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

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# Abstract:

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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 (Macauley 2006 Measuring the contribution, Fritz et al. 2008, Rydzak et al. 2010, Tassa 2020). 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 (Zhu et al. 2019), supporting societal benefits as varied as impeding transmission of polio in Nigeria (Borowitz et al. 2023), protecting blue whales in the Eastern Pacific (Bernknopf et al. 2021), improving targeting of cash transfers to poor villages in sub-Saharan Africa (Varshney et al. 2015, Smythe and Blumenstock 2022), and empowering indigenous communities to monitor deforestation (Gonzalez and Kroger, 2023). 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 (Macauley 2006 Ascribing Societal Benefit), 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 (Macauley 2006 VOI, 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., Chan et al. 2016, Pascual et al. 2017, Klimkova 2018, Fazendeiro 2021). The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) Values Assessment (IPBES 2022), 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”) (Himes et al. 2024). 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 (Glynn et al. 2022 Exploring Behaviors). 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) (Arias-Arevalo et al. 2018). 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) 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 (REF). 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. (2008) 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 (2022) 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 (Li et al. 2017), and one for assessing preferences for living and recreating in disturbed landscapes (Altamirano et al. 2020).

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 (Parajuli et al. 2020) and Tanzania (Eilola et al. 2021).

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. (2021) 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. (2003) 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, n = 68). VOI is a well established and intuitive method, and Macaulay (2006) described a framework for applying VOI to ESI contexts that continues to influence recent research initiatives (e.g., VALUABLES REF). 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. 5), 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, n = 25). 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 (REF Cash et al). Five example studies in our corpus help illustrate this. Altamirano et al (2020) 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. (2021) 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 (2023) 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 (2020) 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 (2018) 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. (2009, 2009a, 2009b, 2011) applied a 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. (2003) 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 (Harris and Miller, 2011). 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 (Zhu et al. 2019; Loomis et al. 2015). Alvarez Leon and Gleason (2017) 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 (Alvarez and Gleason, 2017).

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 (Kganyago and Mhangara 2019), and poor integration with ground-based and local knowledge hampers development of machine learning algorithms to translate remote sensing imagery into actionable information (Adelusi et al. 2025; Burke et al. 2021; King & Halpern 2025). Capacity building can help local communities and indigenous groups access and incorporate ESI to co-produce knowledge across contexts including conservation (e.g., Pintea 2021), deforestation (e.g., Gonzalez and Kroger 2023), marine resource management (e.g., Lauer and Aswani 2008, Mackenzie et al. 2019), and resilience to climate change (Luseno et al. 2003, Manga 2023). 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 (Manga 2023, Gonzalez and Kroger 2023); 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 (Gonzalez & Kroger 2023)

* 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 the reflective models and Deep Research are likely to become important tools in the arsenal of anyone performing a systematic literature search

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 (1995) 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 (Gleason & Hamdan 2017), supporting human rights (Notley & Webb-Gannon 2016), and responding to genocide (Levinger 2009). 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 (Brennan & Macauley 1995). 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., Bernknopf et al. 2021, monetising the savings). 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 (Kopacz et al. 2020), 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 (Hope et al. 2024). 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 (Macauley 2006), promote diffusion of use and applications (Macauley 2010), and identify gaps and priorities for future applications and missions (Zell et al. 2012, Andries et al. 2022). 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 (Macauley et al. 2010, From Science to Applications), 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 (Perrels et al 2013).

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

### Analysis grid

All spatial analyses were calculated on a gridded global map using a Mollweide equal-area projection coordinate reference system (CRS), gridded to 10 km x 10 km resolution. See SI Methods for additional details on preparing the analysis grid.

### Species distributions

The 21,159 species (including subpopulations) considered in this assessment are limited to those animal species with data on spatial distribution as well as sufficient trait data to estimate vulnerability and assign species to functional entities. These species represent only a small subset of the >240,000 marine species identified in the World Register of Marine Species (WoRMS, (**vandepitte\_DecadeWorld\_2018?**)); however, this subset includes most known marine mammals, marine reptiles, seabirds, and cartilaginous fishes, as well as about half of marine bony fishes and warm-water corals (S1 Table by class, S2 Table vertebrates by order). Together these species represent most top predators, many mid-trophic species, and ecologically critical habitat-forming species. Relatively fewer other invertebrates were included, as most lacked spatial data, trait data, or both.

Species distribution data were taken from AquaMaps (**kaschner\_AquaMapsPredicted\_2019?**) (n = 18,480) and IUCN species distribution maps (**iucn\_IUCNRed\_2021?**, **bli\_2018?**) (n = 2,679). For species appearing in both distribution map datasets, the AquaMaps distribution maps, based on transparent and repeatable algorithms using publicly available data, were preferred over IUCN range maps, which integrate data and expert knowledge but may include mapping decisions that are difficult to replicate. For species represented by the AquaMaps dataset, presence was calculated as any 0.5° cell with a probability of occurrence of 0.5 or greater; the resulting cells were then reprojected to the 10 km Mollweide analysis grid. For species represented by IUCN Red List rangemaps, the polygons were reprojected and rasterized to the resolution and CRS of the analysis grid. See SI Methods for additional details on preparing species distributions. See S2 Fig. for a map of species richness generated from these species distributions.

### Vulnerability estimates

Vulnerability weights, i.e., the relative effect of a given stressor on the fitness/health of a given species, were determined based on methods of Butt et al. (**butt\_TraitbasedFramework\_2022?**). Briefly, that study estimated vulnerability of species to each of a suite of stressors based on presence of certain traits that are likely to increase the species’ physiological sensitivity (e.g., calcium external structures indicate higher sensitivity to ocean acidification), ability to adapt to or avoid that specific stressor (e.g., high mobility makes it easier to avoid localized stressors), and life history and population-level traits that affect the population’s ability to adapt to or recover from disturbances in general (e.g., high fecundity suggests easier recovery from a disturbance). A binary exposure multiplier (zero or one) prevents nonsensical results for certain stressors where exposure is limited to certain depths or ocean zones, e.g., ship strikes will not affect mesopelagic species. Trait values for species were gathered through expert elicitation and provided as ordinal or nominal categorical values. Vulnerability weights range from 0 (a stressor does not affect a species) to 1 (a stressor imposes extreme adverse effects on a species).

See SI Methods and S3 Table for details on traits and calculations.

### Stressor layers for species-focused analysis

For the species-focused analysis, the intensity of exposure to a stressor depends on the spatial distribution of the stressor relative to the spatial distribution of the species. Spatial data for stressors is typically available as gridded data of some physical quantity related to anthropogenic activity, e.g., brightness of nighttime lights, tonnes of nutrient fertilizer runoff, population density within 25 km of coast, or value of aragonite saturation state. For each stressor, a reference value was determined from the data (typically 99.9th percentile of observed values), a historic baseline (e.g., mean/standard deviation of sea surface temperature from 1985-2015), or ecologically relevant value (e.g., aragonite saturation state of 1) (S4 Table). We calculated stressor distributions as a value from 0 (stressor not present) to 1 (stressor at reference point, indicating maximum intensity).

For most of the included stressors, a single map of relative stressor intensity was created from gridded data and applied to all species, although vulnerability to the stressor varied by species. These stressors include sea surface temperature (SST) extremes, ocean acidification, ultraviolet radiation, sea level rise, nutrient pollution (runoff), direct human disturbance, light pollution, shipping (ship strikes), and habitat destruction driven by demersal destructive fishing and the footprint of benthic structures.

However, there were also several stressors for which intensity (again ranging from 0 to 1) depends on species-specific information. These stressors include bycatch (dependent on water column position, i.e., benthic, pelagic, or both), biomass removal (dependent on catch that is directly targeting that species), and increase in mean SST (dependent on species thermal tolerance). For these stressors, individual maps were generated for each species (biomass removal, SST rise) or for each water-column position category (bycatch).

See SI Methods and S4 Table for details on the data source, transformation, and reference point used for these stressor layers.

### Stressor layers for habitat-focused analysis

The habitat-focused analysis was similar to that for species, with the intensity of exposure to a stressor depending on the spatial distribution of the stressor relative to the distribution of the habitat. For this approach, fisheries stressors were calculated using the same source as the species-level stressors, i.e., Watson (**watson\_DatabaseGlobal\_2017?**), but aggregated by fishing gear, depth, and scale according to their effects on various habitat types as described in Halpern et al. (**halpern\_RecentPace\_2019?**): commercial pelagic and demersal low bycatch, commercial pelagic high bycatch, commercial demersal destructive, and artisanal/small scale fishing. For SST extremes, ocean acidification, ultraviolet radiation, sea level rise, nutrient pollution (runoff), direct human disturbance, light pollution, shipping, benthic structures, and demersal destructive fishing, we used the identical stressor layers prepared for the species-level analysis. The species-specific stress of increasing mean SST relative to their thermal tolerance was omitted, as it would not be feasible to determine an analogous habitat-level thermal tolerance. See SI Methods and S4 Table for details on the data source, transformation, and reference point used for these stressor layers.

### Cumulative human impacts: species method

#### Estimating impact at species level per grid cell

We modeled the impact on species of stressor in a given location (i.e., grid cell) as the product of stressor intensity and vulnerability of that species to that stressor :

Cumulative impact on species in a given location was determined by summing impacts across all stressors (or subset, e.g., climate vs. non-climate stressors) in that location:

Note that this additive model does not account for compound effects of multiple stressors acting in combination, i.e., synergistic or antagonistic effects. Meta-analyses examining two-stressor interactions (**crain\_InteractiveCumulative\_2008?**, **stockbridge\_MetaanalysisMultiple\_2020?**) have observed some non-additive stressor interactions, but additive effects were more commonly reported. Additionally, an additive model requires fewer assumptions, is conceptually tractable, and likely results in more conservative results.

#### Estimating species-level mean cumulative impact across species range

For each species , we calculated a cumulative impact score accounting for impacts across its entire range as an average of per-grid-cell impacts for all cells in the species’ range . For a single stressor :

Cumulative impact scores across multiple stressors (climate, non-climate, and total) were determined as the sum of single-stressor impact scores.

#### Estimating impact across species per grid cell

The species-mean method for calculating the impact score for stressor in a given cell was determined by taking an unweighted mean across all species present (or a taxonomic subset, e.g., all elasmobranchs):

and the cumulative impact is the sum of impacts across all (or a subset of) stressors within that cell.

### Cumulative human impacts: habitat method

To compare the results of our species-based cumulative impact approach to those of a habitat-based approach (e.g., (**halpern\_GlobalMap\_2008?**); (**halpern\_RecentPace\_2019?**)), we recreated habitat maps at the same resolution and projection as the species-based analysis, aggregating habitat presence maps at ~1 km resolution to determine proportional habitat representation within each 10 km grid cell. Using these habitat maps, we applied habitat vulnerability weights from Halpern et al. (**halpern\_RecentPace\_2019?**) to determine impacts based on largely the same stressor maps data sources used for the species-based assessment.

To identify vulnerability of each habitat to various stressors we used the matrix of habitat vulnerability from Halpern et al. (**halpern\_RecentPace\_2019?**).

Per-grid-cell habitat impact scores for each stressor were created as the product of habitat vulnerability for each habitat and intensity of stressor , averaged over the proportional inclusion of that habitat in a given cell:

Cumulative impact per pixel is the sum of habitat-based impacts across all (or subset) of stressors.

### Cumulative human impacts: functional entity method

#### Functional entities

To estimate cumulative impact on functional diversity, we first assigned species to functional entities based on categorical values of four traits (maximum body length, adult mobility, position in water column, and adult trophic level) that roughly determine a species’ ecological niche with regard to regulation of food webs and nutrient cycling, following Mouillot et al. (**mouillot\_FunctionalOverredundancy\_2014?**). Due to limited trait data available across a broad range of taxa, we relied on a smaller set of traits (those four noted previously) for assignment of functional entity than the six traits used in Mouillot et al. (**mouillot\_FunctionalOverredundancy\_2014?**), resulting in fewer but more populous functional entities and therefore a more conservative estimate of functional vulnerability.

Trait values were gleaned from (**butt\_TraitbasedFramework\_2022?**, **froese\_FishBase\_2022?**, **palomares\_SeaLifeBase\_2022?**); missing values were imputed using Multiple Imputation by Chained Equation (MICE) in the R package mice (**vanbuuren\_MiceMultivariate\_2011?**) using all other traits plus fecundity (where available), generation time (where available), order, and family. See SI Methods for details on the trait values used to assign functional entities, along with analyses to test sensitivity of functional vulnerability and cumulative impact to potential error in imputation of traits.

#### Estimating impact at functional entity level per grid cell

For each functional entity consisting of some subset of species in a particular location, the impact of stressor on the functional entity is the mean impact across all species in that functional entity in that location:

Cumulative impact of all stressors on this functional entity in this location is the sum of impacts across all stressors (or a subset).

#### Estimating impact across functional entities per grid cell

The functional entity method for calculating the impact score for stressor in a given location was determined by taking a weighted mean across all functional entities present. Weighting for each functional entity was based on the functional vulnerability, *sensu* Mouillot et al. (**mouillot\_FunctionalOverredundancy\_2014?**) with a slight modification (see below).

Mouillot et al. (**mouillot\_FunctionalOverredundancy\_2014?**) scored vulnerability of a functional entity as 1 if that entity was represented by a single species and 0 otherwise. Here we calculated functional vulnerability based on an inverse exponential of the number of species that represent that functional entity in that location, where functional vulnerability of entity was calculated as , accounting for low-membership entities but rapidly asymptotically approaching zero as membership increases.

As for the species-based approach, the cumulative impact is the sum of impacts across all (or a subset of) stressors within that cell.

### Code and packages

All analysis was performed in R statistical software, version 4.0.4 (**rcoreteam\_LanguageEnvironment\_2022?**), relying primarily on packages tidyverse (**wickham\_WelcomeTidyverse\_2019?**), terra (**hijmans\_TerraSpatial\_2022?**), sf (**pebesma\_SimpleFeatures\_2018?**), taxize (**chamberlain\_TaxizeTaxonomic\_2013?**, **chamberlain\_TaxizeTaxonomic\_2020?**), rfishbase (**boettiger\_RfishbaseExploring\_2012?**).

## 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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# References