Surveying the landscape of approaches to assessing societal benefits of Earth science information

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## Introduction

In recent decades, remotely sensed information about the state of our planet has become increasingly vital for understanding and addressing global challenges such as climate change, water resource management, biodiversity conservation, sustainable development, and public health (4). Rapid technological progress has led to widespread availability of Earth science information (ESI), comprising global or regional datasets from remote sensing (e.g., satellite hyperspectral imagery, aerial drone photography, in-situ sensor networks) as well as models founded on such data (e.g., climate forecast models, famine early warning systems), at increasingly detailed and nearly continuous spatial and temporal coverage of the planet’s surface (REFS). These advances in the availability and sophistication of ESI have accelerated its application across a wide range of decision contexts (5), supporting societal benefits as varied as impeding transmission of polio in Nigeria (Borowitz et al. 2023), protecting blue whales in the Eastern Pacific (6), improving targeting of cash transfers to poor villages in sub-Saharan Africa (7, 8), and empowering indigenous communities to monitor deforestation (9). However, while the contribution of ESI to such societal benefits is undeniable, the magnitude of this contribution attributable to ESI is rarely assessed. In other words, how different would the outcome have been in the absence of ESI?

This gap is due in part to the separation of Earth system science from social and decision sciences, and further compounded by a lack of integrated valuation frameworks that can span different value domains. Understanding the magnitude of societal benefit of ESI, i.e., the value of practical application that goes beyond the scientific merit of the data and data products (1), is important for guiding and justifying investment in future missions, enhancing public support, incentivizing ESI uptake, and ensuring that science and policy goals are well aligned.

The mechanism by which ESI, indeed any information, generates value is through its ability to improve decision making toward socially desirable outcomes, by reducing uncertainty in the decision context and thus reducing the likelihood of making a sub-optimal decision. Economic frameworks to quantify the value of information typically calculate the difference in expected outcome of a decision made in a world with the information and the decision made in a world without that information. Such value of information models have played a critical role in demonstrating ESI’s potential to improve instrumental societal outcomes [(10); others?]. However, not all societal values can be so readily quantified in instrumental terms.

Inclusive and pluralistic value systems that go beyond instrumental value have long been a topic of discussion in conservation science and sustainable development (e.g., (11–14)). The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) Values Assessment (15), a multi-year effort by scores of experts in diverse forms of valuation, identified three categories of value that reflect the ways in which nature and ecosystems are important for people: instrumental (value as a means to satisfying specific human needs or interests), intrinsic (value independent of reference of people as valuers, inherent moral value), and relational (value deriving from meaningful, just, and reciprocal relationships with people and nature, toward living a “good life”) (16). While the IPBES assessment focused on value types and valuation methods in the context of ecosystem services, we can expand these considerations to examine values related to our relationship with Earth systems as observed through ESI. Failing to capture potential gains related to non-instrumental values risks greatly underestimating the contribution of ESI to societal benefits.

One of the main tools for measuring instrumental value is decision analytic value of information models, but these models are less suitable for capturing the pluralistic ways in which ESI can contribute to intrinsic and relational values such as sustainability, justice, and human well-being (17). Other valuation methods can account for instrumental and non-instrumental values alike by eliciting individual and societal preferences for goods and services through strategies across quantitative, qualitative, and mixed-methods approaches (e.g., market price, stated/revealed preference, surveys, interviews, focus groups) (18). While these methods are commonly used for valuation of goods and services, they can also be leveraged to estimate the value of information in cases where they are used to account for the value of the differential outcome between a decision made with ESI relative to the decision made without.

In this study, we ask four questions: To what degree have various valuation methods been used to evaluate the societal value of ESI? Which types of value (instrumental, intrinsic, relational) do these methods capture, and how are these values articulated? How are qualitative, quantitative, and mixed-method approaches distributed across sectors and use cases? And finally, what opportunities exist to develop more inclusive, systematic, and interdisciplinary approaches to ESI valuation? To address these questions, we develop a systematic map of the peer reviewed literature by querying two literature databases (Scopus and Web of Science) and a curated library of ESI valuation literature, the [USGS Joint Societal Benefits of Earth Observation Digital Library](https://doi.sciencebase.gov/hd/#/geo-value?p=0&l=50&yearMin=1863&yearMax=2024) (hereafter, Societal Benefits Library or SBL) (USGS 2024 REF) using a search string that included three facets: (1) Application of ESI (2) within a decision context (3) whose outcome translated into some societal benefit (See SI XXX for search string). The resulting citations were screened for relevance with assistance of machine learning tools to identify studies where a valuation method was used to compare the difference in value between a decision made using ESI relative to the decision made using some other information source. By addressing these questions through a systematic map of the peer-reviewed literature across a wide range of disciplines, we aim to clarify the current landscape of ESI valuation, identify methodological and disciplinary gaps, highlight emerging practices, and point toward a more pluralistic and actionable valuation framework. Our goal is to ensure that investments in Earth observations not only expand scientific understanding but also deliver equitable and measurable benefits across diverse communities and decision contexts.

## Results

### Screening Process

Application of the search string (see SI XXX) to the Scopus and Web of Science databases, combined with references from the SBL, resulted in 28,331 papers. Pre-screening to eliminate conference abstracts, spurious matches, duplicates, and incomplete records resulted in 13,823 unique citations (See Fig. XXX and SXXX) that were then subjected to screening. In brief, screening criteria consisted of: 1) the study made substantive use of ESI; 2) the ESI was applied in a decision context; 3) the predicted or realized outcome of an ESI-based decision was compared to the predicted or realized outcome of the decision under an alternative information set; and 4) the difference in outcome was translated into some measure of societal benefit. Reviews and studies not published in English were excluded. Through a machine-learning assisted title/abstract screening process, 770 documents were identified for full text screening, resulting in 170 documents that met all criteria (see Fig. XXX and SXXX).

### Valuation Methods

Across the 170 included documents we observed 224 instances of valuation methods (i.e., 54 studies included two methods). The most common approaches to assessing societal benefits of ESI in the literature were quantitative economic approaches: Value of Information (VOI) methods (n = 81; 48% of papers) and Cost-Benefit Analysis (CBA) (n = 33; 19%) (Fig. 1; see Table SXXX for operational definitions used to categorize valuation methods). Applied qualitative or subjective methods were also frequently observed, including surveys of preference assessments (n = 26; 15%) and semi-structured or in-depth interviews (n = 23; 14%). Deliberative and consensus-based approaches were rare (X and Y studies, respectively). Methods based on decision analysis (n = 144) were more frequently observed than methods based on preference elicitation (n = 80)

Figure 1. Number of valuation methods observed across included studies. Some studies applied multiple methods for valuation, thus the total number of methods (224) exceeds the total number of studies (170). Color indicates value types used to assess societal benefits: instrumental, i.e., means to an end, and relational, i.e., deriving from meaningful and often reciprocal relationships among people, nature, and society (see Table XXX).

These methods most commonly measured societal benefits in terms of instrumental values (e.g., improved profit, pollution reduction, lives saved) (n = 209), often accounting for multiple instrumental metrics simultaneously (e.g., reduced crop pesticide application and the associated increase in profit; see Table SXXX for definitions and examples in included corpus). Methods that measured societal benefits as relational values (e.g., poverty alleviation, social justice, knowledge transfer among community, Table SXXX) were far less common in the literature (n = 15) and were studied more frequently using qualitative preference elicitation methods, especially surveys, interviews, and focus groups. Relational values were rarely the sole focus of an assessment, but rather were typically examined alongside instrumental values; for example, recreational fishing both as a pastime and as an economic activity (19). No studies in our resulting corpus evaluated ESI outcomes in terms of intrinsic value.

Studies that were coded as implementing multiple methods (n = 54) most commonly combined two decision-analytic methods, particularly VOI with CBA (n = 12) (Fig. 4). For example, Fritz et al. (2) apply the counterfactual framework of VOI to estimate benefit, then model marginal cost based on CBA to construct their benefit chain model for valuing ESI from hypothetical satellite remote sensing data. Another common pairing combined qualitative preference elicitation methods of individual interviews and focus groups (n = 8). For example, Roberts et al. (20) used focus groups/workshops to qualitatively predict the value of forecast information for avoiding storm-related drownings in Lake Victoria, then after implementation of a severe weather warning system, followed with user interviews to quantify the realized benefits in lives saved. Of the remaining 34 multiple-method studies, 14 combined VOI with some other method (excluding VOI + CBA) and 16 combined surveys with some other method (excluding VOI + survey). Paired quantitative methods were more common (n = 26) than paired qualitative (n = 16) and mixed methods (n = 12). Most of the mixed methods studies combined surveys with some quantitative method (n = 8).

Figure 2. Number of papers applying multiple approaches to valuing ESI. The quadrants and colors at each intersection indicate which value types were examined; the size of the quad rants indicate how many papers examined that value type. The number in the bottom left quadrant indicates the total number of papers that implemented the combination of methods. The majority of papers did not use a combination of methods.

### Societal Benefit Domains

Across the 170 included studies we observed societal benefits in 215 contexts (i.e., 45 studies examined societal benefits in multiple contexts). Studies largely focused on the societal benefits of ESI within agriculture, including fisheries and forestry (n = 78, 46% of studies). A smaller but still substantial number of studies examined benefits across multiple contexts (n = 27, 16%), climate (n = 25, 15%), water resources (n = 22, 13%), and ecological conservation (n = 22, 13%) (Fig. 5). Societal benefits were least frequently examined in contexts of disaster response (n = 9, 5%), health and air quality (n = 8, 5%), and wildfires (n = 6, 4%). Two studies focused on ESI benefits in other areas: one for monitoring pavement infrastructure (21), and one for assessing preferences for living and recreating in disturbed landscapes (22).

Figure 3. Number of studies investigating value of information in different societal benefit areas (combined GEOSS Societal Benefit Areas and NASA Applied Sciences themes). Some studies examined more than one societal benefit area, thus the total number of contexts (215) exceeds the total number of studies (170). “(various)” indicates studies where three or more societal benefit areas were discussed; “(other)” indicates studies where the societal benefit did not fit into any of these categories. Color indicates value types used to assess societal benefits: instrumental, i.e., means to an end, and relational, i.e., deriving from meaningful and often reciprocal relationships among people, nature, and society (see Table XXX).

Studies that valued ESI across multiple benefit areas (n = 45) most frequently examined agricultural impacts alongside water resources (n = 10), climate (n = 8), ecological conservation (n = 4), and capacity building (n = 4) (Fig. 6). Four studies examined capacity building across various contexts, involving training and supporting groups of stakeholders with diverse roles within their communities, e.g., participatory mapping projects in Nepal (23) and Tanzania (24).

Figure 4. Number of papers valuing ESI in multiple contexts. The quadrants and colors at each intersection indicate which value types were examined; the size of the quadrants indicate how many papers examined that value type. The number in the bottom left quadrant indicates the total number of papers involving that pair of contexts.

## Discussion

Despite a broad, inclusive search for research on diverse methods for valuing earth observation information, we found very few examples of ESI applied in decision-support contexts that had been evaluated for its societal benefit. Such a low inclusion rate (1.2%) is in part to be expected, as our inclusion criteria are specific to methods of valuing information and data, but our search string was intentionally designed to be inclusive to maximize opportunities to find edge cases in the literature. The paucity of research directly addressing the value of ESI suggests a strong need to better understand and address how such information can be used in order to support and motivate further investments in ESI.

The challenge of valuing information, as opposed to valuing goods or services, lies in identifying a relevant counterfactual information set as the basis of comparison. For the purposes of our analysis, we focused only on valuation methods that were used in a manner that was responsive to the ESI in a decision context. In many of the publications we identified, multiple valuation methods were used in sequence to first identify the difference in outcome based on the inclusion of ESI, and then to translate that difference in outcome to some other metric, usually monetary. The first step is clearly dependent upon the availability of the ESI in question; the second step may or may not be, depending on the assumptions of a given study. For example, Späti et al. (25) modeled the effect of variable-rate nitrogen application on crop yield for small-scale farmers based on several levels of spatial data resolution; they then valued the increased yield and reduced nitrogen into economic terms (Swiss francs) using market prices. However, the nitrogen and crop prices were treated as independent of the ESI - a reasonable assumption for a small-scale farmer trading commodities within a global market - and thus this second valuation step was effectively a unit conversion, and not germane to our study. Conversely, Adams et al. (26) modeled the benefits of an El Niño early warning system for agriculture across five Mexican states, accounting for alternative cropping decisions to optimize yield in the face of seasonal predictions, then translated the resulting crop yield into economic terms using modeled market prices. In this case, the market model accounted for changes in price due to ESI-driven changes in supply, and therefore this second valuation step was considered relevant for our study.

We found that VOI methods dominate the current literature evaluating the societal benefits for ESI for decision support (Fig. 3). VOI is a well established and intuitive method, and Macaulay (10) described a framework for applying VOI to ESI contexts that continues to influence recent research initiatives (e.g.,(27)). VOI methods are very well suited to situations where a reduction in uncertainty, based on an improved information set, can be expected to drive a clear and measurable improvement in decision outcomes. This is especially the case where costs of a mistake are high, where benefits can be expressed as objective quantities (typically instrumental value), and where the outcome is highly responsive to the set of actions that can be taken. For these reasons, VOI is particularly suited to agricultural contexts (Fig. 3), where an improved seasonal forecast can improve farmers’ decisions about crop choices and crop management to maximize yield and profit in the face of uncertainty; this is reflected in the high rates of VOI use in agricultural studies.

CBA is the second most prevalent method identified in our corpus (Fig. 3). CBA is a well established and reasonably intuitive manner of estimating the net present value of a particular investment decision over an extended time frame, generally with an implicit counterfactual of not making the investment. In an information context, this could be considered as the expected net benefit of investment in the infrastructure required to generate ESI, such as aerial drones or satellite instruments, and/or investment in equipment and labor to process ESI. Using CBA in valuation of ESI is most commonly observed in agriculture and conservation contexts, and like VOI, is focused primarily on instrumental value due to its traditionally monetary nature.

Valuation methods based on decision analysis necessarily focus on decision outcomes that can be quantified. However, many decision outcomes valued by individuals and society are impossible to objectively quantify and/or can be qualitatively valued across multiple, potentially incommensurable, value domains. Preference elicitation methods can readily account for qualitative benefits related to ESI-based decision outcomes in instrumental and non-instrumental terms, and additionally may provide insights into procedural benefits as ESI use addresses issues of saliency and legitimacy of decision making (28). Five example studies in our corpus help illustrate this. Altamirano et al. (22) used eye-level and aerial photos of various landscape disturbance gradients to survey preferences for visiting, living, scenic beauty, and well being in each landscape. Eilola et al. (24) used interviews and focus groups to study how participatory mapping using ESI improved practitioners’ perceptions of work quality, professional competence, participation, spatial understanding. Gonzalez and Kroger (9) used focus groups and interviews to examine how training in and adoption of remote observation technology improved empowerment and agency of Indigenous people in protecting their land from illegal deforestation. Colloredo-Mansfeld et al. (29) used participatory mapping and in-depth, semi-structured interviews to understand how UAV photography affected farming practices and perceptions, leading to a greater sense of scale and interconnectedness. Styers (30) surveyed her undergraduate students to gauge how the incorporation of satellite data into her courses improved student engagement, curiosity, collaborative skills, and learning outcomes. In these cases and others, quantitative measures would clearly be inappropriate to capture the breadth and depth of societal benefits accrued from access to and use of ESI. A few studies bridged the divide between decision-analytic methods and preference-elicitation methods. In several related studies, Bouma et al. (31–34) applied Bayesian decision analysis to quantify societal benefits of ESI for managing water quality, but leveraged surveys of experts to elicit prior beliefs and expectations of accuracy of the ESI to inform the Bayesian analysis. Flipping that script, Luseno et al. (35) used a conceptual Bayesian framework to guide the design of surveys and interviews of pastoralists in Ethiopia and Kenya to understand their preferences around ESI-derived climate forecasts, including the pastoralists’ prior beliefs based on traditional forecasting methods, trust in ESI forecast skill, and likelihood of using the ESI-based forecasts.

The scientific, political, and commercial structures governing ESI - especially whether datasets are publicly accessible or proprietary, freely available or commercial - determine who is likely to benefit from their societal value (36). Clearly, free versus commercial availability of ESI data has implications for its ability to generate societal benefits; for example, following Landsat’s shift from a paid service to a free and open data policy in 2008, downloads and citations for Landsat data surged, generating billions of dollars in new scientific and societal benefits (5, 37). Alvarez León and Gleason (38) analyze how varying property rights can reinforce or challenge assumptions of scientific objectivity and ultimately users’ ability to translate ESI into scientific and societal value. For example, recent data from the European Space Agency (ESA)’s SPOT (Satellite Pour l’Observation de la Terre) mission is commercially available, and users can request that the sensor can be directed to capture imagery of particular regions of commercial interest. As a result, historical SPOT data (through 2015), while freely available through various portals, are skewed toward scenes that were valuable to commercial users at the time of capture. In contrast, Landsat data of USGS are freely and openly available, and as the sensing path is not subject to user control, the data are unlikely to show commercial bias - although as a product of the US government they may have undergone prior filtering to remove classified or sensitive information (38).

However, even for freely and openly available satellite data, barriers to technical expertise and capacity pose significant hurdles to using for practitioners in developing countries (39), and poor integration with ground-based and local knowledge hampers development of machine learning algorithms to translate remote sensing imagery into actionable information (40–42). Capacity building can help local communities and indigenous groups access and incorporate ESI to co-produce knowledge across contexts including conservation (e.g., (43)), deforestation (e.g., (9)), marine resource management (e.g., (44, 45), and resilience to climate change (35, 46). Such collaborations can reduce power asymmetries and increase agency and self-governance of communities as they seek to address challenges facing indigenous landscapes and territories (9, 46); however, they can also result in internal power divisions between tech adopters and non-adopters, potentially resulting in shifts in or loss of cultural values (9).

* Our process leveraged machine learning to make it feasible (“enfeasen”) to approach the question so openly and cast such a wide net expecting a low inclusion rate
* Colandr - several years old (check with Sam to see if the algorithm has changed with new tool availability) but still helpful, and external colandr companion provides real time feedback on inclusion/exclusion rate to allow for quantitative criteria for early stopping - other ML and AI boosted lit review tools increasingly becoming the norm
* ML classification algorithm to amplify early results using early results as training set - but important to focus on minimizing false negatives - follow up with explicit testing of a sample of predicted “excludes” to improve confidence in exclude predictions
* Even with these tools to boost efficiency of screening, we still faced a high false positive rate…
* probably because our systematic map focused not on study questions or results, typically foregrounded in the title and abstract, but rather on methods, which are often described only vaguely if at all in the abstract, it was not clear that machine learning methods would be able to accurately predict the relevance of any given paper without a substantial training set - a very unbalanced training set required special care
* AI tools such as Elicit, OpenAI Deep Research, and SciSpace Deep Review are likely to become important tools in the arsenal of anyone performing a systematic literature search
* Nature piece on fears and caveats about AI upending the traditional systematic review process

While most of the studies in our corpus identify positive societal benefits due to ESI, the tradeoff between information and privacy becomes increasingly relevant as advancements in the quality and quantity of remote sensing data accelerate the ability to identify and monitor objects and people on the ground. In general, remote sensing allows the observer to shift information asymmetry between the observer and the observed, in favor of the observer. Brennan and Macauley (47) describe several important use cases that determine whether the shift in information asymmetry is potentially beneficial or detrimental to society, based on whether the observer and the observed are state actors or private actors (corporations, groups, individuals) and whether the relationship between observer and observed is adversarial or cooperative. The ability of state actors to monitor and enforce compliance with conservation policy, emissions targets, and peace treaties certainly produce societal benefits by enabling cooperation (REFS?); monitoring also holds promise for reducing international conflict (48), supporting human rights (49), and responding to genocide (50). To the extent that an open, transparent government whose laws and regulations reflect the will of the governed, these information asymmetries may actually promote societal benefits, e.g., reduced crime or pollution (47). However, the risks of abuse loom large, creating a clear tradeoff between the increasing capabilities of remote sensing technology and the privacy rights of the individual.

While most of the papers excluded from our target corpus either did not apply ESI data (e.g., spurious matches that were missed during our preliminary screening), or applied ESI data to calculate some other outcome (e.g., using land cover classification data to estimate ecosystem service value, but no further examination of the value of the ESI itself), two categories of excluded papers merit further consideration. These two categories of studies offer clear opportunities for those interested in evaluating the societal benefits of ESI.

First, a number of papers explicitly used cost-benefit analysis to demonstrate that an ESI data set could achieve equal or near-equal performance for a decision context but with less cost (e.g., reduced costs of labor or equipment relative to on-the-ground research) (e.g., (51)). However, we did not include these in our final corpus, reasoning that if the information itself is essentially identical between the ESI and non-ESI alternative, any outcome of a given decision would necessarily be identical, and therefore no additional marginal societal benefit would result from use of the ESI. We acknowledge that in resource-constrained settings, government or NGO cost savings can closely translate into improved societal outcomes (e.g., lowering taxes on lower income people, or increasing budgets for social safety nets), but these second-order benefits were not explicitly examined in any of the papers we screened. While these excluded studies focused on a one-time analysis, reduced costs of labor and/or equipment imply the potential for increased frequency of measurement, which would prove valuable for certain types of decision contexts that involve rapidly changing phenomena, e.g., disaster response or wildfire management. We included several studies that explicitly valued the benefits of higher spatial resolution, though we encountered no studies that explicitly accounted for the value of higher temporal resolution. This suggests an opportunity for future valuation studies, especially in light of trends toward increasingly fine temporal resolution of accessible satellite data.

Second, a larger subset of excluded papers compared the ability of ESI to accurately predict on-the-ground phenomena by comparing values to those measured by some other means, for example, EXAMPLE (REFS). Such validation studies typically report accuracy scores, e.g., RMSE or AUC, often demonstrating the superiority of a particular ESI dataset or algorithm over the alternative approach. Importantly, while these studies presented results in terms of scientific value, they did not examine how the improved scientific knowledge would affect the decisions that generate societal benefits - though most included conceptual descriptions of potential decisions or societal value in their conclusions. With often minor additional information or economic modeling, many calibration/validation studies (e.g., REFS of examples here) could readily translate the improved scientific accuracy of an ESI dataset relative into a hypothetical or realized decision that could be translated into calculable societal benefits (e.g., REFS of papers that make this leap?).

We note that many ESI applications may rely on highly derived, modeled, or processed data, such that the word satellite or the name of the initial sensor does not appear in the paper, which may limit the citations in our corpus but excluding the ESI term would make the search impossibly large.

## Conclusion

As advances in electronics and ease of launch bring down costs to put instruments into low earth orbit (52), microsatellites dedicated to specific missions will become increasingly useful for informing on-the ground decisions and management. For example, Canada’s WildfireSat constellation of mission-specific microsatellites, slated to launch in 2029, will image the entirety of Canada in near real time to inform wildfire management, potentially saving billions of dollars in avoided damages as wildfire regimes become increasingly extreme (53). However, as all this technology opens up new possibilities for management and decision contexts, there will remain a need to weigh the costs against potential benefits to society - many of which are likely to be non-instrumental. Considering societal benefits beyond the merely instrumental will expand the scope of what is deemed worth investing in.

Examining the contributions of Earth observation to societal benefits is important to justify existing and future investment (10), promote diffusion of use and applications (54), and identify gaps and priorities for future applications and missions (55, 56). Methods exist to evaluate ESI contributions across societal benefit areas and value domains. However, even as the use of ESI data has grown to encompass a wide range of applications across the globe (54), published peer reviewed studies that attempt to qualitatively or quantitatively assess these contributions remain rare.

Our literature screening process revealed a large subset of research that demonstrated the scientific value of particular ESI datasets and models but did not proceed to translate this scientific value into explicit societal value. A major impediment to the uptake of valuation methods as applied to ESI may lie in the gap between science and policy. This gap may be attributable in part to lack of in-house social science and policy knowledge to apply valuation methods, and in part to poor engagement between academics and user communities (57).

As technical capabilities of ESI instruments and machine learning models rapidly increase, opportunities to translate raw observations into actionable intelligence into measurable societal benefit will multiply, but only if the methods used to apply ESI data are used appropriately. Here we have identified concrete examples of qualitative and quantitative valuation methods across a range of societal benefit areas and value domains. By doing so, we hope to inspire other ESI researchers to explore the societal benefit of their own work and contribute to a greater network of valuation practitioners.

## Methods

Our analysis of the literature consisted of five major phases (described in detail below): 1) developing a search string; 2) applying the search string to academic databases to acquire a set of citations; 3) screening citations by the title and abstract; 4) screening the full text of papers that passed the title and abstract screening stage using natural language processing (NLP) and language models; and 5) coding the papers to identify ESI data source, valuation method, societal benefit area, and value domain.

To develop a search string (see SI), we focused on three key domains: 1) application of ESI, 2) a decision context or analysis framework in which the ESI is applied, and 3) an expected or observed change in societal benefits based on decision outcome due to use of ESI. The research team collected (via Google Scholar searches) and solicited (via professional networks) a preliminary set of 72 candidate documents, which were screened based on these three domains. Of these 72 candidate documents, 14 were identified as a benchmark set that the research team felt exemplified valuation of ESI. From this benchmark set, we developed a preliminary search string combining the three domains: ESI (e.g., “remote sensing”, “satellite”, “Sentinel”, “Landsat”), decision context (e.g., “management”, “policy”, “cost-benefit”, “contingent valuation”), and societal benefit (e.g., “value”, “benefit”, or “utility” combined with terms such as “societal”, “cultural”, “environmental”, “ecosystem service”, or terms related to GEOSS societal benefit areas). The preliminary set of terms was used to collect citations (title, abstract, authors, metadata) from Web of Science (n = 1,158). We applied the functionality of the litsearchr package in R (REF) to this preliminary citation set, using text mining and keyword co-occurrence networks to identify additional terms to increase the inclusion of our search string (Grames et al. 2019). The final search string (see SI XXX) was used to collect citations from Web of Science (January 26, 2024, n = 9,488) and Scopus (February 4, 2024, n = 18,585), including all 14 benchmark papers. In addition to these two citation sets we included a curated set of citations from the USGS Joint Societal Benefits of Earth Observation Digital Library (USGS 2024) (SBL, n = 258). See Fig. SXXX for PRISMA flow diagram.

The results of the search (Web of Science and Scopus) were then cleaned. Citations noted as conference abstracts or proceedings (n = 1,030 and n = 4,109 respectively) were dropped. Then, citations with missing title, author, abstract, or digital object identifier (DOI) field (n = 319 and n = 1,226 respectively) were dropped. After resolving minor differences among titles, author names, and DOI fields, 6,840 duplicate citations were removed from the combined citation set. The resulting set of 14,807 distinct citations were subjected to a preliminary screening to remove known spurious matches (n = 984), leaving n = 13,823 citations for screening and analysis (Fig. 1).

Figure 5. Citation retrieval and pre-screening results. Documents noted as “Include” proceeded to title/abstract screening stage (see Fig. 6)

Screening was performed in two stages, to enable implementation of a classification algorithm to more efficiently screen papers (Fig. 6). In the first stage, the citations from the SBL and a random sample of ~1000 citations from the Web of Science/Scopus corpus were subjected to title/abstract screening, and then full-text screening on the title/abstract “include” papers, based on a set of inclusion criteria (See Table XXX for screening criteria). All title/abstract screening was performed using the Colandr web-based screening application (Cheng et al. 2018), which uses machine learning and natural language processing to continually predict and sort citations in order of predicted relevance based on user screening decisions.

The resulting set from this first stage (86 includes, 1207 excludes) was then used to train a classification model based on the XLNet generalized autoregressive pretraining algorithm, which considers all permutations of dependencies between sets of words in the citation titles and abstracts to “understand” the context (Yang et al. 2019), to classify citations in the remainder of the corpus as either “include” or “exclude”. The predicted “include” citations were then title/abstract screened (using Colandr) and those that passed were full-text screened. The include/exclude classification model showed a low false negative rate (1.2%, sensitivity 92.3%) on the training data, but to ensure this held true of the larger document set, a random sample of 1000 predicted “excludes” was uploaded to Colandr. After screening 200 of these documents and finding no relevant matches to our screening criteria despite Colandr’s ability to prioritize articles of interest, this screening phase was stopped early. While the classifier’s false positive rate was higher (27.1%, specificity 71.2%), these false positives were subject to title/abstract screening so were not a concern. Of the 13,823 unique citations retrieved from Scopus, Web of Science, and the SBL, our screening process resulted in only n = 170 documents that met all screening criteria for inclusion (see Table XXX) in our corpus, for a final inclusion rate of 1.2%.

Figure 6. Citation screening and full text screening results. Following pre-screening (Fig. 1), the n = 13,823 documents were considered for inclusion or exclusion based on title and abstract. Title/abstract screening was performed in the Colandr web-based machine-learning assisted screening app. Full text screening was performed using Zotero reference management software.

Documents included in the final corpus were screened and coded to identify valuation methods, societal benefit areas, and value types according to <XXX typology in SI, or tables here in main text?>.

## Author Contributions

Conceptualization, TBD; Methodology, TBD; Software, CCO; Formal Analysis, CCO; Data Curation, CCO; Writing - Original Draft, CCO; Writing - Review & Editing, CCO, TBD; Visualization, CCO; Supervision, BSH, BCK; Funding Acquisition, BSH, BCK.

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