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The value of information: Measuring the contribution of space-derived earth science data to resource management

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Abstract

Governments around the world, as well as private industry, invest heavily in remote sensing spacecraft to obtain data about natural and environmental resources, climate change, and the relationship of earth science to human health and quality of life. Numerous studies have been undertaken to describe and measure the value of the data from these spacecraft in order to justify further investments. The studies use a wide variety of methods and generally find a large range of benefits, from quite small to very large, in part because of differences in methodologies. This article offers a general framework for measuring the value of information. The framework serves two purposes. One is provision of a comprehensive and common basis by which to conduct and evaluate studies of the value of earth science. The second is to better inform decision makers about the value of data. Decision makers comprise three communities: consumers and producers of information, public officials whose job is to invest in data acquisition and information development (including sensors and other hardware, algorithm design and software tools, and a trained labor force), and the public at large.

1. Introduction

> We find the value of information (VOI) is not zero, but it is not enormous, either. (William D. Nordhaus, Sterling Professor of Economics, Yale University, writing about the value of weather and climate information, 1986) [1].

> If we'd been able to produce a forecast last spring that California would be deluged this winter, it would have been worth whatever research investment was involved, if only because of the human misery it would have relieved. (D. James Baker, then Administrator of the National Oceanic and Atmospheric Administration, writing shortly after heavy rains had flooded many parts of California, 1995) [2]

The mystery of the 'value' of information … So often studies of information find its economic benefit—one measure of its value—to be smaller than conventional belief might suggest. In other cases, studies find benefits so large as to justify nearly infinite amounts of investment. The explanation lies in the characteristics of information, how decision makers use it, and differences in how analysts model this relationship.

This article first reviews frameworks previously developed by scholars for conceptualizing the economic VOI in general terms. It then illustrates how the frameworks might be used to value information from earth science data. The article seeks to fill a gap in linking previous generic research with its specific applicability to earth science from space remote sensing. Filling this gap serves two purposes. One purpose is provision of a common basis by which to conduct and evaluate studies of the value of earth science information in serving a variety of uses, from improving environmental quality to protecting public health and safety. The second is to better inform decision makers about the value of data and information. Decision makers include public officials and agencies, other consumers and producers of information (such as farmers, climate change scientists, oil companies), and the public at large. Equally importantly, public officials whose job is to invest in data acquisition and information development (including sensors and other hardware, algorithm design and software tools, and a trained labor force) wrestle with how to justify these investments. As countries consider

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their contributions to the new Global Earth Observation System of Systems (GEOSS), credibly communicating the value of earth science information is key to engaging public support as well as the support of finance ministers [3,4]. In the USA the reallocation of the space budget towards human exploration activities calls for evermore convincing discussion of the relative merit of earth science activities [5].

The next section of this paper describes the VOI framework and previous studies. The paper then assesses directions for next steps in improving understanding of the VOI obtainable from applications of earth science data to real-world resource management. The focus is on the economic value of information, which refers to many of the benefits society obtains but does not include other important benefits, such as, for example, the scientific value of better understanding Earth's geology or atmosphere.

2. Overview: the 'value' of information

VOI is essentially an outcome of choice in uncertain situations. Imagine the weather concerns of a farmer, a businessperson on her way to work, or a trucking company considering whether to place tarpaulins across the top of its trucks to protect their cargo. These individuals may be willing to pay for information depending on how uncertain they are about the weather, and on what is at stake in the event of bad weather. They may be willing to pay for additional information, or improved information, as long as the expected gain exceeds the cost of the information—inclusive of the cost of gathering and processing these data to render them useful in the particular circumstance.

More specifically, the general conclusions from models of information [6,7] are that its value largely depends on several factors, explained more fully below:

1. how uncertain decision makers are;
2. what is at stake as an outcome of their decisions;
3. how much it will cost to use the information to make decisions; and
4. the price of the next-best substitute for the information.

From (1), VOI depends on the mean and spread of uncertainty surrounding the decision in question. In a study of the use of space-derived earth science data about crop leaf areas, Harris seeks to measure the reduction enabled in the forecast error in British Sugar PLCs sugar beet yield [8]. Harris thus illustrates that VOI can be measured based on how its value changes with changes in different attributes of information. Attributes may include improved accuracy in terms of spatial, spectral, or temporal resolution, or greater frequency of collection, or other specific characteristics of the data product itself.

From (2), the value depends on the value of output in the market—that is, the aggregate value of the resources or activities that are managed, monitored, or regulated. In other words, a willingness to pay for data about crop production conditions depends in part on the value of agricultural output, while the value of earth science data about oil exploration potential is in part a function of the price of gas. More formally, willingness to pay for information is *derived* demand—demand emanating from value of the services, products, or other results that in part determine this worth. In cases where VOI pertains to non-market goods and services, output measures can also used. For instance, in the case of human health or safety, the "output" measure is typically expressed in terms of the value of a statistical life (a measure routinely used by government safety and health regulators). In cases where the information pertains to the environment, the 'output' can be expressed in terms of measures of the value of environmental quality or the value of damage avoided thanks to actions that may be taken in light of the information. In this regard, Backhaus and Beule acknowledge the difficulty of conventional cost–benefit evaluation of earth science because the data are about public goods—the environment, natural resources have no 'price' against which to measure costs and benefits [9]. As a result, Backhaus and Beule suggest surveys of users to ascertain which attributes of earth science products are most useful (more on this in Section 2.2.3).

From (3) and (4), it is important to note that there are usually substitutes for information (traditional 'windshield' surveys and aerial photography are used instead of satellite data for monitoring some types of land use, for instance). In addition, processing and interpreting data to make them usable can often be a major roadblock to realizing the value of data and information. For example, a recent US National Research Council study emphasizes the gap between raw data (the bytes or pixels) and the useable information required by users, and identifies such problems as the format of the data and whether they have been validated and verified for accuracy [10]. The report emphasizes further that most state and local decision makers lack financial, workforce, and technical (hardware and software) resources to use remote sensing data or apply tools for its interpretation and use, even though the data could prove very useful for certain types of decisions.

Sen discusses the usefulness to the energy industry of space-derived remote sensing weather information, including details such as solar irradiance and sea wind data [11]. He concludes (p. 23) "What we are really talking about here is not the value of a physical product, but the *information* it can yield (emphasis in the original). In this regard, a satellite by itself is useless without the supporting IT infrastructure to support the flow of data and make sense of it… The data, too, are useless unless they can be accessed and interpreted by people who need the information they hold."

Generally, the larger are (1) and (2), the larger is VOI. The larger are (3) and (4), the smaller is the value. These values also depend on the individual who is using the information. A decision maker usually has subjective probabilities about the quality of the information and will make use of additional information to 'update' his or her prior beliefs. (This influence on VOI—outside the scope of this article—is the widely accepted applicability of Bayesian probabilities to characterize how individuals perform this updating.)

2.1. The usual framework

A standard mathematical formulation describes these general characteristics of information. Individuals are assumed to form their own opinions about the probabilities of two states of the world, say, the simple case of 'rain' and 'no rain'. The VOI is in permitting the person to revise their estimates of these probabilities. In the cases of some of the applications currently under way in earth sciences activities, the counterparts to 'rain' and 'no rain' might be described along these lines:

Energy forecasting: the presence of solar thermal or geothermal resources compared with their absence. In this application, a possible contribution of earth science to supporting decisions is an improved toolkit with which to assess the likelihood of quantities of these resources and more accurately map their spatial distribution for the purpose of using and managing global energy resources.

Carbon management: improved modeling and measurement of the carbon cycle compared with current understanding of the cycle. Here, earth science may provide improvements that are sufficiently adequate to enable policy makers to implement an effective carbon management regime (e.g. carbon control or carbon trading).

Aviation safety: improvements in weather forecasting. Earth science may enable increased efficiency and safety of air travel.

Formally, the typical model follows this specification:

Maximize expected value: $E(y|A) = py_{A1} + (1\text{-}\ p\ )y_{A2}$
Subject to a budget constraint: $y = P_X X + P_I\ I.$

In the first equation, y is a budget, A is the state of the world (say, A_1 is crop yield if it rains; A_2 is yield if it does not rain), and p is the probability of rain. The second equation represents the limits, or budget constraint, facing the individual in spending resources to purchase, process, and use information I at price P_I and to purchase and use all other goods and services X at price P_X.

The result of the maximization calculus is that the person should buy additional information until the expected marginal gain from another piece of information is equal to its cost. Usually, this expected value is depicted to reflect the individual's attitude toward taking a risk (she can be a risk lover, or be averse to risk, or be risk neutral).

One of the best textbook examples of how this model operates is reproduced in Table 1 and Fig. 1 (this example is from [12]; see also additional discussion in [13]). Suppose

Table 1
The payoff matrix (from [7], p. 309)

Nature: decision:	Heavy rain tomorrow	No heavy rain tomorrow
A. Harvest all today	\$40,000	\$40,000
B. Harvest over two days	\$22,500	\$45,000

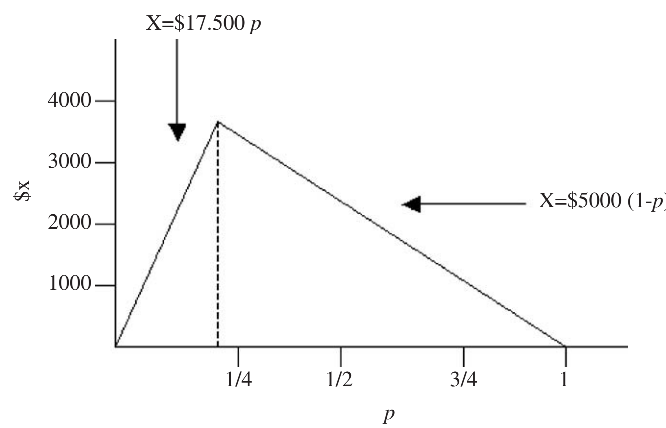

Fig. 1. Value of information (based on [12]).

a farmer can harvest his entire crop today at a cost of \$10 000 or half today, half tomorrow at a cost of \$2500 per day. The harvested crop is worth \$50 000. Table 1 indicates the 'payoff' to the farmer in the event of heavy rain. In expected-value terms, these payoffs are \$40 000 to decision A and p (\$22 500) + (1−p) (\$45 000) to decision B. If $p = 5/22.5$, then the decisions give the same payoff if the farmer is 'risk neutral'. If he were risk averse, he would want a lower value of p before he would wait to harvest.

If it is possible to forecast the weather, then p is the probability that the information the farmer receives is that there will be heavy rain tomorrow with certainty (and (1−p) is no rain, with certainty). Since it is a subjective probability, p can vary among farmers. The expected payoff with information is then

$$p(\$40\,000) + (1 - p)(\$45\,000).$$

If \$$x$ is the most the farmer would pay for information, then \$$x$ is equal to the difference between the expected payoff with information, and the expected payoff without information.

The key message is that the VOI varies with p as in Fig. 1. The value is greatest at $p = 5/22.5$ (where $\$x = \$3888$); as above, this is the p at which the farmer flips a coin. In other words, the VOI is largest when the farmer is the most uncertain. Information can thus make the biggest difference here. The VOI is zero at $p = 0$ and $p = 1$, since, at these extremes, the farmer is already certain in his own mind whether it is going to rain, and information is extraneous (even if the farmer is wrong).

Applications of the model can show the effects of changing the amount or quality of information as well as subsequent revisions that the individual may make of the probability (the Bayesian updating referred to earlier).

Revisiting the overview in this section, then, the implications for VOI from this approach are as follows:

Information is without value

- when individual's beliefs are at extremes ($p = 0$ or $p = 1$);
- when there are no costs associated with making the wrong decision;
- when there are no actions that can be taken in light of the information.

Information has less value

- when individual's beliefs are close to extremes;
- when the costs of making the wrong decision are low;
- when actions to take are very limited.

Information has the most value

- the more indifferent is the decision maker among her alternatives (she flips a coin);
- the larger are the costs of making the wrong decision;
- the more responsive are the actions that can be taken.

These implications explain the plight of many populations in developing countries: even if severe-weather forecasts were more accurate, in many cases there are few actions that can be taken in light of the information. They also account for the well-documented incentive for people in the USA to build homes along floodplains: even if these are better mapped, the costs of making the wrong decision can be low, mitigated by US federal flood insurance.

It is important to note that information cannot only influence probability but also inform the decision maker by affecting his expected value of the harvest based on information about crop quality and other conditions *unrelated* to the probability of rain. For example, the choice of whether to harvest may be influenced by information about crop health, irrespective of the probability of rain. A slightly more complex specification of the mathematical model that makes these relationships explicit is in [14].

From this discussion, ultimately a decision maker must process a host of information into a decision that reflects assessment of the probabilities of various outcomes. To the extent that information alters a priori probabilities (the likelihood of rain) or improves understanding of the choices themselves (the quality of the harvest) and allows individuals to make better decisions, information is a resource that has economic value.

In applying the model, government agencies may or may not be able to express their budget constraint formally, but most will certainly be able to describe the resources they save, the productivity they gain, or the reallocation of resources from other activities (the X) to the space-derived information (the I). All of these are suitable approximations for the values reflected in the model.

2.2. Previous studies

Studies of the VOI have a long and far-ranging history that brings a wealth of examples with which to extend approaches for earth science applications. Analysts studying the value of earth science information have used some but not all of these techniques; accordingly, the next sections inventory these approaches. The studies fall into three types of models: econometric estimation of output or productivity gains thanks to information; hedonic price studies; and contingent valuation surveys.

2.2.1. VOI measured by gains in output or productivity

Most of the early VOI studies focused on the topic of the value of weather information for agricultural production and management. Johnson and Holt note 20 such studies dating from the 1960s onwards, including applications to bud damage and loss; haymaking; irrigation frequency; production of peas, grain, soybeans and grapes (raisins); fed beef; wool; and fruit [15]. More recently, Adams and co-authors observed changes in crop yields associated with phases of the El Niño-southern oscillation (ENSO) and used the market value of the yield differences to estimate the commercial value of the ENSO phenomenon [16]. Other studies include [17–22]. Some studies use a times series of the behavior of commodity prices in futures markets to infer weather-related values. Two examples are Roll, who studied orange juice futures [23], and Bradford and Kelejian, who studied stock prices of wheat [24]. Changes in futures and stock prices following weather predictions over time are taken as measures of the value of the forecast.

Additional studies have encompassed a wide variety of other topics, ranging from the effects of weather forecasts on the decision to use tarpaulins in the trucking industry [25] to the effects of information about differences in oil prices on petrol demand in urban areas [26] and the problem of risk assessment by insurers. A classic discussion of this extensive literature is in [27]. Other recent studies focus on the value of space-derived data for natural disasters [28,29], geomagnetic storm forecasts [30], geologic maps [31] and deforestation in the Brazilian Amazon [32]. The latest detailed applications of VOI are to studies of the information role played by the internet; for example, how consumers' ability to obtain information through the internet and shop online influences prices charged for goods and services [33].

The approaches used range from highly sophisticated econometric studies and detailed simulation models to less detailed, 'back-of-the-envelope' estimates. Given abundant information—for example, the large amounts of data on crop yields, rainfall, and crop prices in the case of agricultural production—researchers can undertake rich statistical analyses. The typical study of the value of weather information for agriculture compares expected farm profits under average but uncertain weather patterns with profits that might be expected if rain could be accurately forecast. In other topic areas, too few data may be available and the studies tend to be anecdotal.

All the studies start from the basis of the contribution of information to the value of output, as pointed out above. Many of the socioeconomic benefits described in current earth science programs are based on a similar approach: they multiply the total value of output, at-risk assets, and other aggregate activity by an estimated percentage by which the activity may be affected by earth science "information outputs." For instance, the total annual benefit to the electric utility industry of better forecasts of hot and cold weather is a basis benchmark for measuring the incremental contributions of earth science outputs. Preparedness for disaster management can use the total value of loss to life and property associated with natural disasters as a basis benchmark.

In a review of studies that have followed this approach, Nordhaus notes ([1], p. 3):

> All of the studies I know of the value of perfect information find its value to be on the order of one percent of the value of output. For example…one study found that if you halve the standard error of precipitation and temperature, say from one percent to one-half percent, or one degree to one-half a degree, you get an improvement in the value of the output on the order of 2 percent of the value of wheat production. A study of cotton gave the same order of magnitude. I have looked at a number of studies in the area of nuclear power and energy, trying to determine the value of knowing whether nuclear power is ever going to pan out. Again, perfect information is worth on the order of one percent of the value of the output.

Roll reaches similar conclusions in his study of the effect of weather information on the behavior of futures markets for orange juice and the effect of weather information on these markets, finding that "there is a puzzle in the orange juice futures market. Even though weather is the most obvious and significant influence on the orange crop, weather surprises explain only a small fraction of the observed variability in futures prices" [23].

If conclusions such as these are borne out, then compared with the value of the final product, whether measured as the value of production or capitalized into futures prices, the incremental gain from information appears to be small. But of course, in industries where the value of output is in the billions of dollars, a small percentage of a large number is a large number for the value of information.

Many observers wonder why the values are not larger. This observation is illustrated in an editorial by a former administrator of the National Oceanic and Atmospheric Administration, quoted in the introduction [2]. His conclusion might be easier after the fact ("If only I had known"). It is much more difficult to arrive at such a conclusion before the fact, however. Some of the reasons why relate to the four characteristics of information in Section 2: using information can be costly, and there are often good substitutes for different kinds of information at lower cost. In general, it is only *ex ante*—before the event—that we are willing to pay for information, because afterward it is less important. Indeed, the *ex ante*, or expected value, is what experts agree determines the value of information, as in the model described earlier. If the probability of an event is either very unlikely or very likely, or if the actions that can be taken to avert its effects are minimal, then this value can be quite low.

In addition, VOI can be reduced after second- and third-order effects, or repercussions, formally known as the dynamic responses. For instance, in the case of agricultural production, increased output brought about by better weather information can cause crop prices to fall, thereby resulting in a decline in the value of output and a decline in the VOI for the industry (although of course, consumers would benefit from the lower prices).

2.2.2. *Hedonic pricing studies*

Another large literature has not yet been applied to earth science but may prove useful. These studies date from the 1970s and use wages and housing prices to infer the value of weather information, under the hypothesis that it is capitalized into the prices of such goods and services. These studies are premised on hedonic price theory, by which researchers model the market for a commodity and then infer the value of specific characteristics of the commodity.

Rosen's study is among the seminal theoretical and empirical research that considers the extent to which differences in wages among workers in different cities (in a given set of occupations) reflect differences in urban quality of life [35]. He considers not only personal characteristics influencing wages, such as education and age, but also measures of urban amenities and disamenities. These 'quality-of-life' factors include pollution (water pollution, particulates, sulfur dioxide, inversion events), the crime rate, crowding (population density, population size, central city density), market conditions (unemployment rate, population growth), and climate (number of rainy and sunny days, number of extremely hot days). He expects higher wages in cities with disamenities compared with nicer cities, and this compensating differential is expected to work in the opposite direction for urban amenities: a city with pleasant weather, for example, may not have to offer higher-than-average wages to attract workers and may even be able to offer lower wages. Rosen finds that climate variables are statistically significant in the expected directions. Wage rates are higher, for instance, in cities with rainy or extremely hot weather.

In a study of housing prices Blomquist and co-authors estimate differences in inter-urban quality-of-life measures using households' monthly housing expenditures (rent for tenants, imputed rent for homeowners) and measures of climate, environmental quality, crime, and other variables [36]. The climate measures include precipitation, humidity, heating degree-days, cooling degree-days, wind speed, and sunshine. All the climate variables are found to be statistically significant determinants of housing expenditure, with an inverse correlation between expenditure and precipitation, humidity, and heating and cooling degree-days and a positive correlation between expenditure, wind, and sunshine.

Blomquist and co-authors also include wages in their study and combine the housing expenditure and wage data in a model that estimates the "full implicit price" of urban area quality-of-life variables. They find negative prices (that is, a marginal net disamenity) for precipitation, humidity, heating and cooling degree-days, and wind speed.

Hedonic approaches to valuing amenities are not without problems of data availability, modeling assumptions, and econometric issues. Freeman surveys and critiques the methodology of most of the studies to date linking wages and housing prices with environmental amenities [37]. Nonetheless, extending the approaches to include not only average temperatures but also, say, weather variability could enable the models to more closely proxy the VOI associated with weather forecasting.

In addition, the hedonic methods could be used to identify the most useful attributes of data. To illustrate, Ausubel [38] shows the influence of the accuracy of data, based on a statistical measure of accuracy, the standard deviation, on the value of a weather forecast (see Fig. 2). The shape of the curve plotted in that figure shows important information for a decision maker who must decide how to invest in a new system, say, if the goal is "better data." At an accuracy level of a 2-degree or 2 inch error, the graph shows that the value of the forecast is quite low. Unless the new system can do better in terms of data accuracy, it may not be worth the investment.

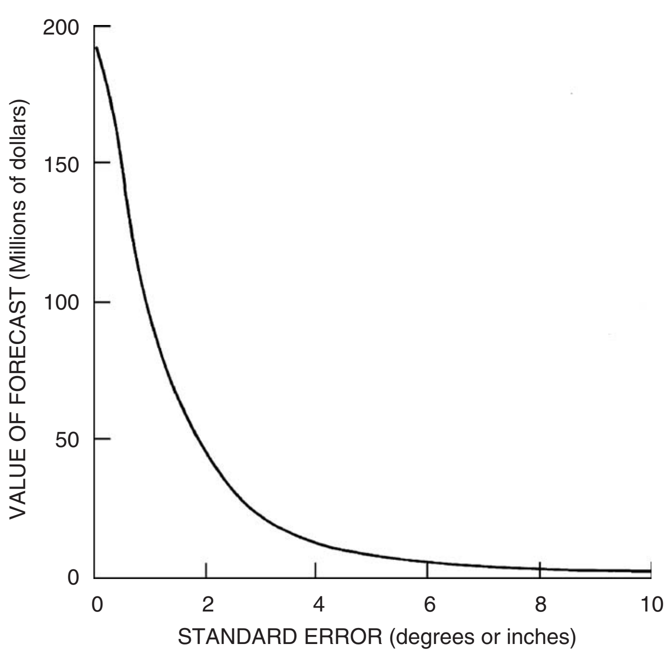

Fig. 2. The value of information and its characteristics ([38]).

In similar spirit, Nelson and Winter use an expected value approach to show which attributes of a forecast, such as spatial coverage, accuracy in degrees or inches, or frequency of updating, matter most to the trucking industry [25]. These authors do not use hedonic techniques but their data could be amenable to these techniques because the writers focus on attributes of the data—their accuracy (standard deviation) and other specific characteristics. As noted earlier, Harris [8] identifies data characteristics—specifically, measures of accuracy—in his study of the value of space data in producing British sugar beet.

3. Further applications to space-derived earth science

This section illustrates approaches for future in-depth study, review, and application. The purpose of the VOI studies would be to better understand, explain, and where possible assess the cost-effectiveness of assimilation and operational use of earth science data and science results.

Linking the application of earth science to services provided for the public—the situation of space-derived earth science in most countries—means that demand for applications tools is derived demand—that is, demand derived from government requirements to fulfill responsibilities. A critical challenge in this case is separating progress toward objectives from the impact of external factors, since the objectives of many government programs are the result of complex political decisions outside the program's control. It may also be the case that a tool designed for a specific government project may be orphaned if the project is canceled. In a narrow sense the usefulness of earth science applications is thus critically dependent on other government policies for public health and safety, the environment, and natural resources.

Table 2 outlines a set of questions that might be asked of government offices to document the value of earth science outputs or information as they implement a hypothetical mandate to monitor invasive plant species. The questions ask what difference the earth science contribution has made in improving the ability of the office to carry out its tasks more productively or achieve its goals. A key to credible responses from agencies is the criterion underlying contingent valuation (CV) in Section 2. The aim is to ascertain what agencies would be willing to pay to use the outputs: what do the outputs save or enable, what would an agency do *without* the outputs, and how much more would it cost or how much less effective would the results be? That is, rather than saying, "The earth science contribution is terrific!" the agency's response should be, "Because of the earth science contribution, we have saved x amount of money and improved implementation of our mission by y."

Table 2
Enabling and improving human health and environmental protection: a *Hypothetical* earth science application for monitoring invasive plant species

(a) Benchmark: cost factors		(b) Benchmark: allocation of costs	(c) Earth science contribution to cost reduction	(d) Enabled cost reduction$ millions/ year
Data collection In situ $20 million/year				
	Access	80%	↓ 5% to 8%	$0.8–1.28
	Routine measurement	5%		
	Frequency of measurement	5%	↓ 20% to 25%	$0.2–0.25
	Quality	10%		
Remote $10 million/year				
Validation and verification $.05 million/year				
Data analysis $15 million/ year				
	Interpretation	80%		
	Forecast, prediction	15%	↓ 3% to 8%	$.07–0.2
	Quality control	5%		

Note: All entries are fictional.

Table 3
"Impact" or "socioeconomic benefit" measures based on earth science VOI: a stylized description

(1) Agency mandate: save lives, protect environment, improve agricultural competitiveness, etc.
→ (2a) Range of values of agency cost of DSS to implement (1).
(3a) Range of values of savings or productivity gains due to earth science data By way of DSS.
(4a) Rough estimate of VOI (subtract (3a) from (2a) and express as a range, with associated contingencies/uncertainties/caveats described).
_Toc104259113OR_Toc104259113
→ (2b) Range of size of benefit due to earth science via DSS in implementing (1).
(3b) Rough estimate of VOI (weight (multiply) (2b) by relevant base value).

Examples*:*
Aviation safety
Benefits per year (estimates of lives saved) enabled by earth science data: y to z lives/year.
Implied earth science "VOI": y to z multiplied by federal value of statistical life ($/year).
Agricultural competitiveness
Value of output: $$x$/year.
Improvement in output due to earth science data via DSS: y to z%/year.
Implied earth science "VOI": product of $$x$ and y to z%/ year.

NOTE: DSS is "decision support system," or the computer models and other tools that make use of earth science data.

In the illustration in Table 2 it is assumed in column (a) that data to monitor invasive plants can be collected *in situ* at a cost of $20 million/year, or remotely for $10 million/year. In addition, quality control (validation and verification) costs $0.05 million/year and analysis to render the data useful information (transforming the pixels into useful information) costs $15 million/year. In column (b), for collecting the data, 80% of the cost is to access the location of the invasive plants, and the other 20% is spread across the costs of making a measurement, how frequently the measurements are made, and other quality dimensions of the data. For the category of data analysis, the costs are spread among interpretation, prediction, and validation and verification. With this explicit list of cost categories, the potential VOI of a new sensor for data on invasive species becomes clearer. In other words, if the space earth science community says that it can design a new sensor to enable cost reductions in some of these cost factors as shown as a percentage in column (c), the cost savings enabled by the space-derived data are as in column (d). These potential cost savings can be used by the decision maker in comparing the cost of the sensor with these savings to decide if the investment is justified. The virtue of a table such as that illustrated here is to make explicit the exact nature of the improvement in the VOI that will be offered by, say, a new sensor.

Table 3 suggests steps to take to identify and measure the most difficult but most salient performance measure, 'socioeconomic benefit'. These steps follow the VOI model in Section 2. In the table, an agency is assumed to have a mandate such as to save lives or to improve agricultural productivity. In order to use most data, the agency typically will employ a 'decision support tool', often a computer model or other framework. (In the USA, for example, the Department of Energy has a large model called The National Energy Modeling System, the Environmental Protection Agency has numerous air quality models, and the weather service has many forecast models.) The VOI from the data is, then, the difference between the model results with and without the earth science data. Table 3 lists examples for aviation safety, where the VOI is related to lives saved, and agricultural competitiveness, where the VOI is related to the value of farm production. As an actual example, in the case of renewable energy forecasting, the US space agency NASA identifies the potential percentage cost savings in energy forecasts carried out by the US Department of Energy and expected to be enabled by earth science outputs, then multiplies these savings by the forecasted value of the output of the relevant energy industries to project dollar benefits (see [39]).

4. Conclusions

This paper has reviewed models and studies of the VOI and offered preliminary observations about using these approaches to design and implement measures of performance for earth science activities.

The state of the art in understanding the VOI reflects general agreement on how to model an individual's or a government's decision and some useful implications about the value of information: when it is most and least valuable, its relationship to subjective prior opinions, and the decision maker's ability to take action in light of the information. The VOI can be nil if, say, a decision maker cannot take action even if good information is available. The VOI can be quite large if the decision maker can take action—saving lives, increasing productivity, and so forth. Most estimates of the VOI suggest that it is not large as a percentage of final output (in agriculture, road transportation, and other markets). This result seems inconsistent with some perspectives of the value of information, such as information on natural disasters and loss of life. But in these cases, the *ex ante* and *ex post* values of information need to be distinguished; in some instances, people's prior beliefs about the low probability of hazards figure prominently in reducing the perceived value of the information. Finally, consideration must be given to the costs of actions that could be taken, or not taken, in anticipation of and in response to the information. The paper has reviewed generic models of information and suggested several approaches for analysts to use in systematically assessing the VOI from space-derived earth science.

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