1.6980**	**0.0064**
Spatial Resolution in Meters	**-2.9698**	**0.9179**	**0.0019**
Swath Width KW NADIR	0.0553	0.0884	0.5333
Revisit Time in Days	-0.6120	0.4724	0.1997
Coastal Aerosol	4.5653	4.2742	0.2894
Blue/Red/Green	-4.4643	4.3076	0.3038
Yellow	-6.8295	5.1029	0.1854
SWIR	1.7080	9.1358	0.8523
F-Statistic	7.70	–	<.0001
R-Squared	0.5102	–	–

a. Rows in bold have statistically significant coefficients.

In the forward fitting model, the resulting R-squared is 51.2 percent, meaning that 51 percent of the variation in price is explained by the explanatory variables. This is reasonable explanatory power using data on market observations. F-statistic for the overall model is highly significant, indicating that when taken as a group, the independent variables in the regression are statistically different from zero. Spatial resolution in meters is also the most significant and increasing the fineness of the resolution by one meter – which is decreasing spatial resolution – increases the price $2.97 per meter of improved spatial resolution. This significance is consistent with what was found in the registered Landsat user survey data: Resolution is important. The advantage of the regression is that improving spatial resolution from 30 meters in Landsat 8 to 10 meters in Landsat Next increases the value of the image by $60 per 1km^2 image, or $111 for a standard size Landsat image, which is 1.85 times a 1km^2 image. Suspected sharpening is the second most significant variable and sharpened images increases the image value $4.78. Number of bands in an image begins the list of marginally significant continuous variables and increasing the number of bands by one band increases the price $1.38 per image. Improving revisit time in Days, i.e., reducing the number of days between revisits (more frequent visits), increases the image price by $0.61 (the coefficient on revisit time is negative, so reducing days increases the value). This measure is significant at the 20 percent level. Likewise, increasing swath width by one unit increases the price by $0.055. The presence of the Yellow band decreases the image price by $6.82. This unique aspect of imagery does not have positive value. The presence of the combined Blue/Green/Red band decreases the image price by $4.46. This aspect of imagery is so common in the imagery available that having it decreases what can be charged. Coastal Aerosol increases the value $4.57 but is significant only at the 30 percent level. Swath width and SWIR are important early in the fitting process but are very insignificant towards the end – other variables are correlated and reduce the importance of measure that fit early.

Backward fitting proceeds in a reverse manner. It starts with the total possible candidate variables and removes the least significant variable one at a time. This is done until all remaining variables are significant at the 10 percent level. This model is provided in Table 3-9. Again, caution is needed in that removing a single variable may improve – but can decrease – the statistical significance of the remining variables.

Table 3-9 Backward Fitting Private Imagery Price and Imagery Characteristics[a]

Variable	Coefficient	Standard Error	P-Value
Intercept	**13.8255**	**1.4087**	**<.0001**
Number Bands in Image	**1.3039**	**0.2856**	**<.0001**
Suspected Sharpening	**4.1039**	**1.4386**	**0.0057**
Spatial Resolution in Meters	**-2.4031**	**0.4691**	**<.0001**
Revisit Time in Days	**-0.7706**	**0.4456**	**0.0882**
Blue/Red/Green	**-4.2245**	**1.6441**	**0.0882**
F-Statistic	13.60	–	<.0001
R-Squared	0.4927	–	–

a. Rows in bold have statistically significant coefficients.

What is learned from these regressions? One element is that a great deal of private satellite imagery is similar, and there are not enough differences across all different imagery characteristics to be able to determine statistically significant different values of all the different imagery characteristics. It is difficult to tell if this is purely a statistical issue, or rather, there are a lot of imagery characteristics that do not have much market value added by themselves. It is possible that a single feature of imagery in isolation, which is what we are trying to model, may not have a great deal of value by itself. Rather its value is in combination with several other features, that produce a valuable and saleable imagery product. This could be explored via testing a wide variety of interaction effects but given the relatively small sample and the fact that the presence of several features in the imagery have a high degree of correlation between some of the features, it is not immediately clear if this undertaking would serve our purposes of estimating the value of specific features of Landsat Next.

Across the two methods, backward fitting results in a model with more statistically significant explanatory variables. The process includes the most variables likely to be important for estimating the gain value due to improvements in imagery arising with Landsat Next. However, in all the models tests, spatial resolution was consistently statistically significant. This is consistent with what registered Landsat users reported in their survey responses in the prior major section of this chapter, as well. Nonetheless, there are several other aspects of imagery that have clear value. Besides spatial resolution, the revisit rate, number of bands in the image, and processing like sharpening all contribute a significant amount of value. While statistically these characteristics have an identifiable value, nonetheless, the individual value is modest. However, when the individual values are multiplied by the amounts of improvements in Landsat Next (e.g., spatial resolution going from 30 m in Landsat 8/9 to 15 m in Landsat Next), and then added up across all the other improvements in Landsat Next, the total increase in value of the improvements in Landsat Next imagery is sizeable.

Application of Regression Results to Estimating the Increase in Value of Landsat Next

In the regression model in Table 3-9, the resulting R squared is 49.3 percent, meaning nearly half the variation in price per image is explained by regression equation. The F-statistic for the overall model significance of the coefficients when considered as a group is highly significant, well beyond the 1 percent level. This model has the most statistically significant variables of interest for matching between Landsat 8/9 and Landsat Next, so we use this model to estimate the incremental value associated with improvements in Landsat Next imagery. Relying on information from prices and features of commercial satellites and their imagery seems appropriate for making inferences about the value of improvements in Landsat Next for two reasons. First, some users of remote sensing imagery combine Landsat imagery and commercial imagery in their applications. Second, commercial satellite imagery companies often use Landsat to calibrate the imagery from their smaller commercial satellites. Thus, we feel it is reasonable to use data from prices and features of commercial satellites to estimate the incremental value of improvements of Landsat Next that have features found on commercial satellites.

- Increasing the number of bands in an image increases the price by $1.30 per band. This is the second most statistically significant variable. Landsat 8/9 has a total of 11 bands[62]. Landsat Next has 26 bands. The additional 15 bands are estimated to increase the value of a 1km^2 scene by $19.56, or $36.18 for a standard Landsat scene.
- Spatial Resolution in meters is the most significant variable and increasing the fineness of the spatial resolution one unit increases the price $2.40 per meter. Applying this rate of gain in value with each 1-meter increase in resolution yields a gain in the value Landsat Next. While resolution varies by band, 8 of the 11 bands in Landsat 8/9 have 30-meter resolution[63]. If the basis of comparison is Landsat 8/9, then improving spatial resolution from 30 meters in Landsat 8/9 to 10 meters in Landsat Next, increases the value of the image by $48 per 1km^2 image or $88.91 for a standard size Landsat image which is 1.85 times a 1km^2 image. However, when comparing the spatial resolution of all the bands between Landsat 8/9 and Landsat Next's 26 bands, USGS often indicates Landsat Next would have a doubling of Landsat 8/9's resolution. Using the doubling of resolution would indicate an average improvement of resolution to 15 meters in Landsat Next. Therefore, using the same $2.40 a meter, the gain with Landsat Next would be $36.05 per 1km^2. This would translate into $66.69 per standard size Landsat image.
- Improving revisit time in days increases the price of imagery $0.77 for each day sooner the satellite orbits the Earth. Landsat 8/9 has a revisit time of 16 days[64]. Landsat Next has a revisit time of six days, or 10 fewer days. This adds $7.70 per 1km^2 image, or $14.26 per standard Landsat image.

If an image has been or can be sharpened it increases the value of the image by $4.10. According to NASA[65], Landsat 8/9 imagery can currently be sharpened. While this makes Landsat 8/9 imagery more valuable, presumably Landsat Next may also have the capability for sharpening of images or Landsat Next's substantially improved resolution may yield the equivalent of currently sharpened images in Landsat 8/9. If this potential for sharpening of images or lack of need for sharpening is the case for Landsat Next, then there is no difference in value between Landsat Next images over Landsat 8/9 images *with respect to the suspected sharpening variable.*

The presence of the Blue/Red/Green bands decreases the value of imagery by $4.22, and this is likely due to the ubiquitousness of these characteristics. However, both Landsat 8/9 and Landsat Next will have the same Blue/Red/Green bands, so there is no net effect on value.

When we add up the increments in value from the improvements in spatial resolution, increases in the number of bands, and more frequent revisit time, the gain in value is $117 for a Landsat Next

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[62] https://www.usgs.gov/faqs/what-are-band-designations-landsat-satellites#:~:text=Landsat%208%20and%20Landsat%209,bands%2C%20and%20two%20thermal%20bands

[63] https://www.usgs.gov/faqs/what-are-band-designations-landsat-satellites#:~:text=Landsat%208%20and%20Landsat%209,bands%2C%20and%20two%20thermal%20bands

[64] https://www.usgs.gov/faqs/what-are-acquisition-schedules-landsat-satellites

[65] https://earthobservatory.nasa.gov/blogs/earthmatters/2017/06/13/how-to-pan-sharpen-landsat-imagery/

scene as compared to Landsat 8/9[66]. In 2023, there were an estimated 65.65 million scene-equivalents accessed, so the increment in value for Landsat Next scenes in 2023 would be $7.69 billion. Adding the $7.69 billion to the estimate of the direct registered Landsat user value reported in Chapter 1 of $25.63 billion and holding the number of scene-equivalent accessed constant at the 2023 levels, the total value just to direct registered users of Landsat Next would be $33.32 billion in 2023. This represents a 30 percent increase in value over Landsat 8/9. It is worth mentioning this $33.32 billion represents the value only to those direct users that access through USGS EarthExplorer and does not reflect benefits to other users who access Landsat imagery through one of several commercial cloud providers. Thus, the $32.32 billion is a lower bound of the total benefits to users of Landsat Next. As shown in Chapter 2, there are also hundreds of millions of dollars in indirect benefits and costs savings associated with Landsat imagery today, which is expected to increase with the improvements planned for Landsat Next.

[66] The $117 gain per scene uses the doubling of resolution. If one used the increase in resolution of 20 meters, the gain per scene would be $139.

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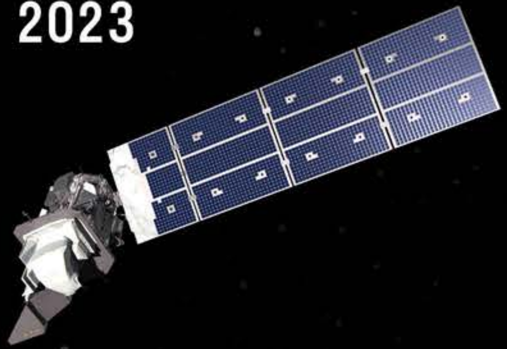
Landsat
ECONOMIC VALUATION 2023



DIRECT VALUE
$25B
Economic Benefits to Direct Users

INDIRECT VALUE GENERATED

- **$255M** Discovery of Mineral Reserves
- **$583M** Scientific Publications
- **$41M** Patent Applications

INDIRECT COST SAVED

- **$51M** Water Quality Monitoring
- **$20M** Unmetered Irrigation Wells
- **$90M** Shoreline Mapping
- **$100M** Crop Insurance Fraud Reduction
- **$300M** Lower Crop Flood Insurance Rates
- **$100M** Updating Global Maps
- **$2-9M** Wildfire Restoration
- **$4M** Monitoring Eucalyptus Tree Growth

Landsat Next Capabilities Will Improve User Applications

- Natural Disasters
- Biodiversity
- Agriculture
- Urban Planning
- Deforestation
- Coastline Shifting
- Snow/Ice Detection/ Clouds
- Water Quality and Management
- Atmospheric Pollutant Detection
- Wildfire
- Albedo Estimation

$33B Direct Value with Landsat Next
(30% increase)

Legend
○ PUBLIC ● PRIVATE
M MILLION B BILLION