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Bayesian framework for assessing the value of scientific space systems: Value of information approach with application to earth science spacecraft

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ABSTRACT

Space systems play an important role in today's society by generating or transmitting information from source to sink(s). The acquisition of the space system is often justified by the type, quantity and quality of information provided or transmitted. This work posits that the value of a class of space systems derives from and can be assessed through the value of information these systems provide. To this effect, a Bayesian framework is developed to assess system value in which systems are viewed as information sources, and stakeholders as information recipients. Information has value to stakeholders as it helps to update their beliefs, enabling them to make decisions that can yield higher expected pay-offs than in the absence of information. This increase in expected pay-offs is ascribed to the value of the system. Based on this idea, a new metric, *Value-of-Design* (*VOD*), is introduced to quantify the value of a class of space systems with unpriced services. The Bayesian framework assesses the *Value-of-Design* for the space system by considering the impact of the information transmitted on the actions taken by stakeholders, and estimating the resulting pay-offs from these actions. The framework here developed is then applied to the case of an Earth Science satellite that provides hurricane information to oil rig operators in the Gulf of Mexico. Probability models of stakeholders' beliefs, and economic models of pay-offs are developed and integrated with a spacecraft design tool. Results from the application point to clusters of payload instruments that yielded higher information value, and minimum information thresholds below which it is difficult to justify the acquisition of the system. Additionally, the system is analyzed in *Cost-VOD* trade space to provide program managers with additional insights into the coupling of a system's predicted value generation and its associated lifecycle cost.

1. Introduction

In 1958, the National Aeronautics and Space Act established the National Aeronautics and Space Administration (NASA) with one of NASA's key mandates being to advance the civil space program. Under this Act, the newly established agency was directed to focus on the "expansion of human knowledge of the Earth and of phenomena in the atmosphere and in space" [1]. The agency was tasked with identifying and executing space missions based on scientific merit so as to increase the knowledge of the scientific community, and subsequently, of society at large. The Act thus established a knowledge and information driven agency. The 2011 annual report of

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the Aerospace Advisory Safety Board stated, "one overarching and fundamental purpose of NASA is to create knowledge…[and] ensuring that this knowledge is captured and available to future generations is more than an obligation, it is a sacred trust" [2]. The premise of this work, that NASA is a knowledge generation agency, is thus well established and acknowledged. However, limited considerations have been given to assessing and articulating the value of the knowledge created and the linkages between knowledge generation in the scientific community, and their trickle-down effect and applications to society at large. In the past (and present) space system selection and linkages to knowledge generation were conducted using multi-criteria decision making techniques. System engineers were tasked with identifying a set of optimal design vectors that satisfies multiple conflicting objectives simultaneously; one of these criteria being the knowledge generated. The practice of systematically pinpointing this optimal set is known as vectorial optimization, and a wide array of concepts and methodologies have been developed that enables engineers to solve these optimization problems. While these methodologies offer a structured approach for decision-making in space system design and analysis, these methodologies indirectly, and at times obscurely, link the attributes of the space system to the societal value of knowledge generated by the space system.

In recent years, political and economic conditions led to calls for providing a sharper definition to this linkage and a better articulation of the value of the knowledge generated and the value of the space missions proposed. Ascribing social benefits to the data collected by space-borne scientific instruments is receiving greater attention as program managers are asked to justify space missions based in part on the relevance of the missions' resulting information products and the potential applications enabled to the wider society. In fact, as early as 1992, the imperative to provide a definitive link between the generation of scientific knowledge and the societal applications is evident in reports on setting priorities in space-based research. In 1992, the National Academies Space Studies Board noted "the collection of data, the creation of information through its analysis, and the subsequent development of insight and understanding should be key governing objectives for scientific research in space" [3]. The Space Studies Board further noted in the report "it behooves scientists seeking public support to demonstrate to the public and its representatives that the fruits of scientific research do indeed enhance the quality of life and the welfare of the nation's citizens" [3]. From these two statements, one can infer that as early as 1992, there was a desire to articulate the value of space missions and explicitly link the information generated from space-based research to societal benefits. More recently in 2007, NASA, the National Oceanic and Atmospheric Administration (NOAA), and the US Geological Survey (USGS) commissioned a report, *Earth Science and Applications from Space: National Imperatives for the Next Decade and Beyond*, to identify flight missions that should be deemed high priority over the next decade [4]. Part of the impetus for this report is the desire to create a strategic plan for space missions that support national needs for research and monitoring of Earth's ecological, atmospheric and geological systems. Eight criteria were identified as being critical to executing a successful space based national strategy in earth science. Two of the criteria applicable to this research are the "contribution to applications and policy making" and "affordability (cost considerations, either total costs for missions or costs per year)". The first criterion explicitly calls for identifying the linkage between advancements in scientific knowledge and societal benefits, while the second criterion recognizes the need for fiscal responsibility. One important corollary of this discussion is that if NASA is fundamentally a knowledge generation agency, then analyzing the value of knowledge generated should be a key imperative in the planning and execution of space missions.

Effectively, reports on setting priorities for space based research, such as that by the Space Studies Board and the Earth Science and Applications decadal report, called for a stronger emphasis on the assessment of the value of spacecraft and how scientific knowledge generated by said systems may be leveraged by the greater society. In doing so, these reports implicitly conceptualized scientific spacecraft as value delivery artifacts, and proposed that their value ought to be articulated and assessed. When the services provided by a system are priced in a given market (e.g., transponders on-board communication satellites leased or rented), the value of the system as seen from its owner or principal can be assessed through traditional discounted cash flow techniques such as the calculation of its Net Present Value [5]. Such a value analysis however is not feasible for a class of systems whose services are unpriced (no cash inflow) such as scientific spacecraft. In short, there is on the one hand an increased emphasis on the need to assess and articulate the value of scientific spacecraft, and on the other hand, traditional valuation techniques are not applicable to this class of systems. To address this challenge, we propose in this work that the value of such spacecraft derives from the value of information they provide.[1] To this effect, we develop a Bayesian framework to assess system value in which spacecraft are viewed as information sources, and stakeholders as information recipients. Information has value to stakeholders as it helps to update their beliefs, enabling them to make decisions that can yield higher expected pay-offs than in the absence of information. This increase in expected pay-offs is ascribed to the value of the system. The remainder of this work further develops this idea, provides an analytic framework for capturing the value of information provided, and applies it to the case of an Earth science spacecraft. Section 2 discusses the various definitions of information in an engineering context and provides a definition of information for space system design and acquisition. Section 3 develops a theoretical framework using Bayesian updating for

[1] Although we acknowledge space systems provide several distinctive value flows to a variety of stakeholders (see Refs. [4,6]) with each flow being an important component in the value generation of space systems, we focus in this work on the value of information provided by the system.

assessing the value of space systems considered in this work. Section 4 applies the Bayesian framework to an Earth science spacecraft and offers a detailed description of the stakeholder's belief models and economic pay-off models. Section 5 discusses the design implications emerging from the Bayesian framework and an analysis of the system in the *Cost-Value* trade space to guide system design decisions. Section 6 concludes this work.

2. Defining information

Information stems from the Latin *informatio* meaning to communicate or impart an idea or conception through instruction and teaching [7–9]. The Oxford English Dictionary defines information as knowledge communicated concerning some particular fact, subject or event [7]. Understanding these general definitions of a word is useful to understanding its usage, as important elements are often drawn from the root and colloquial meanings of the word to construct a more precise definition within the relevant theoretical framework. For example, the etymology of information indicates that information may be thought of as a "flow", transmitted from one entity, the source, to another, the recipient. From this commonality, more specific definitions of information are derived, each having different implications for the usage of the word.

In the context of engineering, some of the earliest attempts at defining information may be traced to the field of communications, and the necessity to solve various communication problems. In their seminal book on the mathematical theory of communication, Weaver and Shannon identified three levels of communication problems [10], the technical problems, the semantic problems, and the effectiveness problems. Technical problems deal with the question of how accurately the message is transferred from source to sink. Thus, when defining information the only aspect of interest for these types of communication problems is the accuracy of information (or data) transference from source to the sink. Semantic problems attempt to assess how well a transmitted message conveys its intended meaning. Thus the semantic problems are not necessarily concerned with the accurate transference of information, but the interpretation of this information by the recipient. Effectiveness problems are concerned with the level of success with which the message conveyed leads the recipient to take the desired action. Similar to semantic problems, effectiveness problems are concerned with the meaning of the conveyed message to the recipient. Based on these types of communications problems, taxonomically, the definitions of information may be divided into two categories, statistical and pragmatic definitions; these are discussed next.

2.1. Statistical definitions of information

Statistical definitions of information are primarily concerned with the accuracy with which data is transmitted from the source to the sink. These definitions have two distinctive characteristics. The first is the separation of the meaning of the message to the recipient from the accuracy of the received message from the sender. For statistical definitions, the level of information content of the message is defined based on the degree of accuracy of the transmitted message from source to sink. Traditionally, incorporation of the meaning of information for technical problems (e.g., designing a communication subsystem) is considered "irrelevant to the engineering problem", and reduces the tractability of quantifying information [10–12]. Thus, the semantic properties of information are considered to be independent of the information itself for definitional purposes. Second, statistical definitions of information are theoretical in nature often based on probability theory. Notable statistical definitions include the Shannon entropy definition, Fisher information definition, Blackwell informativeness and Kullback–Leibler divergence definition [13–15]. Given these two characteristics, statistical definitions and their resulting metrics are concerned with the technical and theoretical properties of the data transmitted such as accuracy and coherence [16].

2.2. Pragmatic definitions of information

Unlike statistical definitions of information, pragmatic definitions are concerned with the semantic properties of the information, and are developed to address the last problem identified by Weaver and Shannon (1949), effectiveness problems. There are two distinctive characteristics of pragmatic definitions that separate them from statistical definitions. The first is the connectivity of information to the recipients. These definitions are semantic in nature and states that information is dependent on the recipients, that is, information stems from the interpretation and meaning of the message to the recipients [17,18]. The second characteristic captures the linkage between information and the impact on decision-making. Pragmatic information increases the knowledge of the recipient, and in doing so, results in recipients selecting a desired course of action. Unlike statistical definitions, which are concerned with only the mathematical properties of the message containing the information, pragmatic definitions are concerned with properties of the information such as timeliness and relevance to recipients [16].

2.3. Definition of information in space systems design and acquisition

Although it can be argued that no definition is wrong, some definitions are more useful and suited than others for specific objectives, and for the purposes of this work, the pragmatic definition of information is more relevant. However, as one may have surmised from the discussion on the pragmatic definitions of information, obtaining a functional definition may be difficult. For example, how does one quantify the meaning of the message to different recipients? For this reason, the pragmatic definitions of information are here augmented with a Bayesian construct. One important purpose of information is the transformation of recipients' knowledge base. Suppose at any moment, potential recipients have a certain belief about the states of the environment, such as whether it will rain on a given day. By obtaining information, the recipients will update their belief about these states, for example update their belief about the occurrence of rain on the given day. From a Bayesian construct, probability is used to quantify rational degrees of belief [19]. Thus, for the purposes of this work information is defined as "any stimulus that has changed the recipient's knowledge, that is, that has changed the recipient's probability distribution over a well-described set of states." [16].

3. A Bayesian framework for the valuation of space systems

Once information is defined, it is possible to develop a Bayesian framework for assessing the value of the information the space system provides the stakeholder. Underlying the framework is the premise that the space system is an information provider (i.e., source) and the stakeholder an information recipient (i.e., sink). In particular, the information from the space system has value as it aids the stakeholder in addressing a decision problem. This decision problem is expressed as a problem of selecting a course of action from a set of possible courses of action that may be taken [20]. To solve this decision problem, three sets of variables are introduced. The first is the set of all possible actions available to the stakeholder, which will be denoted hereafter as **A.** The second set of variables is the possible outcomes, or set of pay-offs, from taking a particular course of action. This set of pay-offs is denoted **Π**. The outcome variables provide the incentive for the stakeholder to select a course of action and are critical elements in solving the decision problem. The third set of variables is the environmental state variables and is denoted as **S**. The environment is defined as a set of factors that are beyond the control of the stakeholder but impacts the pay-off from the taken course of action [20]. Intuitively, one can understand why information is important to solving this decision problem. From modern economic theory, information is viewed as a major factor in decision-making, which reduces uncertainty or aids in correcting misconceptions about the possible states of the environment, where stakeholders' beliefs about environmental states are modeled using probability. Thus the set of information products (IP_j) provided by the space system j (denoted D_j) enables stakeholders to update their beliefs about the occurrence of environmental states and, in doing so, stakeholders make decisions that may yield higher expected pay-offs than in the absence of information. The Bayesian framework integrates the set information products provided by the space system, $IP(D_j)$, with these three inputs (set of actions (**A**), set of state variables (**S**), and set of outcomes (**Π**)), and ascribes the increases in expected pay-offs as a result of the information products provided to the value of the system. The framework here developed is illustrated in Fig. 1.

The Bayesian framework is articulated in the following manner. Consider a stakeholder faced with a decision problem of selecting a course of action from the action space, **A**. This action space is represented by the central box in Fig. 1. For simplicity, it is assumed that the action space contains the complete set of actions that the stakeholder may take, and these actions are both discrete and countable. Next, assume that uncertainty is captured by a number of scenarios. In this world, a number of scenarios or environmental states (s_1, s_2, s_3, ..., s_m) may occur. For simplicity, these states are also assumed to be both discrete and countable. The stakeholder will select a course of action based on his/her belief about the

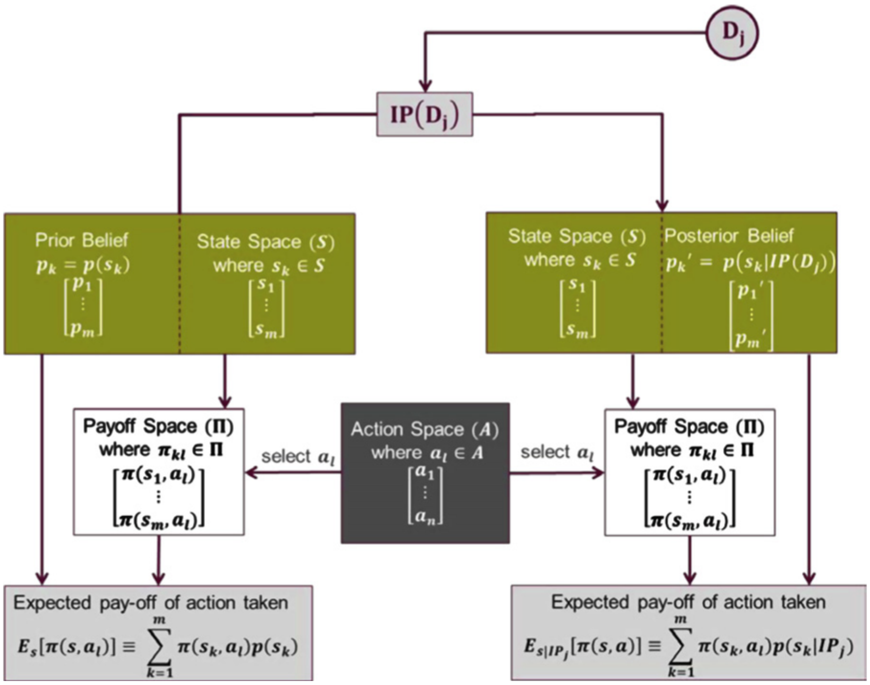


Fig. 1. Bayesian framework for the valuation of unpriced space systems.

probable occurrence of these states. Using a Bayesian construct, the stakeholder's belief about the occurrence of each state can be represented by a probability mass function (p_1, p_2, p_3, …, p_m) where

$$p_k = p(s_k) \tag{1}$$

The state space and probability mass function are represented by the top left box in Fig. 1. The stakeholder will make a decision by selecting a course of action ($a_l \in \mathbf{A}$). If state s_k occurs, the stakeholder will desire to select an action that maximizes the pay-off (or minimizes cost) (π)

$$\pi(a^* | s_k) = \max_a \pi(a | s_k) \tag{2}$$

However, the stakeholder does not know which state will occur before selecting the course of action. In other words, the stakeholder is faced with making a decision under uncertainty. For any given course of action ($a_l \in \mathbf{A}$), there are a number of possible pay-offs to the stakeholder depending on which scenario materializes. The set of possible pay-offs for the selected action as shown in Fig. 1 may be represented as

$$\pi_l = \begin{bmatrix} \pi(s_1, a_l) \\ \vdots \\ \pi(s_m, a_l) \end{bmatrix} \tag{3}$$

Under uncertainty, the stakeholder requires an objective function by which to evaluate alternative courses of action. The objective function will enable the stakeholder to rank and select the preferred courses of action. A number of objective functions are available for defining "preferred" and for ranking different options. One common objective function is the expected pay-off. For each course of action, the expected pay-off weights each possible payoff by the probability that the pay-off occurs. For example, the expected pay-off from choosing the course of action a_l in the discrete case treated here is given by

$$E_s[\pi(s, a_l)] \equiv \sum_{k=1}^{m} \pi(s_k, a_l) p(s_k) \tag{4}$$

Defining the objective function as the expected pay-off allows for the definition of an action rule for the stakeholder (rational consistency). If the stakeholder wishes to maximize the expected pay-off, then the action rule will be to select the course of action that maximizes the expected pay-off

$$\max_a \; E_s[\pi(s, a)] \equiv \max_a \sum_{k=1}^{m} \pi(s_k, a) p(s_k) \tag{5}$$

Having discussed the left-hand side of Fig. 1, we now proceed to its right-hand side, which models the impact of the information product generated by the spacecraft on the beliefs of stakeholders, and propagates this impact to changes in expected pay-offs to the stakeholders. Consider for example the space system (D_j) in the upper right corner of Fig. 1. This system acts as an information source to the stakeholder by generating a set of information products, $IP(D_j)$ or simply IP_j, which the stakeholder utilizes to update his/her current beliefs. For example, an Earth science space system may provide geomorphologic information to scientists allowing them to update their belief about the occurrence of a volcanic explosion, and better handle this risk and mitigate economic and human losses. Based on the set of information products (IP_j), the stakeholder possesses new beliefs about the occurrence of each environmental state as shown in the top right box in Fig. 1. These updated beliefs may be represented by the probability mass function (p'_1, p'_2, p'_3, …, p'_m) where

$$p'_k = p(s_k | IP_j) \tag{6}$$

As the stakeholder's belief about the probable occurrence of these states is updated, the expected pay-off for each course of action will also be updated:

$$E_{s|IP_j}[\pi(s, a_l)] \equiv \sum_{k=1}^{m} \pi(s_k, a_l) p(s_k | IP_j) \tag{7}$$

In updating the expected pay-off for each course of action, the action rule is modified as follows:

$$\max_a E_{s|IP_j}[\pi(s, a)] \equiv \max_a \sum_{k=1}^{m} \pi(s_k, a) p(s_k | IP_j) \tag{8}$$

The stakeholder selects the course of action that maximizes the new expected pay-off based on information obtained from the space system. It is well established that information is important as decisions made in its presence increases the expected pay-off to, or modifies the risk exposure of, stakeholders relative to decisions made in the absence of information [16,21]. Thus, the value of having that information may be assessed in part as the difference in expected pay-offs between these two cases.[2] As a result, the value of the information provided by the space system to the stakeholder, hereafter referred to more succinctly as the value of the design (VOD_j), may be expressed as

$$VOD_j = \max_a E_{s|IP_j}[\pi(s, a)] - \max_a E_s[\pi(s, a)] \tag{9}$$

This theoretical framework can be integrated into the conceptual design stage of the space system acquisition process, particularly for Earth science satellites, to aid program managers and engineers in making design and acquisition decisions, and/or to help articulate the value of said systems to decision-makers and the public. The following section illustrates one possible application of this Bayesian framework to the case of an Earth science spacecraft. Highlighted are the steps for operationalizing this framework, the insights that can be gleaned from its application, and the challenges it raises.

4. Application of Bayesian framework to earth science satellites

In this section, the Bayesian framework is applied to a space system design problem for a proposed environmental monitoring mission. It is expected that the data gathered from this mission, when integrated with current weather prediction models, will yield increased accuracy

[2] The modification of risk exposure as a component of the value of information is left as an important direction for future research.

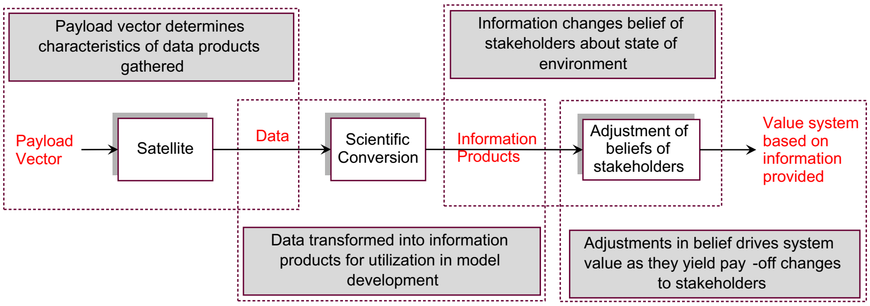


Fig. 2. Operationalizing the Bayesian framework.

in forecasting severe weather events such as hurricanes and flash floods. The objective is to value inform selection given the environmental information to be provided by different candidate designs. The Bayesian framework is operationalized and applied to the Earth science application using the process shown in Fig. 2.

Operationalizing the Bayesian framework involves the four steps shown in Fig. 2: data product generation, scientific conversion, adjustment in beliefs, and estimation of the value of information. The purpose of the data product generation step is twofold. First, this step identifies a set of system design candidates, which are likely to satisfy mission requirements. Second, after the set of system design candidates are determined, this step also evaluates the type, quality and quantity of the data products provided by each design. In the second step, scientific conversion, the data products are converted into useful information products for the stakeholder (hereafter we assume one stakeholder for simplicity and illustrative purposes). More specifically, this step determines what information products, or improvements in information products, may be generated from the data products provided by each system design. The third step, adjustment in stakeholder's beliefs, assesses how the stakeholder utilizes the new or improved information product to adjust his beliefs about the possible occurrence of the states of his environment. Specifically, this step assesses the change in the probability distribution of the occurrence of the environmental states. The final step in operationalizing the Bayesian framework, the value of information estimation, involves four components. First, the set of possible actions the stakeholder may take in response to his environment has to be defined. Second, a pay-off scheme is devised which reflects the consequences of taking a particular course of action. Third, an action rule is constructed which guides the course of action taken. Finally, the value of the information provided by the space system may be determined based on the difference between the expected pay-off achieved in the presence of the new or improved information product, and the expected pay-off achieved in the absence of the new or improved information product. The steps for operationalization of the Bayesian framework are briefly presented to orient the reader as the process is applied to the selection of an Earth science satellite which aids in hurricane predictions. Greater detail is provided on each of these steps in the context of the example mission, and the design and acquisition implications of the proposed Bayesian valuation framework are discussed.

Table 1
Candidate system designs.

Instrument	D_1	D_2	D_3	D_4	D_5	D_6	D_7
X_1	1	0	0	1	1	0	1
X_2	0	1	0	1	0	1	1
X_3	0	0	1	0	1	1	1

4.1. Data product generation

The generation of data products depends on the scientific instruments in the payload vector of the space system. As such, for illustrative purposes in this analysis, we consider for this environmental mission three hypothetical instruments, X_1, X_2 and X_3.[3] Given the three instruments, a set of seven system designs are considered with the instrument suite of each system design comprising some combination of the three instruments. The designs are defined as shown in Table 1.

In Table 1, the instrument X_i is modeled as an indicator variable, where $X_i = 1$ indicates the presence of instrument X_i in the payload vector of system design D_j, and $X_i = 0$ is the absence of the instrument in the payload vector. *For example, design D_5 includes only X_1 and X_3*. From each instrument, a set of data products is generated. Instrument X_1 generates data about cloud imagery and near-surface wind vectors over global oceans. Instrument X_2 gathers data for the construction of atmospheric temperature profiles, as well as the temperature profiles of clouds. Instrument X_3 measures atmospheric water content, cloud liquid as well as provide cloud imagery. Based on its payload vector, each system design is mapped to a set of data products. The mapping of the payload vector to data products is assumed to be linear, that is, no data products emerged from the presence of an additional instrument on board which could not be obtained by at least one of the instruments in the payload vector. This assumption can be easily modified to accommodate synergetic instruments.

[3] Examples of instruments that these hypothetical instruments represent include imagers, sounders, microwave spectrometers and microwave scatterometers to name a few [22–26].

Table 2
Examples of data products provided by system designs.

Data products	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Real time imagery	1	0	1	1	1	1	1
Temperature profiles	0	1	0	1	0	1	1
Moisture profiles	0	0	1	0	1	1	1
Sea surface temperature	0	1	0	1	0	1	1
Wind speed	1	0	0	1	1	0	1

Examples of the data products generated by each system are given in Table 2. Similar to Table 1, a value of one in the system design (D_j) columns indicate that system design generates the corresponding data product and a value of zero indicates the data product is not generated.

4.2. Scientific conversion of data products

The data products when integrated into weather prediction models aid in improving the accuracy of those models. Examples of the information products related to hurricane forecasting that utilizes the generated data products include the forecast error, the hurricane intensity, and the strike probability. For illustrative purposes, we focus in this work on the forecast error. The forecast error is defined based on the deviation of the hurricane from its predicted path at a given point in time. The National Hurricane Center utilizes the types of data products given in Table 2 to predict the position or track of the hurricane's center at 12-h intervals up to 48-h, and 24-h intervals up to 120-h. The conversion of these data products to forecast hurricane tracks involves some degree of subjective judgment as well as quantitative analysis [27]. Thus, in addition to providing the forecast track of the hurricane at given points in time, the National Hurricane Center also provides a historical distribution of the forecast error. Mathematically, the forecast error of a given hurricane computed using Cartesian coordinates is as follows [28]:

$$FE^T = \sqrt{[(x_a - x_p)^2 + (y_a - y_p)^2]} \tag{10}$$

where FE^T is the forecast error at a certain point in time (e.g., 48 h), and $[x_a, y_a]$ and $[x_p, y_p]$ are the actual and forecast positions of the hurricane, respectively, at time T. Data on the 48 h forecast error over the last 5 years (2006–2010) is shown in Fig. 3 [28].

The cumulative distribution of the forecast error describes the percentage of forecast error that falls below a certain level. To facilitate automated analysis, the probability distribution of the forecast error is modeled using a lognormal distribution with parameters μ_0 and σ_0^2, where μ_0 and σ_0^2 are the mean and variance of the natural logarithm of the forecast error, ln (FE^{48}), respectively. Based on this distribution, the probability density function for the forecast error is given as

$$f(fe^{48}|\mu_0,\sigma_0) = (e^{-(\ln(fe^{48})-\mu_0)^2/2\sigma_0^2})/(fe^{48}\sqrt{2\pi\sigma_0^2}) \tag{11}$$

where the parameters μ_0 and σ_0^2 of the lognormal distribution are related to the mean, m_0, and variance, v_0, of the forecast error (FE^{48}) as follows [29]:

$$m_0 = e^{\mu_0+\sigma_0^2/2}.$$

$$v_0 = e^{2\mu_0+\sigma_0^2}(e^{\sigma_0^2}-1). \tag{12}$$

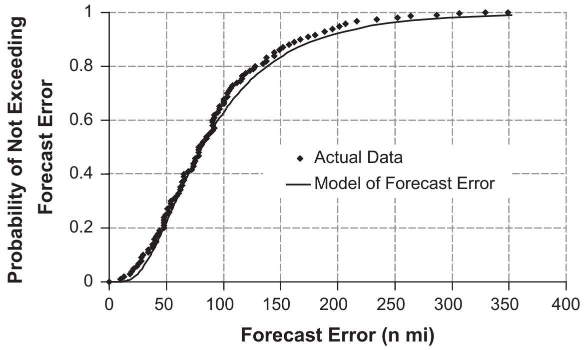


Fig. 3. Cumulative distribution of 5-year forecast error (Atlantic Basin).

The mean forecast error, m_0, is determined to be approximately 99 nmi while the variance, v_0, of the forecast error is calculated to be approximately 69^2 nmi^2. This yielded parameter values of μ_0 equals 4.4 and σ_0^2 equals 0.4.

The definition and model of the forecast error provide a benchmark against which improvements in the information product supported by the spacecraft can be assessed. The type and magnitude of the improvements may be determined using subject matter experts who possess detailed knowledge of how the information products are generated from their data components. For this analysis, the improvement in the forecast error is modeled as a percentage reduction (r_j) in the mean forecast error, that is, the space system provides data, which in turn improves the accuracy of hurricane forecasting. The variance of the forecast error is assumed to be unchanged. The updated mean and variance of the forecast error based on the information products from a space system with design D_j are described as follows:

$$m_j = (1-r_j) \times m_0, \quad r_j \in [0,1], \tag{13}$$

$$v_j = v_0. \tag{14}$$

Determining the reduction in the mean forecast error is a complex process due the various uncertainties associated with converting data products into improvements in information products. Examples of these uncertainties include uncertainty in the quality of data products generated, and uncertainty in quantifying how the data products impact the information product. For each system design, the improvement in the information product is assumed to be uniformly distributed between the ranges as shown in Table 3.

Once the mapping of the data product to improvements in the information is completed, the next step in operationalizing the Bayesian framework is to determine how these improvements affect the stakeholder's belief about the probable states of the environment.

Table 3
Reduction in forecast error from system design.

Reduction	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Mean	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Max	0.2	0.3	0.4	0.5	0.6	0.7	0.8
Min	0.0	0.1	0.2	0.3	0.4	0.5	0.6

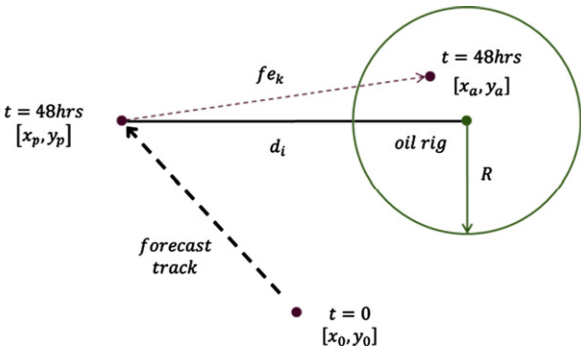


Fig. 4. Oil rig in strike zone. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

4.3. Adjustment in stakeholder's belief

For this application, the stakeholder of interest will be an oil rig operator in the Gulf of Mexico. There are two relevant environmental states to the oil rig operator as related to hurricane forecasting: (1) the oil rig is in the hurricane strike zone, and (2) the oil rig is not in the hurricane strike zone. Based on the size of a typical hurricane, the strike zone is defined as an area swept out by a radial line of length 62.5 nmi with the center of the hurricane as the focus of the circular area [30]. For the purposes of this analysis, this scenario may be stated as follows: given the distance of the hurricane from the oil rig is forecasted to be d_i, the oil rig will be in the strike zone if the hurricane deviates from its forecasted track such that it passes within 62.5 nmi of the oil rig. This scenario is shown in Fig. 4 with the red dots representing the hurricane.

From the formulation of this problem, it is possible to assess the probability of the oil rig being in the strike zone based on the probability distribution of the forecast error. The National Hurricane Center provided data about the absolute forecast error but did not indicate any directional tendency. As such, it is assumed that if the hurricane deviated by a distance fe_k from its original path, this deviation can occur randomly (without bias) in any direction. For a given deviation between fe_k and fe_{k+1},[4] the hurricane will be located in a circular band, with the center of this circular band being the predicted location of the hurricane. If this circular band intersects the strike zone, the probability a hurricane, which deviated between fe_k and fe_{k+1}, is in the strike zone is proportional to fraction of the circular band intersecting the strike zone area. For simplicity, this area of intersection is termed *AI*. The area, *AI*, is a function of the radius of the strike zone, *R*, the forecast deviations, fe_k and fe_{k+1}, and is derived from basic geometric relations. Based on the area of intersection, the probability of the oil rig being in the strike zone is given by

$$\Pr\{SZ|H,d_i\}_j = \sum_{k=0}^{N} \frac{AI}{2\pi(fe_{k+1}^2 - fe_k^2)} \left[erf\left(\frac{\ln(fe_{k+1}) - \mu_j}{\sqrt{2\sigma_j{}^2}} \right) - erf\left(\frac{\ln(fe_k) - \mu_j}{\sqrt{2\sigma_j{}^2}} \right) \right], \tag{15}$$

$$fe_0 = \begin{cases} 0, & d_i < R, \\ d_i - R, & d_i \geq R, \end{cases} \tag{16}$$

$$fe_{k+1} = fe_k + \Delta d, \tag{17}$$

$$N = \begin{cases} \frac{R+d_i}{\Delta d} & d_i < R, \\ \frac{2R}{\Delta d} & d_i \geq R, \end{cases} \tag{18}$$

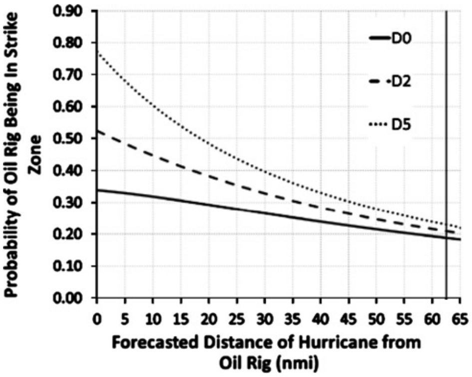
where Δd is the incremental increase in the forecast track error, and μ_j and σ_j are respectively the mean and variance of the lognormal of the forecast error based on information from system design D_j. Fig. 5 illustrates the likelihood that the oil rig is in the strike zone given the hurricane's forecasted track is a distance (d_i) from the oil rig. Two panels are presented in Fig. 5, each with a different scale that enables the reader to easily ascertain the probability of being in the strike given the forecasted distance.

In Fig. 5 the probability estimation based on the current data provided by the National Hurricane Center is indicated by D_0. The updated probability estimation given the information provided by system designs are shown for only two systems, D_2 and D_5. For example, if the hurricane is forecasted to pass a distance of 30 nmi from the oil rig, Fig. 5 indicates that there is a 40% probability that the oil rig will actually be in the strike zone based on information obtained from system D_5. Likewise, if the hurricane is forecasted to pass a distance of 90 nmi from the oil rig, the figure indicates there is an 8% probability that the oil rig will actually be in the strike zone based on information obtained from system D_5. In the figure, the black line demarcates 62.5 nmi from the oil rig.

4.4. Value of information estimation

To the oil rig operator, hurricane forecasts are important as forecasts guide decisions or actions, and these actions have important consequences, financial and other. For the oil rig operator, the action space consists of two possible actions. Once a hurricane is expected to be within the region of the oil rig, the operator must decide whether to shut down or continue operations. This is not a trivial decision, as shutting down operations will lead to loss income (or the income that the oil rig operator forfeited in shutting down operations) and evacuation

[4] fe_{k+1} and fe_k are possible values of the forecast error at time $t=0$ separated by a distance Δd. The relationship between fe_{k+1} and fe_k is defined in Eq. (17).



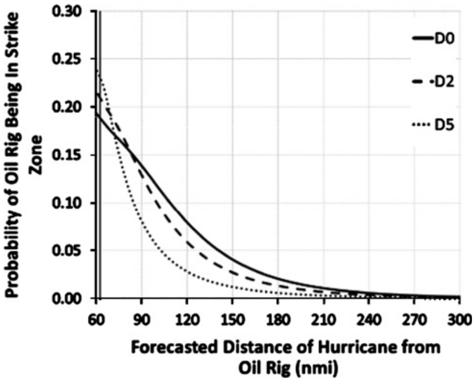


Fig. 5. Probability of oil rig being in strike zone.

Table 4
Summary of costs used in example.

Evacuation costs (C_e)	\$25,182
Loss income (C_l)	\$266,047
Value of life (C_v)[a]	\$5,418,000

[a] The value of life is obtained from Ref. [33], adjusted for inflation and scaled to reflect the value of lives lost should the oil rig be hit by a hurricane. This illustrative example assumes 50 workers are lost if a hurricane hits the oil rig.

costs, while continued operations may lead to loss lives if the oil rig is struck by a hurricane. Guidance for these various costs are obtained from a number of sources including the Energy Information Administration and National Ocean Industries Association [31–33]. A summary of these costs is shown in Table 4.

The action taken by the oil rig operator will be guided by some objective function. It is assumed that the objective of the operator is to minimize the expected costs associated with responding to the hurricane forecast. For example, should the operator decide to shut down operations in the event of a hurricane, the company will incur an expected cost given by

$$E[C_e+C_l|H,d_i,IP_j]=[C_e+C_l]\Pr\{SZ|H,d_i,IP_j\} +[C_e+C_l]\,[1-\Pr\{SZ|H,d_i,IP_j\}], \tag{19}$$

where C_e and C_l indicates evacuation costs and loss income respectively, H indicates the expected presence of a hurricane in the Gulf of Mexico, d_i is the forecasted distance of the hurricane from the oil rig, SZ indicates the oil rig is in the strike zone and IP_j is the information product enabled by D_j upon which the probability estimates are based. In the event of a hurricane and the operator decides not to shut down operations, the company can expect to incur costs of

$$E[C_v|H,d_i,IP_j]=[C_v]\Pr\{SZ|H,d_i,IP_j\}, \tag{20}$$

with C_v being the value of lives lost. The expected cost associated with each action is utilized to formulate an action rule. The decision to shut down ($a=1$) is discrete and dependent on the relative magnitudes of the expected cost of shutting and the expected cost of continued operations

$$\begin{aligned} a&=0 \quad \text{if } E[C_e+C_l|H,d_i,IP_j]>E[C_v|H,d_i,IP_j],\\ a&=1 \quad \text{if } E[C_e+C_l|H,d_i,IP_j]\le E[C_v|H,d_i,IP_j]. \end{aligned} \tag{21}$$

The oil rig operator chooses to shut down if the expected cost of shutting down does not exceed the expected cost of continued operations. Otherwise, the operator continues operating ($a=0$). The value of information provided by the system design D_j given a hurricane is expected to hit the Gulf of Mexico is the cost savings to the stakeholder based on current data provided by the National Hurricane Center (i.e., information provided by D_0) and the updated information product provided by system design, D_j. Mathematically, this is given by

$$\begin{aligned} VOI_j=&\min\{E[C_e+C_l|H,d_i,IP_0],\ E[C_v|H,d_i,IP_0]\}\\ &-\min\{E[C_e+C_l|H,d_i,IP_j],\ E[C_v|H,d_i,IP_j]\}. \end{aligned} \tag{22}$$

Finally, assuming the forecast distance of a hurricane from the oil rig is uniformly distributed between 0 nmi and 300 nmi, the value of the system design based on the value of the information it provides the stakeholder in the expected presence of a hurricane may be determined as follows:

$$VOD_j=E_d[VOI_j|H,IP_j]. \tag{23}$$

The quantitative models presented in operationalizing the Bayesian framework are fed into a simulation environment. This simulation environment utilizes a Monte Carlo approach to propagate the aforementioned uncertainty in the information product to uncertainty in the value of the design. The simulation environment outputs an estimate of the probability mass function of VOD_j for each system design. The results from the simulation process are utilized to understand the design and value implications of each system design to the stakeholder. These value and design implications are discussed in the next section.

5. Results and analysis

The purpose of this section is to illustrate how value-informed decision-making for unpriced systems is enabled by the Bayesian framework in Fig. 1. The results from the simulation environment are visualized and the system design and acquisition implications of the framework are analyzed.

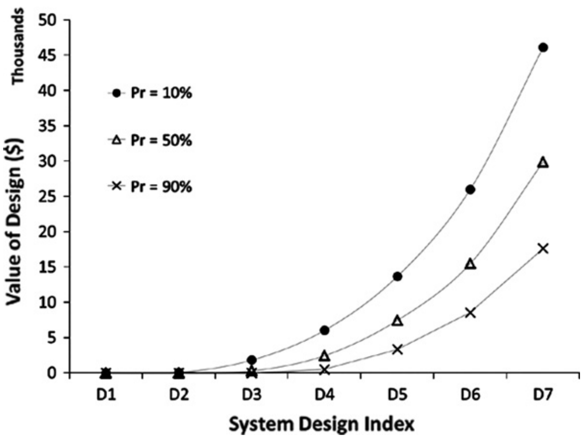


Fig. 6. Value of system design to an oil rig operator.

5.1. Value contours and design selection

The results from the simulation are displayed in Fig. 6. For each system design considered, the value of the design to the stakeholder (in this case, the oil rig operator; if multiple stakeholders are considered, the results can be cumulated accordingly) is given in the form of a complementary cumulative distribution function, with the contours representing the probability (pr) that the value of the design meets or exceeds some level, l.[5] Formally, the contours are be defined as

$$p(VOD_j \geq l) = pr. \tag{24}$$

Displayed as the complementary cumulative distribution function, the data provided in Fig. 6 may be interpreted in a number of ways. First, the figure informs engineers of the value generating capability of a given system. Consider system design five (D_5) and the probability contour

$$p(VOD_j \geq l) = 10\%. \tag{25}$$

The data from Fig. 6 indicates that there is a 10% probability that value of system design D_5 to the oil rig operator is greater than \$13,700. Phrased differently, the acquisition of system design D_5 has a 10% probability of providing at least a \$13,700 reduction in expected costs to one oil rig operator in the Gulf of Mexico given a hurricane is predicted to enter the Gulf of Mexico. Assume there are roughly 4000 oil rigs in the Gulf of Mexico, this system represents an expected total cost savings of at least \$54.8 million dollars to operators in the event of a hurricane. Consider another probability contour

$$p(VOD_j \geq l) = 90\%. \tag{26}$$

Fig. 6 indicates that there is a 90% probability that the cost savings to one oil rig operator for a single oil rig from the acquisition of D_5 is \$3356. Thus, there is a high degree of certainty that the acquisition of D_5 will provide over \$3000 in savings to the oil rig operator based on a single oil rig if a hurricane is expected. Furthermore, if this analysis is extended to consider not just a single oil rig or oil rig operator, but the total number of oil rig operators, the size of each operator's fleet, the expected number of hurricanes per year and the number of years each oil rig operates, it quickly becomes evident that the total cost savings to oil rig operators in the Gulf of Mexico can be substantial and on the order of a few hundred million dollars. An alternative interpretation of the data in Fig. 6 may be formulated in the context of multiple systems. Suppose engineers are interested in designing a system that meets or exceeds a certain value performance. For this illustration, assume that the value performance is a cost saving of \$10,000 associated with a single oil rig or as shown in the equation

$$p(VOD_j \geq \$10{,}000) = pr. \tag{27}$$

From Fig. 6, it is evident that system designs D_1 through D_4 are highly unlikely to meet the requirements, as the probability of these four designs meeting the cost savings requirements is less than 10%. While there is a greater probability of system design D_5 meeting these requirements, the probability is still relatively low at 30%. System design D_6 has the capability to meet the requirements with an 80% probability and system design D_7 with a probability greater than 90%. In this application, engineers are able to link the acquisition of the space system to the probable pay-offs (in this case the cost savings) to the stakeholder. Motivated by the national imperatives for space based earth science applications, these results demonstrate that this Bayesian framework provides a sharper definition of the linkage between the scientific data provided by the space system and the societal benefits provided to stakeholders.

Equally important to the interpretation of the data in Fig. 6 are the design inferences that may be drawn. The Bayesian framework indicates that there are system designs that provide information of no value to the oil rig operator. In particular, these are system designs D_1 and D_2, with system design D_3 providing information of marginal value to the oil rig operator. The ability of a system to generate valuable information products or valuable improvements in the information products is based primarily on its instrument suite. Recall from Table 1 that system design D_1 through system design D_3 has an instrument suite consisting of a single instrument. The low value of information provided by these three systems indicates that the data products generated by the individual instruments are not sufficient to result in valuable improvements in the information products. It is only when combined with other instruments that the pooled data products generated results in valuable improvements in information products. Thus the Bayesian framework allows the engineer to identify clusters of system designs or regions in the design space that offer the greatest value to stakeholders.

5.2. Integrating cost considerations

The previous discussion explored the information value that the space system generates for a stakeholder. However,

[5] VOD_j is the value of the system design to the oil rig operator given the expected presence of a hurricane in the Gulf of Mexico. For brevity, this full description of VOD_j will be shortened to simply the value of design when discussing the results.

system designs will rarely be selected solely on value (as defined and estimated here). Incorporating the lifecycle cost into system decision-making is critical as program managers are constrained by budgets. It is important for the program manager to understand the cost implications of acquiring a system that provides the required value performance. For this analysis, the cost of system designs D_1 through D_7 were estimated by: (1) determining the weight of the instrument suite based on representative instruments that could constitute the payload, (2) estimating the spacecraft dry weight parametrically based on the payload weight, and (3) estimating the cost of the system using the NASA Spacecraft Level cost model that takes spacecraft dry weight as an input [22–26,34,36]. Launch vehicle and operations costs were estimated using parametric cost estimating relationships based on the spacecraft dry weight and the NASA Mission Operations cost model [35,36]. The resulting lifecycle cost (LCC_j) of the system design is shown in Table 5.

The process of integrating cost considerations into the Bayesian value analysis is performed for all seven system designs with the results for each design shown in Fig. 7.

Fig. 7 displays the *Cost-VoD* trade space. In the figure, the VoD_j is plotted on the ordinate and the LCC_j on the abscissa. The black dots indicate the mean VoD_j for system D_j while the black bars indicate the range, bounded by the 10 percentile and the 90 percentile, within which the system value is likely to fall.

Note in the figure systems D_1 and D_2 are not present as these two systems offer no value to the stakeholder under consideration. The cost dynamic leads to interesting dynamics in the *Cost-VoD* trade space. For instance, although system D_6 has a higher mean value of design than systems D_4 and D_5, it provides this value at a lower lifecycle cost. Even when considering the uncertainty in the value of design, there is an 87% likelihood that D_6 outperforms D_5, and greater than a 95% likelihood that D_6 outperforms D_4.

Table 5
Lifecycle costs.

System Design	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Lifecycle cost ($Mil)	696	403	377	959	882	617	1096

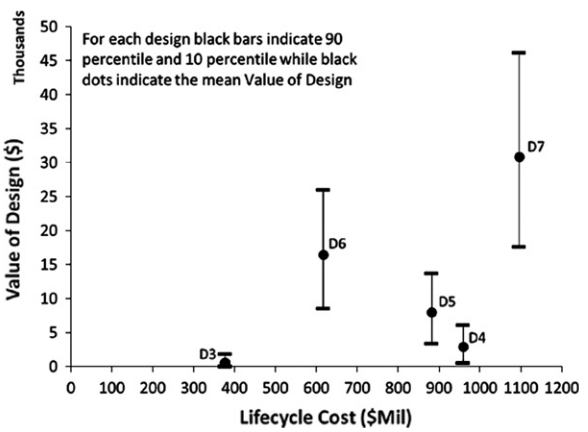


Fig. 7. *Cost-VoD* trade space.

Thus, it may be concluded that a rational decision-maker who prefers higher design value and lower lifecycle cost would be incline to select system design D_6 over system designs D_4 and D_5. This idea of vectorial optimization (i.e., there are two or more objective functions that the decision-maker wishes to optimize) points to the concept of Pareto optimality. Under Pareto optimality, a system dominated in both objectives by another system is eliminated from consideration. In this case, systems D_4 and D_5 are both dominated by system D_6 for both the value and cost objectives, and therefore eliminated from further consideration.

While it may be possible to articulate a definitive preference for D_6 over D_4 and D_5 based on the information in Fig. 7, ranking systems D_3, D_6, and D_7 in order of preference is more complicated. System D_3 provides a lower value than all other systems but at the lowest lifecycle cost. System D_7 provides the greatest value to the stakeholder of all systems but will incur the highest lifecycle costs. In fact, there is an 88% likelihood that system D_7 will outperform D_6, and greater than a 99% probability that D_6 will outperform D_3. From visualizing the *Cost-VoD* trade space through Fig. 7, the program manager is able to reduce the design space and select a set of designs for further consideration by identifying those designs for which is not possible to reduce lifecycle without an accompanying reduction in the value of design. Under the concept of Pareto optimality, these non-dominated system designs are termed Pareto optimal designs. As shown in Fig. 7, the set of Pareto optimal designs consists of D_3, D_6 and D_7. Further reduction in the design space will depend on additional factors such as budget constraints and minimum value requirements.

6. Conclusion

In recent years, the space studies board advocated for a strong linkage between the societal benefits of a space system and the technical attributes of the system. Motivated by the decadal survey, program managers often justify space missions based on the information the system is expected to provide stakeholders. In this work, a quantitative Bayesian theoretical framework is developed for the valuation of a particular class of space systems based on the value of the information they provide to stakeholders. This Bayesian framework is premised on the fact that a space system is an information provider (source) and the stakeholder an information recipient (sink), and the value of the space system stems from, and can be assessed through the value of the information it provides to stakeholders. The Bayesian analysis here proposed and developed is important for two purposes. First, during the down-selection process the Bayesian framework helps to identify system designs for further consideration and eliminate design options, which offers limited value for stakeholders. Second after system acquisition, the Bayesian analysis can help articulate the value of the system to the public, lawmakers, and other non-technical decision-makers.

Although, the Bayesian framework presented herein offers engineers and program managers a theoretical basis for quantitatively linking the scientific information provided by the space system to the broader societal applications engendered, there are a few limitations to this work, which constitute fruitful avenues for further research. These limitations include the following: (1) the Bayesian framework as described should not be applied to the valuation of information that simply updates the belief of the stakeholder with no immediate apparent pay-offs or costs, (2) the information gathered by the space systems may not reduce uncertainty but lead to a modification of risk expectations, making an assessment of information value through the marginal increase in expected pay-off difficult, (3) establishing the posterior probability distribution of the occurrence of the environmental states may be problematic, and (4) selection of time horizons and discount rates, although directed by guidelines, remains subjective to some extent. Thus, future avenues of research will focus on extending Bayesian framework to assess not only the value of the pragmatic information (i.e., actionable information) provided by the system, but also the value of the statistical information, (i.e., information that only changes the rational beliefs of the stakeholder) gained from the space system; and developing appropriate pay-off functions when a modification of risk expectations in the stakeholder's beliefs occur. Other important extensions of this research may come in two areas. The first area is the applicability of the framework to the valuation of flexibility. An increasingly important innovation in the design of space systems is system flexibility. In design, flexibility may be thought of as the ability of the system to adapt to a changing environment such that the performance of the system is improved relative to a non-adapted system. This framework may be extended to measure the value of this design feature by assessing the marginal increase in information value due to a flexible design using the traditional design as the baseline. The second extension of the framework considers the multi-stakeholder nature of space systems. Evaluation of multiple stakeholders increases the complexity of system design and acquisition decisions as increases in benefits to one stakeholder may come at a cost to another stakeholder. Each stakeholder receives a unique value flow from the space system depending on the probable environmental factors, the system technical attributes and the stakeholder's objectives. Greater research is needed in understanding multi-stakeholder issues in the space system acquisition and design and, how to articulate design solutions in such stakeholder environments.

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