Earth Observation of Ecosystem Structure and Function in Ecosystem Service Models

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August 2024

A thesis submitted to McGill University in partial fulfillment of the requirements of the degree of Master of Science

ABSTRACT

Ecosystem services (ES) are the benefits that flow from ecosystems to people, contributing to human well-being. The ES concept provides an important framework, or starting place, for quantifying, analyzing, and managing these benefits that flow from ecosystems to humans. Yet the capability to assess provision of these services accurately across large spatial and temporal extents remains limited. Therefore, spatial modelling and regular monitoring approaches of ES are a critical tool for evaluating their state across space and time. Many current ES spatial models rely on representations of land-use and land-cover (LULC), with the assumption that most ecosystem properties within a LULC type are identical. To represent ecosystem heterogeneity more precisely, there have been calls within the ES community to explore modelling approaches that incorporate Earth Observation (EO) data that are able to capture ecosystem properties beyond LULC, such as patterns of vegetation density or age structure of forests. It has also been suggested that EO can increase the spatial extent of ES models while maintaining fine temporal and spatial resolutions.

In the manuscript chapter of my thesis, I systematically reviewed the use of EO data in ES models over ten years (2012-2021), highlighting which EO datasets, at which geographical extents and spatial/temporal resolutions, have been used in ES models; investigating whether the claims for use of EO to improve ES models are generally borne out in the literature. This review of 39 paper and 138 individual models, spans all categories of ES models and shows the direct linkages between individual EO datasets and ES models. For example, MODIS Normalized Difference Vegetation Index was the most used EO data input found in this review process and was used as a proxy for live vegetation cover in 58% of all ES models, and 83% of regulating service models (e.g., flood regulation, sediment retention, heat mitigation). This study shows that there have been changes in the last ten years in the sensors that are capturing EO data, the indicators that are being created from these data, and the breadth of services being modelled using these remotely sensed indicators. While the promise of increased information resolution has been partially realized for some ES models, there are more opportunities still for the ES field

to evolve; with a critical need during this period of methodological exploration for more transparent and common definitions, validation schemes, and documentation of emerging methodologies.

RÉSUMÉ

Les services écosystémiques (SE) sont les avantages que les écosystèmes procurent aux humains et qui contribuent à leur bien-être. Le concept de SE fournit un cadre important ou un point de départ pour la quantification, l'analyse et la gestion de ces avantages qui découlent des écosystèmes pour les humains. Cependant, la capacité d'évaluer avec précision la fourniture de ces services sur de vastes étendues spatiales et temporelles reste limitée. Par conséquent, la modélisation spatiale et les approches de suivi régulier des SE constituent un outil essentiel pour évaluer leur état dans l'espace et dans le temps. De nombreux modèles spatiaux actuels des SE reposent sur des représentations de l'utilisation et de la couverture des sols (LULC), en partant du principe que toutes les propriétés des écosystèmes au sein d'un type de LULC sont identiques. Pour représenter plus précisément l'hétérogénéité des écosystèmes, des voix se sont élevées au sein de la communauté des SE pour explorer des approches de modélisation intégrant des données d'observation de la terre (OT) capables de capturer les propriétés des écosystèmes au-delà de l'UTCL, telles que les schémas de densité de la végétation ou la structure d'âge des forêts. Il a également été suggéré que l'observation de la terre pouvait augmenter l'étendue spatiale des modèles d'SE tout en maintenant des résolutions temporelles et spatiales fines.

Dans le premier chapitre de ma thèse, j'ai procédé à une revue systématique de l'utilisation des données d'OT dans les modèles d'SE sur une période de dix ans (2012-2021), en soulignant quels ensembles de données d'OT, à quelles étendues géographiques et à quelles résolutions spatiales/temporelles, ont été utilisés dans les modèles d'SE ; j'ai cherché à savoir si les allégations d'utilisation de l'OT pour améliorer les modèles d'SE sont généralement confirmées dans la littérature. Cette revue de 39 articles et de 138 modèles individuels couvre toutes les

catégories de modèles d'SE et montre les liens directs entre les ensembles de données d'OT et les modèles d'SE. Par exemple, l'indice de végétation par différence normalisée de MODIS a été l'entrée de données d'observation de la Terre la plus utilisée dans ce processus de revue et a servi de substitut à la couverture végétale vivante dans 58 % de tous les modèles d'écosystèmes et 83 % des modèles de services de régulation (par exemple, régulation des inondations, rétention des sédiments, atténuation des effets de la chaleur). Cette étude montre qu'il y a eu des changements au cours des dix dernières années dans les capteurs qui capturent les données d'observation de la Terre, les indices qui sont créés à partir de ces données et l'étendue des services modélisés à l'aide de ces indices. Si la promesse d'une meilleure résolution de l'information s'est partiellement concrétisée pour certains modèles d'SE, le domaine de l'SE a encore d'autres possibilités d'évoluer, avec un besoin critique, pendant cette période d'exploration méthodologique, de définitions plus transparentes et communes, de schémas de validation et de documentation sur les méthodologies émergentes.

ACKNOWLEDGMENTS

I would like to thank my supervisor, Dr. Elena Bennett, for her support and mentorship over the course of my MSc at McGill. Above all else, I am grateful for the patience, encouragement, kindness, and enthusiasm you've shown for my project and inclusion in the lab group. Your scientific insight, editing, and feedback has been critical to my development as a scientific thinker. I would like to thank my supervisor, Dr. Klara Winkler, for her encouragements, scientific insights, and kindnesses, which have been invaluable to my evolution as a person.

To my collaborators on different projects throughout the process, colleagues, and committee member, Graham MacDonald, thank you for your time, insights, and for making science a fun and collaborative process. To the ever-evolving lab group – Agnes, Andrew, Anna, Catherine, Chris, Ela, Elson, Heather, Jackie, Jeff, John, Karina, Klara, Nikki, Marie, Olivia, Peter, Sophie – thank you all for the thoughtful discussions and kindnesses over the past years. I am truly grateful to have met a group that has pushed me to be a more critical thinker and better person.

I would like to acknowledge the Elizabeth and Andrew Rossinger Fellowship, the McGill Department of Natural Resource Sciences, and the NSERC ResNet for funding my research. It has been a unique privilege to be a part of the NSERC ResNet project during my MSc. To the many individuals that I have met across Canada due to ResNet, I would like to thank you for being such a supportive and positive community.

To my past teachers, friends, colleagues, mentors, you are all present in who I am today.

To my parents, Jim and Susan, brother, Jeremy, and friends, thank you for your constant encouragement and many forms of support when I have needed it. To my partner, Monica, thank you for going together – through time and the world.

PREFACE

This thesis is manuscript based. The two main chapters represent a literature review and a research-based systematic literature review manuscript. Within these two chapters, I aim to investigate the evolving use of earth observation, or remotely-sensed, data in landscape-scale ecosystem service models. Chapter 1 is a comprehensive literature survey that is not meant for publication at this time. Chapter 2 is prepared as a manuscript for submission to the journal *Ecological Indicators*.

CONTRIBUTION OF AUTHORS

As the MSc Candidate, I, David Ferguson, am responsible for leading the study design, data collection, analyses, and writing of both chapters of this thesis.

The supervisors and co-authors of the manuscript (Chapter Two), Dr. Elena Bennett and Dr. Klara Winkler, were involved in all steps of the research process and aided in the original conceptualization, refining the research questions, reviewing the methods, and gave advice on the data analysis and editing of the thesis writing.

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence

ARIES: ARtificial Intelligence for Environment & Sustainability

CICES: Common International Classification of Ecosystem Services

DMSP: Defense Meteorological Satellite Program

EBV: Essential Biodiversity Variable(s)

EESV: Essential Ecosystem Service Variable(s)

EO: Earth Observation(s)

ES: Ecosystem Service(s)

EVI: Enhanced Vegetation Index

GPP: Gross Primary Productivity

IRECI: Inverted Red-Edge Chlorophyll Index

LAI: Leaf Area Index

LULC: Land-Use Land-Cover

MODIS: Moderate Resolution Imaging Spectroradiometer

InVEST: Natural Capital Project's Integrated Valuation of Ecosystem Services and Tradeoffs

NCP: Nature's Contributions to People

NDWI: Normalized Difference Water Index

NDVI: Normalized Difference Vegetation Index

NPP: Net Primary Productivity

OLS: Operational Linescan System

RS: Remote Sensing or Remotely-Sensed

SPOT: Satellite Pour l'Observation de la Terre

UN: United Nations

UN SEEA EA: United Nations System of Environmental-Economic Accounting Ecosystem Accounting

INTRODUCTION

Ecosystems have the capacity to provide benefits that support human well-being, including water purification, sense of place, food production, among many other direct and indirect contributions of nature to people (Daily 1997). These benefits that people obtain from nature are commonly referred to as Ecosystem Services (ES) (MA 2005) or Nature's Contributions to People (NCP) (IPBES 2017). In the decades since ES was first introduced as a concept, there has been continual exploration and development of tools and methods for modelling and monitoring multiple ES (Burkhard et al. 2018; Carpenter et al. 2009; Chaplin-Kramer et al. 2023; Cheng et al. 2019; Costanza et al. 2017; Malinga et al. 2015; Willcock et al. 2023). With this growing toolbox for understanding, studying, and communicating about ES, there has also been a growing number of choices for ES researchers and practitioners who want to design studies to better understand ES in specific locations. Among these varied tools and methods, there are unique data requirements, verification schemes, accuracies, and relevancies to specific places, ecosystems, and environmental management decisions (Bagstad et al. 2013).

Accurately understanding the conditions and dynamics within ecosystems that lead to ES requires a considerable understanding of ecosystem structure and processes (Fu et al. 2013; Notte et al. 2022). However, appropriate data and methods linking biophysical properties and processes of ecosystems to ES over large spatial extents are often lacking or overly simplified (Lavorel et al. 2017). To represent these ecologically meaningful linkages between ecosystem properties and ES more precisely over larger spatial and temporal extents, the ES community has called for exploration of ES modelling incorporating earth observation (EO) data that capture information on a variety of ecosystem properties across large temporal and spatial extents (Braun et al. 2018; Cord et al. 2017; Galaz García et al. 2023; Ramirez-Reyes et al. 2019).

At the time (2015) of the last review of EO (e.g. satellite or airborne data) technologies used in ES modelling, LULC was found to be the most used EO-derived data to represent ecosystem processes across ES models, used as the sole data product in 56% of studies (De Araujo Barbosa et al. 2015). This LULC-based modelling approach has its benefits as it is relatively easy to implement where LULC maps exist (Burkhard et al. 2009); however, LULC-based approaches to ES modelling might mask important heterogeneity within and across LULC types that is driven by the underlying biophysical properties of ecosystems, such as properties related to an ecosystems' structure (e.g. ecosystem configuration, habitat structure) or processes/function (e.g. ecosystem phenology, primary productivity, disturbance level). This means that the spatial variability of potential ES supply within landscape patches consisting of a single LULC type will be underestimated and, in many cases, missing all together (Eigenbrod et al. 2010). Not having information about how ES varies within landscape patches is a critical gap, as that is a level of information particularly relevant to local and regional scales for land management and engagement with land stewards (Ziter et al. 2013).

ES studies integrating EO data into models over the last ten years have shown promising results that EO is enabling greater inclusion of data relating to diverse ecosystem properties as inputs in modelling ES across broader extents with finer resolution outputs, but this work is still in its early stages. There remain many questions in the ES community about the scale to which EO data can be used in monitoring and modelling ES (Anderson 2018), which EO are appropriate to model which services (de Araujo Barbosa et al. 2015), and how much can be gained, in terms of accuracy and finer resolution (temporal and spatial) outputs, from developing increasingly complex EO-based models (Ayanu et al. 2012; Braun et al. 2017; Hamolová et al. 2014). My thesis will contribute to the growing body of literature addressing some of these questions (Fig. 1.1).

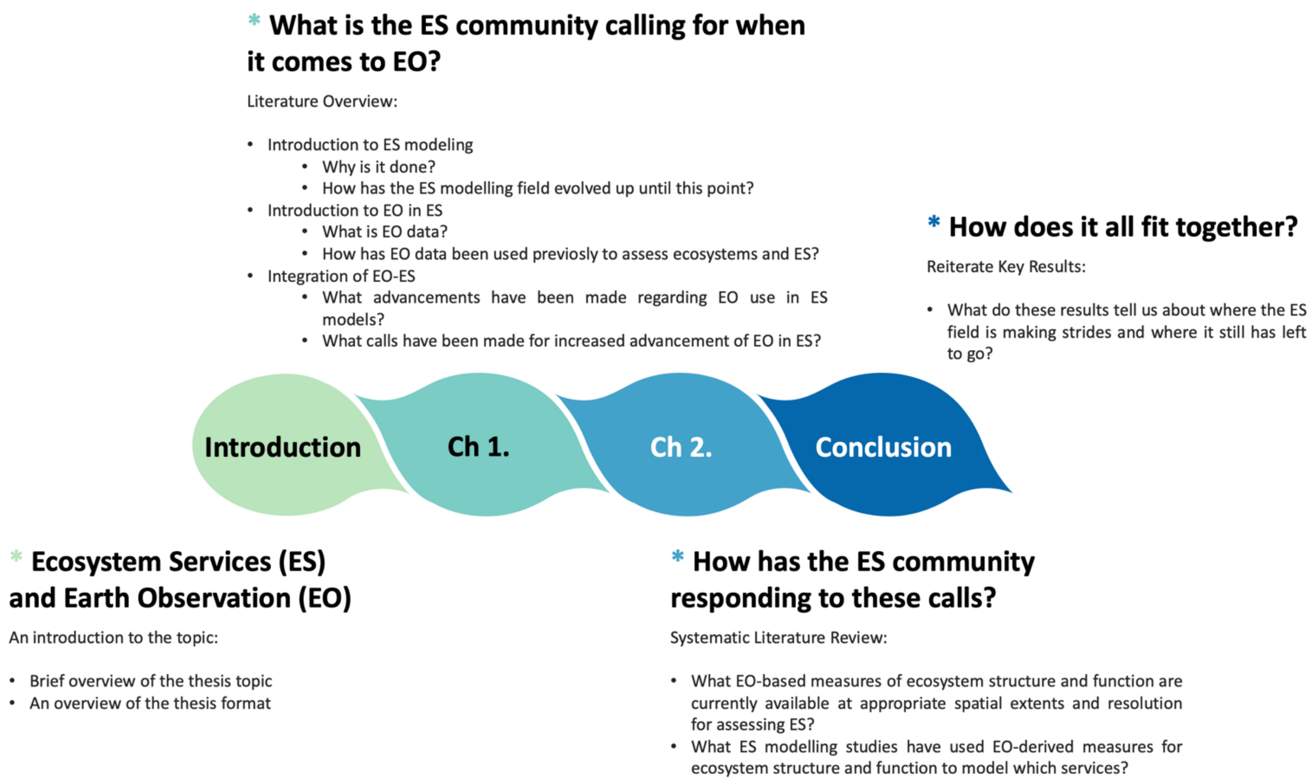

Figure 1.1. Outline of MSc Thesis key research topics and questions

The general outline of my thesis is as follows:

Introduction will provide a brief introduction to the thesis topic, overview the state-of the science in the ES modelling field, and present overall thesis objectives and research questions.

Chapter One of my thesis expands on this introduction through a comprehensive literature survey, examining in greater depth: A) the current state of ES modelling and its applications within longer term ES monitoring schemes, B) what the ES community is calling for in terms of advancements in use of EO data, and C) what has been achieved so far and what gaps remain in EO use for ES purposes.

Chapter Two of my thesis focuses on: A) the growing use of EO to measure properties of ecosystem structure and ecosystem function in landscapes, and B) how the availability of ecosystem structure and function EO data has been integrated into ES modelling studies. Through a systematic literature review of the last ten years of ES modelling papers, I have examined: 1) which EO-derived indicators of ecosystem structure and function are currently available at appropriate scales for assessing ES, and 2) which ES modelling studies have used EO-derived ecosystem structure and function data to model which services.

Comprehensive Scholarly Discussion and **Conclusion** that will summarize and discuss the main findings of the thesis, discuss implications of the work within the field, and provide a concluding summary of the work with potential future research directions.

REFERENCES

Anderson, C. B. (2018). Biodiversity monitoring, earth observations and the ecology of scale. Ecology Letters, 21(10), 1572–1585. https://doi.org/https://doi.org/10.1111/ele.13106

Assessment, M. E. (2005). Ecosystems and human well-being: wetlands and water. World Resources Institute.

Ayanu, Y. Z., Conrad, C., Nauss, T., Wegmann, M., & Koellner, T. (2012). Quantifying and Mapping Ecosystem Services Supplies and Demands: A Review of Remote Sensing Applications. Environmental Science & Technology, 46(16), 8529–8541. https://doi.org/10.1021/es300157u

Bagstad, K. J., Semmens, D. J., Waage, S., & Winthrop, R. (2013). A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosystem Services, 5, 27–39. https://doi.org/https://doi.org/10.1016/j.ecoser.2013.07.004

Braun, D. (2017). Remote sensing of ecosystem services. University of Zurich.

Braun, D., Damm, A., Hein, L., Petchey, O. L., & Schaepman, M. E. (2018). Spatio-temporal trends and trade-offs in ecosystem services: An Earth observation based assessment for Switzerland between 2004 and 2014. Ecological Indicators, 89, 828–839. https://doi.org/https://doi.org/10.1016/j.ecolind.2017.10.016

Burkhard, B., Kroll, F., Müller, F., & Windhorst, W. (2009). Landscapes' capacities to provide ecosystem services - A concept for land-cover based assessments. Landscape Online, 15. https://doi.org/10.3097/LO.200915

Burkhard, B., Santos-Martin, F., Nedkov, S., & Maes, J. (2018). An operational framework for integrated Mapping and Assessment of Ecosystems and their Services (MAES). One Ecosystem, 3, e22831. https://doi.org/10.3897/oneeco.3.e22831

Carpenter, S. R., Mooney, H. A., Agard, J., Capistrano, D., DeFries, R. S., Díaz, S., Dietz, T., Duraiappah, A. K., Oteng-Yeboah, A., Pereira, H. M., Perrings, C., Reid, W. V, Sarukhan, J., Scholes, R. J., & Whyte, A. (2009). Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proceedings of the National Academy of Sciences, 106(5), 1305–1312. https://doi.org/10.1073/pnas.0808772106

Chaplin-Kramer, R., Neugarten, R. A., Sharp, R. P., Collins, P. M., Polasky, S., Hole, D., Schuster, R., Strimas-Mackey, M., Mulligan, M., Brandon, C., Diaz, S., Fluet-Chouinard, E., Gorenflo, L. J., Johnson, J. A., Kennedy, C. M., Keys, P. W., Longley-Wood, K., McIntyre, P. B., Noon, M., … Watson, R. A. (2023). Mapping the planet's critical natural assets. Nature Ecology & Evolution, 7(1), 51–61. https://doi.org/10.1038/s41559-022-01934-5

Cord, A. F., Bartkowski, B., Beckmann, M., Dittrich, A., Hermans-Neumann, K., Kaim, A., Lienhoop, N., Locher-Krause, K., Priess, J., Schröter-Schlaack, C., Schwarz, N., Seppelt, R., Strauch, M., Václavík, T., & Volk, M. (2017). Towards systematic analyses of ecosystem service trade-offs and synergies: Main concepts, methods and the road ahead. Ecosystem Services, 28, 264–272. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.07.012

Costanza, R., de Groot, R., Braat, L., Kubiszewski, I., Fioramonti, L., Sutton, P., Farber, S., & Grasso, M. (2017). Twenty years of ecosystem services: How far have we come and how far do we still need to go? Ecosystem Services, 28, 1–16. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.09.008

Daily, G. C. (1997). Introduction: what are ecosystem services. Nature's Services: Societal Dependence on Natural Ecosystems, 1(1).

de Araujo Barbosa, C. C., Atkinson, P. M., & Dearing, J. A. (2015). Remote sensing of ecosystem services: A systematic review. Ecological Indicators, 52, 430–443. https://doi.org/https://doi.org/10.1016/j.ecolind.2015.01.007

Eigenbrod, F., Armsworth, P. R., Anderson, B. J., Heinemeyer, A., Gillings, S., Roy, D. B., Thomas, C. D., & Gaston, K. J. (2010). The impact of proxy-based methods on mapping the distribution of ecosystem services. Journal of Applied Ecology, 47(2), 377–385. https://doi.org/https://doi.org/10.1111/j.1365-2664.2010.01777.x

Fu, B., Wang, S., Su, C., & Forsius, M. (2013). Linking ecosystem processes and ecosystem services. Current Opinion in Environmental Sustainability, 5(1), 4–10. https://doi.org/https://doi.org/10.1016/j.cosust.2012.12.002

Galaz García, C., Bagstad, K. J., Brun, J., Chaplin-Kramer, R., Dhu, T., Murray, N. J., Nolan, C. J., Ricketts, T. H., Sosik, H. M., Sousa, D., Willard, G., & Halpern, B. S. (2023). The future of ecosystem assessments is automation, collaboration, and artificial intelligence. Environmental Research Letters, 18(1), 011003. https://doi.org/10.1088/1748-9326/acab19

Homolová, L., Schaepman, M. E., Lamarque, P., Clevers, J. G. P. W., de Bello, F., Thuiller, W., & Lavorel, S. (2014). Comparison of remote sensing and plant trait-based modelling to predict ecosystem services in subalpine grasslands. Ecosphere, 5(8), art100. https://doi.org/https://doi.org/10.1890/ES13-00393.1

IPBES. (2019). Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Zenodo. https://doi.org/10.5281/zenodo.6417333

Lavorel, S., Bayer, A., Bondeau, A., Lautenbach, S., Ruiz-Frau, A., Schulp, N., Seppelt, R., Verburg, P., Teeffelen, A. van, Vannier, C., Arneth, A., Cramer, W., & Marba, N. (2017). Pathways to bridge the biophysical realism gap in ecosystem services mapping approaches. Ecological Indicators, 74, 241–260. https://doi.org/https://doi.org/10.1016/j.ecolind.2016.11.015

Malinga, R., Gordon, L. J., Jewitt, G., & Lindborg, R. (2015). Mapping ecosystem services across scales and continents – A review. Ecosystem Services, 13, 57–63. https://doi.org/https://doi.org/10.1016/j.ecoser.2015.01.006

Notte, A. La, Czúcz, B., Vallecillo, S., Polce, C., & Maes, J. (2022). Ecosystem condition underpins the generation of ecosystem services: an accounting perspective. One Ecosystem, 7, e81487. https://doi.org/10.3897/oneeco.7.e81487

Ramirez-Reyes, C., Brauman, K. A., Chaplin-Kramer, R., Galford, G. L., Adamo, S. B., Anderson, C. B., Anderson, C., Allington, G. R. H., Bagstad, K. J., Coe, M. T., Cord, A. F., Dee, L. E., Gould, R. K., Jain, M., Kowal, V. A., Muller-Karger, F. E., Norriss, J., Potapov, P., Qiu, J., … Wright, T. M. (2019). Reimagining the potential of Earth observations for ecosystem service assessments. Science of The Total Environment, 665, 1053–1063. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.02.150

Willcock, S., Hooftman, D. A. P., Neugarten, R. A., Chaplin-Kramer, R., Barredo, J. I., Hickler, T., Kindermann, G., Lewis, A. R., Lindeskog, M., Martínez-López, J., & Bullock, J. M. (2023). Model ensembles of ecosystem services fill global certainty and capacity gaps. Science Advances, 9(14), eadf5492. https://doi.org/10.1126/sciadv.adf5492

Ziter, C., Bennett, E. M., & Gonzalez, A. (2013). Functional diversity and management mediate aboveground carbon stocks in small forest fragments. Ecosphere, 4(7), art85. https://doi.org/https://doi.org/10.1890/ES13-00135.1

CHAPTER ONE

Advancing the Use of Earth Observations of Ecosystem Structure and Function in Ecosystem Service Modelling and Monitoring: Current Trends and Research Directions

1.1 Ecosystem services – a concept linking people to nature

Ecosystems provide benefits that contribute to human well-being, including water purification, recreation opportunities, flood protection, and food production (Daily 1997). These benefits that people obtain from nature are commonly referred to as Ecosystem Services (ES) or Nature's Contributions to People (NCP). The publication of the Millennium Ecosystem Assessment (MA 2005) spurred a rapidly growing field of study on the subject that had continued to the present (see Carpenter et al. 2009; Costanza et al. 2017 for reviews). As first defined by the MA in 2005, ES can take many forms and are broadly grouped into three categories: provisioning services, regulating services, and cultural services. Provisioning services are goods and resources from an ecosystem, such as food supply, timber, and freshwater; regulating services occur due to the regulation of ecosystem processes, such as erosion prevention, heat reduction, and air quality regulation of particulate matter; and cultural services are non-material benefits that people can gain from ecosystems, such as recreation opportunities or connection to place.

Human-induced changes to ecosystems impact their ability to provide services, for better (e.g., the use of fertilizers to improve agricultural production) and for worse (e.g., the eutrophication caused by runoff from those fertilizers). These human-induced changes – which can include land use degradation and conversion, climate change, and pollution – affect ecosystems and their services at both global and local scales (Folke et al. 2016; MA 2005). Understanding and monitoring how these changes affect ecosystem properties, processes, and ultimately the provision of ES is critical to assessing the impacts of these changes on human well-being; in addition to effectively implementing management and policy strategies to establish and meet targets for a more sustainable future (Tallis et al. 2012). As such, the popularization of the ES concept has been foundational to advancing monitoring efforts aimed at capturing information about ecosystem changes and the implications of those changes for human well-being (Balvanera et al. 2022; Karp et al. 2015).

1.2 Ecosystem services – operationalizing monitoring schemes to evaluate multiple ES over space and time

Major global monitoring and assessment efforts linking ecosystems, ES, and human well-being have included the Millennium Ecosystem Assessment (MA 2005), the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) global assessment reports (IPBES 2019), and the United Nations (U.N.) System of Environmental-Economic Accounting Ecosystem Accounting (SEEA EA) framework (United Nations 2021). Beyond the intrinsic value of these monitoring initiatives providing important measurements that allow for tracking change in ecosystem condition and human well-being through time, formalized global agreements (e,g., the Global Biodiversity Framework, U.N. Climate Accords, Sustainable Development Goals) mean that there is an extrinsic requirement in many countries to monitor and report regularly on multiple ES.

Implementation of the ES concept in these assessments is spatial by nature (Andrew et al. 2015; Martínez-Harms & Balvanera 2012), evaluating both where ecosystems are present to supply services and where people are present to receive the benefits of those services. Broadly, a distinction is made between ES potential, the biophysical amount of a service produced by an ecosystem, and ES flow, which is the amount of a service received by people (Hein et al. 2016; Braun 2017). ES potential and ES flow have unique spatial contexts. The spatial patterns of ES potential are linked to the spatial heterogeneity of underlying environmental properties of structure and function, which could also be seen as properties of an ecosystem condition, such as vegetation cover, soil moisture, topography, water quality, and landscape connectivity, among many other potential factors depending on the particular ES (Notte 2022; Schröter et al. 2015). The spatial pattern of ES flow is determined both by the locations of ES potential and the locations of the beneficiaries who will receive the ES. Furthermore, both ES potential and ES flow are affected and mediated by human influences that also have a spatial component, such as the spatial variability of different management systems or built infrastructure. For example, transportation networks in many cases are necessary to bring food from agricultural lands to people.

These variable spatial contexts are important to consider when designing ES monitoring schemes of both ES potential and ES flow. ES potential can spatially overlap with ES flow; for example, in the case of a recreational walking trail located within a neighborhood that people live, which can provide outdoor recreation to local residents. However, the location of ES potential and ES flow do not always overlap. Water regulation services often depend on movement of water and the extent of rivers, streams, and wetlands. For example, flood regulation potential of a property is not only determined by the storage capacity of the nearest body of water, but of the capacity of the connected water system. Furthermore, there are cases where the spatial distribution of an ES flow is not clearly defined or occurs at a different scale of from that of the ES potential, such as the benefits of carbon sequestration in forests, where the ES potential is limited to the extent of the forest, but the benefit of reduced carbon dioxide in the atmosphere is global.

ES assessments have been carried out across the planet at various spatial scales (Malinga et al. 2015), from single river basins (Vargas et al. 2019) to national and continental efforts to global mapping (Chaplin-Kramer et al. 2019). As an example of the diverse efforts happening at just the continental and national scale, presently there are advancements in and funding allocated to Canada's Census of Environment, the European Union's Mapping and Assessment of Ecosystems and their Services, and the United States' National Nature Assessment. The designation and communication of clear spatial boundaries and scale is critical for designing effective monitoring schemes relevant for the stated decision-making and tracking purposes. The outputs of the most well-designed monitoring scheme may not be transferable to other contexts or spatial scales. Due to the complicated nature of spatial dynamics of ES potential and flow, there is often limited the transferability of information across assessments at different scales and questions around scaling the information derived from ES assessments remains a key gap in the ES field (Bennett et al. 2021).

Monitoring refers to repeated assessment over time, and the temporal aspects of an assessment or monitoring scheme is just as important a consideration as the spatial aspects. In the cases mentioned above, such repeated use of assessment is used to track change in ES potential, flow, and related human well-being outcomes. Beyond tracking and quantifying ES, these monitoring schemes often aim to assess and identify the underlying drivers of change through time, from impacts on ecosystem structural characteristics and functions to subsequent consequences in the flow of ES

Temporal mismatches affect ES potential and flow over time that might otherwise be overlooked in one-off assessments (Winkler et al. 2021). For example, shifts in bird populations due to climatic changes may have consequences on the flow of certain cultural services, like bird watching or connection to iconic species; while at the same time climatic shifts may affect (for better and worse, depending on crop type and location) agricultural productivity over time. A one-off assessment, or longer-term monitoring scheme, that does not track climatic drivers through time could potentially miss early warning signs of a change in ES flow. Furthermore, these shifts in ES flow are likely to occur at different rates depending on a variety of factors, such as the variable response rates of different species to climatic changes. Therefore, monitoring schemes that track only drastic changes, such as when an ecosystem shifts from one type to another (e.g., a forest is converted to agricultural field), are insufficient and may miss underlying drivers of changes in ES potential and flow through time (Wilcock et al. 2021).

Finally, in addition to consideration of both spatial and temporal ES dynamics, analysis of ES interactions, such as trade-offs and synergies, is another critical component of effective monitoring (Reib et al. 2017). Within ecosystems, there is potential for not only individual ES, but multiple connected ES. A trade-off between ES occurs when an increase in one ES results in a decrease in another (Bennett et al. 2009). For example, if a forest patch is converted to an agricultural patch, there will be an increase in food provisioning, but a reduction in shading and heat reduction from the loss of canopy. A synergy between ES occurs when an increase in one ES aligns with an increase in another (Bennett et al. 2009). For example, a growing forest understory has the potential to regulate water flow and air quality. Understanding and studying ES together to examine how they interact each other in an ecosystem is critical for making management decisions and reducing potential trade-offs across space and time (Willemen et al. 2012).

Critically, these three choices of spatial scale, temporal scale, and ES considered interact with one another and will shape the dynamics captured by an assessment. For example, understanding and assessment of ES interactions has been shown to be dependent on the spatial scale of assessment (Raudsepp-Hearne and Peterson 2016), yet most studies to-date examine ES interactions at just one scale (Lee and Lautenbach 2016). Furthermore, the temporal scale of a study will also affect the synergies and trade-offs identified. For example, in Quebec's Montérégie the flow and interactions of multiple important ES, such as maple syrup production, crop production, outdoor recreation, and deer hunting, vary significantly depending on the season; an assessment of ES over a year's period would provide a different understanding of the ES across the landscape than an assessment done over just the summer months.

In ES monitoring, choices of spatial scale, temporal scale, and the set of ES considered have major implications for decision-making recommendations and overall understanding of the linkages between ecosystems and human well-being. Transparency and reflexivity around these choices in designing ES monitoring approaches is critical to understanding the fit of different assessments to addressing unique questions in individual places. An assessment that can accurately track information across multiple spatial and temporal scales would be ideal. Further, in designing ES assessments, it is important to consider the underlying frameworks and data that serve as the starting place because those early choices have implications for what drivers of ES change are ultimately considered and tracked through time.

1.3 Ecosystem services – the ES cascade, ecosystem structure, and function

To ensure a sustainable future of the planet, it is not only important to assess ES flow outcomes at a single point in time, but to also monitor and identify the underlying ecosystem properties driving ES change over time, but also the synergies and tradeoffs between these ecosystem properties in geographic space. Monitoring only outcomes and not tracking condition can eventually lead to mismanagement, and eventual loss of ES (Notte et al. 2022). Across frameworks and monitoring schemes, understanding underlying ecosystem properties, processes, and conditions is essential to understanding ES potential (Mace et al. 2012). That is, we cannot really know what services a forest is providing unless we know something about the condition of that forest - for example, the age structure of trees in a forest - and the processes occurring in and around it - such as photosynthesis and carbon sequestration that are influenced by age structure. A small beech forest (condition: type of forest is beech) in the Montérégie might be performing the process of absorbing excess water and therefore provide the service of regulating flooding, while a maple forest (a different condition) could provide the opportunity to produce maple syrup, a different ES.

In thinking about certain ES, such as wheat production, it might be possible to assess the ES flow without knowing anything about an ecosystem's condition. For example, in the Montérégie and many other agricultural landscapes, information is reported by the tons produced of wheat every season. However, knowing the condition of an ecosystem is useful for managing ecosystems for future potential ES. In an agricultural setting, understanding how soil moisture and nutrient levels are changing can lead to a more holistic understanding (and thus better-informed management practices) of that ecosystem and the properties that matter for maintaining ES flow into the future. Furthermore, if we don't understand whether wheat is increasing because of fertilizer use or because of something else (e.g., changing climate), then we haven't really assessed sustainability.

The ES cascade framework of Haines-Young and Potschin (2010) provides a useful way to think about the relationships between condition (what they call biophysical structure), processes (which they call functions), and the flow of ES. The ES cascade framework is central to the Common International Classification of Ecosystem Services (CICES) and other European assessments of ES. In the ES cascade framework (Haines-Young and Potschin 2010), the biophysical ecosystem structure and related processes are included as the starting point from which to quantify ES. Take the example of water quality regulation of phosphorus-rich runoff from an agricultural field into a nearby waterbody. The distance that the runoff passes through a wetland, riparian forest buffer, or other vegetated patch of land (ecosystem structure) will impact the amount of nutrients being taken out of the runoff, but so too will the productivity of the vegetation in those patches (ecosystem function).

Other frameworks are organized around the relationships between ecosystem structure, function, and ES. In the UN SEEA EA framework, ecosystem condition is included as one of five core accounts, drawing a link between the quality of an ecosystem's abiotic and biotic characteristics and an ecosystem's capacity to supply ES (United Nations 2021). And in the Essential Ecosystem Service Variables (EESVs) framework, a direct connection is drawn between the Ecological Supply Variable, representing an ecosystem's potential for ES, and the Essential Biodiversity Variables (EBVs), which include metrics of biodiversity such as ecosystem structure and function (Balvanera et al. 2022; Pereira et al. 2013).

Returning to the ES cascade of Haines-Young and Potschin, this framework highlights the key linkages in the steps to ES flow, in which the structure, or biophysical components, of an ecosystem interact with ecosystem functions, or dynamic biophysical processes, to produce services that people receive. Expanding the definitions further, ecosystem structure refers to the biophysical configuration and spatial patterns of ecosystem components, and ecosystem function refers to the performance of chemical and biological processes within ecosystems that maintain life and are essential for the production of ES (Notte, et al. 2017; Turkelboom et al. 2013). Within a patch of forest, for example, structure would refer to the pattern and biomass of the stranding vegetation and function would include the net primary productivity of the vegetation in a forest; one ES linked to these ecosystem properties in the forest patch is air quality regulation.

While nearly all ES frameworks highlight the complex role of ecosystem structure on function, processes, and, ultimately, ES, these linkages tend to get simplified in most ES assessments done over large scales. Usually, the various components of an ecosystem's structure and functioning are simplified and masked by using land-use/land-cover (LULC), which has established methods of being used to model ES (ES Matrix, NatCap InVest Modelling Suite) across broad spatial extents.

2.1 Ecosystem service modelling – overview (approaches)

It is resource intensive (in terms of both time, money, and people power) to assess and measure ES data in the field for assessments over large landscapes, whole countries, or the entire planet. For that reason, efforts to assess ES across broad areas at fine resolution rely on a growing sub-field within ES research that is ES modelling (Andrew et al. 2015; Hamann et al. 2020; Neugarten et al. 2018).

There are now a wide variety of established and emerging tools and methods that can be used to spatially assess ecosystem properties, processes, and services (Bagstad et al. 2013; Hamann et al. 2020; Lavorel et al. 2017); with different approaches requiring that the researcher or practitioner make determinations and choices in regards to data requirements, spatial scale, temporal scale, accuracy testing, and relevancy to specific questions (Cole et al. 2023; Malinga et al. 2015; Martínez-Harms and Balvanera 2012). Modelling approaches range from models with limited primary inputs, such as modelling ES potential based on LULC maps in combination with expert estimations of services per LULC class (Campagne et al. 2020; Jacobs et al. 2015), to increasingly complex models that incorporate field observations with ecosystem data (e.g. plant surveys, weather data, soil properties) and earth observation/remote-sensing data (e.g. vegetation productivity indices, water quality indices) (del Río-Mena et al. 2020; Lavorel et al. 2011).

ES modelling approaches range from simpler to increasingly complex, depending on data requirements, computational resources, and expertise needed (Martínez-Harms and Balvanera 2012; Schröter et al. 2015). Different ES modelling requires different types of data. These input data requirements for ES models are one factor determining the spatial resolution and accuracy of the modelled ES outputs. LULC is the most commonly used proxy variable to represent ecosystem processes in ES modelling through look-up tables (de Araujo Barbosa et al. 2015), a simplified approach that is relatively easy to implement where LULC maps exist (Burkhard et al. 2009). However, this LULC-driven approach to ES modelling has the potential to mask important heterogeneity within and across LULC types that is driven by underlying characteristics of the ecosystem, such as its structure (e.g., ecosystem configuration, habitat structure) or function (e.g., ecosystem phenology, primary productivity, disturbance level).

Furthermore, by focusing primarily on the LULC composition of an ecosystem, other important factors are often ignored such as the configuration of the landscape as a whole or the ways that the functions of an ecosystem can vary due to human factors, such as management practices. This means that the spatial variability of potential ES supply within LULC blocks can be underestimated and, in many cases, missing all together (Eigenbrod et al. 2010). Not having information about how ES supply varies within LULC patches is a critical gap as that is a level of information relevant at local and regional scales for land management decision-making (Maes et al. 2012; Ziter et al. 2013).

Further still, a reliance on LULC maps can mask the importance of an ecosystem's condition (Notte et al. 2022). Not only do models using LULC miss spatial variability of ES outcomes, it simplifies critical causal links, such as: 1) weakening, or missing altogether, the connection that can be made between individual components of an ecosystem's structure and/or function and ES potential, 2) preventing analysis on the impact of different management approaches that may be happening within a type of LULC (i.e., preventing cross-comparisons of forests under different management plans), and 3) LULC models only allow for monitoring of drastic shifts in ecosystems, but not intermediate changes in ecosystem properties and subsequently ES. A key research frontier in ES modelling, and the ES field more generally, is developing models and understanding that considers these complex interactions and linkages between ES and multiple drivers of change (Gilman and Wu 2023; Theirry et al. 2021).

2.2 Ecosystem service modelling – the growing use of earth observation

Earth Observation (EO; e.g. satellite, spaceborne, or airborne data) is information on the Earth's physical, chemical, and biological systems captured via remote sensors such as satellites and other measuring devices not in direct contact with the object being measured (Ustin and Middleton 2021). EO measures the surface properties of Earth, and it has been applied to studying a range of ecosystem properties, including indicators of structure and function (Pettorelli et al. 2014; Skidmore et al. 2015; Vyvlečka and Pechanec 2023). Benefits of EO use in ES assessments include that EO provides (1) spatially continuous information about the structure and function of ecosystems over large extents; (2) repeated and long-term temporal information, which enables repeated assessment (monitoring), and (3) the relatively fine resolution of EO allows for the EO information to be used at multiple-scales, and verified through field observations (Braun 2017; Braun et al. 2018; Cord et al. 2017; de Araujo Barbosa et al. 2015; Pettorelli et al. 2014; Rose et al. 2015).

Despite the myriad properties that EO can be used to assess, LULC is the most used EO-derived data used in ES assessments (Campagne et al. 2020; de Araujo Barbosa et al. 2015). However, EO measurements can also capture additional data on ecosystem properties and processes, such as vegetation density, water availability, elevation, productivity, and other biophysical information over large areas that could be used in more refined ES models (Andrew et al. 2014; Pettorelli et al. 2018; Wang and Gamon 2021; Vyvlečka and Pechanec 2023).

EO-derived information, beyond LULC, that has been used for assessing ES is often associated with vegetation (e.g., Leaf Area Index (LAI), NDVI and Net Primary Productivity (NPP)), geomorphological indicators (e.g., slope and elevation), disturbance/damage impacts (e.g., fire, human disturbance), water quality indicators (e.g., NDWI, chlorophyll concentrations), and seasonal timing (e.g., phenology). Ground-based EO systems (such as weather stations) also provide important information that can support assessment and development of ecosystem information (e.g., with respect to water availability/precipitation, surface temperature, evapotranspiration). And there may remain several ecosystem properties (e.g., species diversity, soil quality) that require some level of *in-situ* monitoring and validation data. With the growing accessibility of varied EO data, there is growing opportunity for methodological exploration by the ES modelling community that preserves linkages between multiple ecosystem properties and ES potential.

To summarize, the use of EO in ES models has the potential to advance ES modelling in several ways. Expanding the use of EO in ES modelling work can lessen the reliance on LULC as the primary input in most models, moving the modelling field towards more integrated approaches that capture effects of ecosystem properties, processes, and conditions to the potential supply of ES. Further still, because EO provides consistent measures across greater extents and at finer spatial and temporal resolutions, there is hope that EO can make ES assessment more scalable across space and time; moving the field away from either one-time national assessments that don't provide granular information relevant to local contexts or localized field-based assessments that can't be scaled up to larger landscape contexts (Cord et al. 2017, 2015; Galaz García et al. 2023; Pettorelli et al. 2016; Ramirez-Reyes et al. 2019; Rose et al. 2015; Skidmore et al. 2021, 2015).

For further information on the growth of EO use in related fields, and the variety of ecosystem properties that can be captured by EO and linked to ES, there have been several excellent reviews completed recently. Previous reviews have focused on documenting overall use of EO data in ES modelling (Ayanu et al. 2012; De Araujo Barbosa et al. 2015), with more focused reviews in the last few years focusing on EO use in ES assessment in grasslands (Masenyama et al. 2022) and urban vegetation (Taveras et al. 2019; García-Pardo et al. 2022), and EO use among other emerging technologies in ES assessments (Schirpke et al. 2023). Furthermore, there have been reviews of how EO data align with different ecosystem monitoring frameworks, such as Common International Classification of Ecosystem Services (CICES; Grimma et al. 2023), EBVs (Skidmore et al. 2021), and the Sustainable Development Goals (Cochran et al. 2020). In closely related fields, there have been recent reviews of EO use in urban planning (Wellmann et al. 2020),inland water quality (Topp et al. 2020), and environmental justice (Sayyed et al. 2024) studies.

2.3 Ecosystem service modelling – towards the cascade

While the EESVs framework, the ES Cascade framework, and the ES concept more generally suggest that ES potential, and eventual flow, is based on ecosystem properties of structure and function, most ES modelling studies (56 %) use only LULC data to derive ES estimates (de Araujo Barbosa et al. 2015). However, several studies (Braun et al. 2017; del Río-Mena et al. 2020; Hamolová et al. 2014; Vaz et al. 2020) have found promising results of incorporating additional EO data in ES modelling to better reflect ecosystem processes and properties and their effects on services. Braun et al. (2017) paired EO-data (Sun-Induced chlorophyll Fluorescence; a measure of photosynthetic activity) with *in situ* data to model gross primary production (GPP) maps. With the GPP data as an indicator for ecosystem functioning, they used GPP to derive estimates of two ES (carbon dioxide regulation and food supply). After validating their model results with field measurements, they found that the EO models captured heterogeneity in patterns of ES, both within and across land use patches. Hamolová et al. (2014) used five EO-derived ecosystem properties (green biomass, litter mass, crude protein content, species diversity and soil carbon content) to model three ES (agricultural production, aesthetic values, and carbon sequestration).They then compared this EO-based modelling approach with a second modelling approach that modeled ES from LULC and abiotic and plant trait data. Similarly to Braun et al. (2017), Hamolová et al. (2014) found that the EO-properties model provided more accurate insights into the spatial distribution of ES within land use patches, where the more traditional LULC and trait-based modelling approach over emphasized the effects of land use on ES.

Methodologically, there is an exploration happening in the ES modelling literature that recognizes that changes in ES should not only be linked to drastic ecosystem shifts (i.e. the conversation of an area from one LULC to another LULC type), but also to change in ecosystem conditions that affect ecosystem structure, functions, and ES (Braun et al. 2018; Notte et al. 2022). Modelling and monitoring that overly relies on LULC maps provides only individual snapshots in time (Karp et al. 2015). To summarize, EO has the potential to fill a current gap in ES modelling by providing continues ecosystem information across time and space (Braun et al. 2018; Cord et al. 2017; Pettorelli et al. 2016); bringing the ES field closer to the ecological foundations of the ES concept and capturing the varied spatial and temporal dimensions of human-nature interactions (Fig. 2.1.).

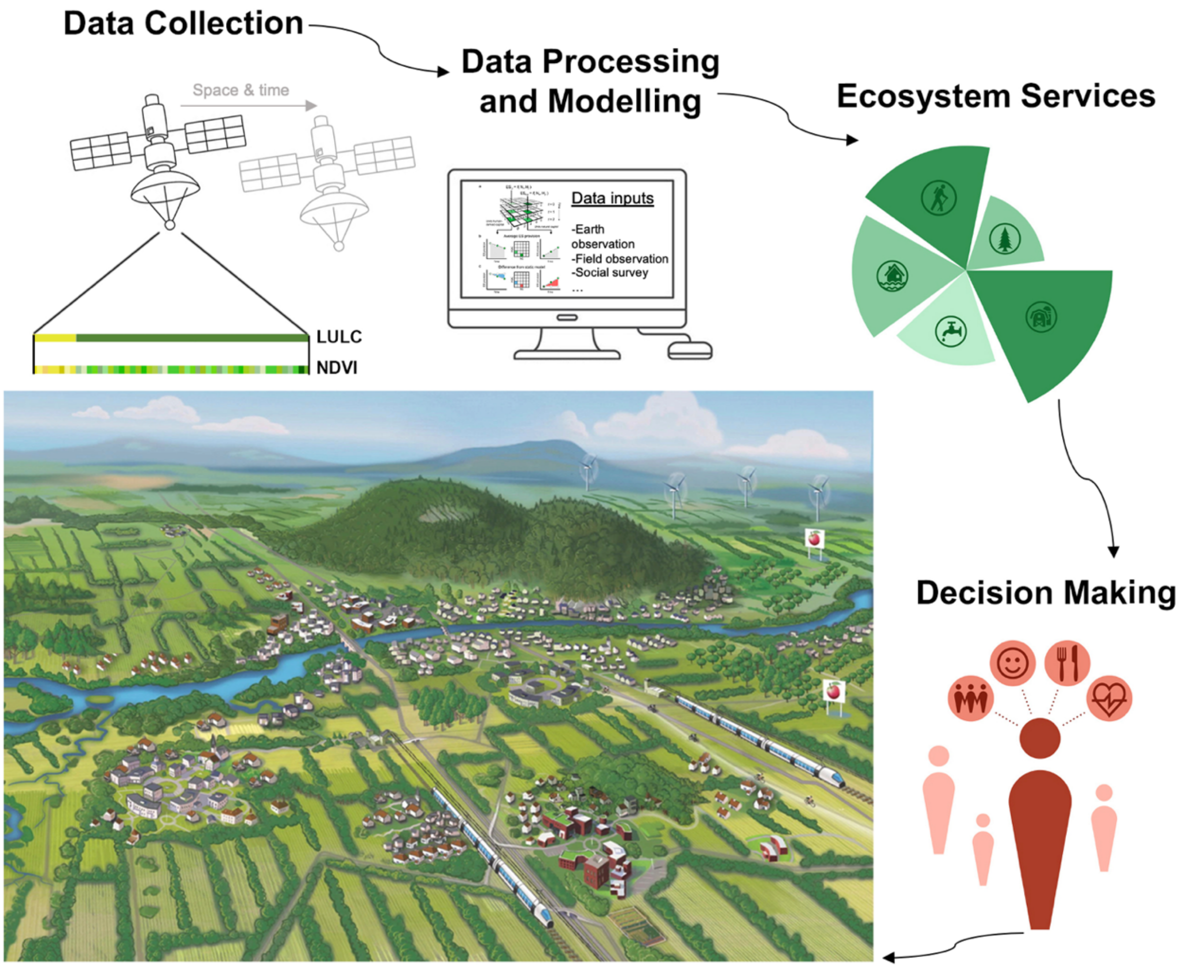

Figure 2.1. Earth observation contributes to ecosystem service modelling and monitoring. At the top of the figure, the three aspects of how EO data is contributing to ES understanding examined in this thesis are shown. Theis refers to EO use in (i) collecting data on ecosystem properties (structure and function) across space and time, (ii) the inclusion of EO data as an input in models of multiple ecosystem services, and (iii) the contribution of EO in studies that examine interactions and tradeoffs of multiple ecosystem services over space and time. The information from these assessments will ideally make its way to decision-makers who then influence management and policy choices that shape landscapes and ecosystem properties, while this is visualized on the right-hand side of the figure above, this thesis does not focus on those aspects of the system. Figure adapted from Braun 2017, with landscape illustration from Mitchell et al. 2015, *ES modelling figure from Reib et al.* 2023, *and ecosystem service and decision-making symbology from Bennett et al.* 2021.

REFERENCES

Anderson, C. B. (2018). Biodiversity monitoring, earth observations and the ecology of scale. Ecology Letters, 21(10), 1572–1585. https://doi.org/https://doi.org/10.1111/ele.13106

Andrew, M. E., Wulder, M. A., Nelson, T. A., & Coops, N. C. (2015). Spatial data, analysis approaches, and information needs for spatial ecosystem service assessments: a review. GIScience & Remote Sensing, 52(3), 344–373. https://doi.org/10.1080/15481603.2015.1033809

Assessment, M. E. (2005). Ecosystems and human well-being: wetlands and water. World Resources Institute.

Ayanu, Y. Z., Conrad, C., Nauss, T., Wegmann, M., & Koellner, T. (2012). Quantifying and Mapping Ecosystem Services Supplies and Demands: A Review of Remote Sensing Applications. Environmental Science & Technology, 46(16), 8529–8541. https://doi.org/10.1021/es300157u

Bagstad, K. J., Semmens, D. J., Waage, S., & Winthrop, R. (2013). A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosystem Services, 5, 27–39. https://doi.org/https://doi.org/10.1016/j.ecoser.2013.07.004

Balvanera, P., Brauman, K. A., Cord, A. F., Drakou, E. G., Geijzendorffer, I. R., Karp, D. S., Martín-López, B., Mwampamba, T. H., & Schröter, M. (2022). Essential ecosystem service variables for monitoring progress towards sustainability. Current Opinion in Environmental Sustainability, 54, 101152. https://doi.org/https://doi.org/10.1016/j.cosust.2022.101152

Bennett, E. M., Baird, J., Baulch, H., Chaplin-Kramer, R., Fraser, E., Loring, P., Morrison, P., Parrott, L., Sherren, K., Winkler, K. J., Cimon-Morin, J., Fortin, M.-J., Kurylyk, B. L., Lundholm, J., Poulin, M., Rieb, J. T., Gonzalez, A., Hickey, G. M., Humphries, M., … Lapen, D. (2021). Chapter One - Ecosystem services and the resilience of agricultural landscapes. In D. A. Bohan & A. J. Vanbergen (Eds.), Advances in Ecological Research (Vol. 64, pp. 1–43). Academic Press. https://doi.org/https://doi.org/10.1016/bs.aecr.2021.01.001

Bennett, E. M., Morrison, P., Holzer, J. M., Winkler, K. J., Fraser, E. D. G., Green, S. J., Robinson, B. E., Sherren, K., Botzas-Coluni, J., & Palen, W. (2021). Facing the challenges of using place-based social-ecological research to support ecosystem service governance at multiple scales. Ecosystems and People, 17(1), 574–589. https://doi.org/10.1080/26395916.2021.1995046

Bennett, E. M., Peterson, G. D., & Gordon, L. J. (2009). Understanding relationships among multiple ecosystem services. Ecology Letters, 12(12), 1394–1404. https://doi.org/https://doi.org/10.1111/j.1461-0248.2009.01387.x

Braun, D. (2017). Remote sensing of ecosystem services. University of Zurich.

Braun, D., Damm, A., Paul-Limoges, E., Revill, A., Buchmann, N., Petchey, O. L., Hein, L., & Schaepman, M. E. (2017). From instantaneous to continuous: Using imaging spectroscopy and in situ data to map two productivity-related ecosystem services. Ecological Indicators, 82, 409–419. https://doi.org/https://doi.org/10.1016/j.ecolind.2017.06.045

Burkhard, B., Kroll, F., Müller, F., & Windhorst, W. (2009). Landscapes' capacities to provide ecosystem services - A concept for land-cover based assessments. Landscape Online, 15. https://doi.org/10.3097/LO.200915

Campagne, C. S., Roche, P., Müller, F., & Burkhard, B. (2020). Ten years of ecosystem services matrix: Review of a (r)evolution. One Ecosystem, 5, e51103. https://doi.org/10.3897/oneeco.5.e51103

Carpenter, S. R., Mooney, H. A., Agard, J., Capistrano, D., DeFries, R. S., Díaz, S., Dietz, T., Duraiappah, A. K., Oteng-Yeboah, A., Pereira, H. M., Perrings, C., Reid, W. V, Sarukhan, J., Scholes, R. J., & Whyte, A. (2009). Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proceedings of the National Academy of Sciences, 106(5), 1305–1312. https://doi.org/10.1073/pnas.0808772106

Chaplin-Kramer, R., Sharp, R. P., Weil, C., Bennett, E. M., Pascual, U., Arkema, K. K., Brauman, K. A., Bryant, B. P., Guerry, A. D., Haddad, N. M., Hamann, M., Hamel, P., Johnson, J. A., Mandle, L., Pereira, H. M., Polasky, S., Ruckelshaus, M., Shaw, M. R., Silver, J. M., … Daily, G. C. (2019). Global modeling of nature's contributions to people. Science, 366(6462), 255–258. https://doi.org/10.1126/science.aaw3372

Cochran, F., Daniel, J., Jackson, L., & Neale, A. (2020). Earth observation-based ecosystem services indicators for national and subnational reporting of the sustainable development goals. Remote Sensing of Environment, 244, 111796. https://doi.org/https://doi.org/10.1016/j.rse.2020.111796

Cole, B., Bradley, A. V, Willcock, S., Gardner, E., Allinson, E., Hagen-Zanker, A., Calo, A. J., Touza, J., Petrovskii, S., Yu, J., & Whelan, M. (2023). Using a multi-lens framework for landscape decisions. People and Nature, 5(4), 1050–1071. https://doi.org/https://doi.org/10.1002/pan3.10474

Cord, A. F., Bartkowski, B., Beckmann, M., Dittrich, A., Hermans-Neumann, K., Kaim, A., Lienhoop, N., Locher-Krause, K., Priess, J., Schröter-Schlaack, C., Schwarz, N., Seppelt, R., Strauch, M., Václavík, T., & Volk, M. (2017). Towards systematic analyses of ecosystem service trade-offs and synergies: Main concepts, methods and the road ahead. Ecosystem Services, 28, 264–272. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.07.012

Costanza, R., de Groot, R., Braat, L., Kubiszewski, I., Fioramonti, L., Sutton, P., Farber, S., & Grasso, M. (2017). Twenty years of ecosystem services: How far have we come and how far do we still need to go? Ecosystem Services, 28, 1–16. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.09.008

Daily, G. C. (1997). Introduction: what are ecosystem services. Nature’s Services: Societal Dependence on Natural Ecosystems, 1(1).

de Araujo Barbosa, C. C., Atkinson, P. M., & Dearing, J. A. (2015). Remote sensing of ecosystem services: A systematic review. Ecological Indicators, 52, 430–443. https://doi.org/https://doi.org/10.1016/j.ecolind.2015.01.007

del Río-Mena, T., Willemen, L., Tesfamariam, G. T., Beukes, O., & Nelson, A. (2020). Remote sensing for mapping ecosystem services to support evaluation of ecological restoration interventions in an arid landscape. Ecological Indicators, 113, 106182. https://doi.org/https://doi.org/10.1016/j.ecolind.2020.106182

Eigenbrod, F., Armsworth, P. R., Anderson, B. J., Heinemeyer, A., Gillings, S., Roy, D. B., Thomas, C. D., & Gaston, K. J. (2010). The impact of proxy-based methods on mapping the distribution of ecosystem services. Journal of Applied Ecology, 47(2), 377–385. https://doi.org/https://doi.org/10.1111/j.1365-2664.2010.01777.x

Folke, C., Biggs, R., Norström, A. V, Reyers, B., & Rockström, J. (2016). Social-ecological resilience and biosphere-based sustainability science. Ecology and Society, 21(3). https://doi.org/10.5751/ES-08748-210341

Galaz García, C., Bagstad, K. J., Brun, J., Chaplin-Kramer, R., Dhu, T., Murray, N. J., Nolan, C. J., Ricketts, T. H., Sosik, H. M., Sousa, D., Willard, G., & Halpern, B. S. (2023). The future of ecosystem assessments is automation, collaboration, and artificial intelligence. Environmental Research Letters, 18(1), 011003. https://doi.org/10.1088/1748-9326/acab19

García-Pardo, K. A., Moreno-Rangel, D., Domínguez-Amarillo, S., & García-Chávez, J. R. (2022). Remote sensing for the assessment of ecosystem services provided by urban vegetation: A review of the methods applied. Urban Forestry & Urban Greening, 74, 127636. https://doi.org/https://doi.org/10.1016/j.ufug.2022.127636

Gilman, J., & Wu, J. (2023). The interactions among landscape pattern, climate change, and ecosystem services: progress and prospects. Regional Environmental Change, 23(2), 67. https://doi.org/10.1007/s10113-023-02060-z

Grima, N., Jutras-Perreault, M.-C., Gobakken, T., Ole Ørka, H., & Vacik, H. (2023). Systematic review for a set of indicators supporting the Common International Classification of Ecosystem Services. Ecological Indicators, 147, 109978. https://doi.org/https://doi.org/10.1016/j.ecolind.2023.109978

Haines-Young, R., & Potschin, M. (2010a). The links between biodiversity, ecosystem services and human well-being. Ecosystem Ecology: A New Synthesis, 110–139.

Haines-Young, R., & Potschin, M. (2010b). The links between biodiversity, ecosystem services and human well-being. Ecosystem Ecology: A New Synthesis, 1, 110–139.

Hamann, M., Johnson, J. A., Chaigneau, T., Chaplin-Kramer, R., Mandle, L., & Rieb, J. T. (2021). Ecosystem service modelling. In The Routledge Handbook of Research Methods for Social-Ecological Systems (pp. 426–439). Routledge. https://doi.org/10.4324/9781003021339-37

Hein, L., Bagstad, K., Edens, B., Obst, C., de Jong, R., & Lesschen, J. P. (2016). Defining Ecosystem Assets for Natural Capital Accounting. PLOS ONE, 11(11), e0164460-. https://doi.org/10.1371/journal.pone.0164460

Homolová, L., Schaepman, M. E., Lamarque, P., Clevers, J. G. P. W., de Bello, F., Thuiller, W., & Lavorel, S. (2014). Comparison of remote sensing and plant trait-based modelling to predict ecosystem services in subalpine grasslands. Ecosphere, 5(8), art100. https://doi.org/https://doi.org/10.1890/ES13-00393.1

IPBES. (2019). Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Zenodo. https://doi.org/10.5281/zenodo.6417333

Jacobs, S., Burkhard, B., Van Daele, T., Staes, J., & Schneiders, A. (2015). 'The Matrix Reloaded': A review of expert knowledge use for mapping ecosystem services. Ecological Modelling, 295, 21–30. https://doi.org/https://doi.org/10.1016/j.ecolmodel.2014.08.024

Kandziora, M., Burkhard, B., & Müller, F. (2013). Interactions of ecosystem properties, ecosystem integrity and ecosystem service indicators—A theoretical matrix exercise. Ecological Indicators, 28, 54–78. https://doi.org/https://doi.org/10.1016/j.ecolind.2012.09.006

Karp, D. S., Tallis, H., Sachse, R., Halpern, B., Thonicke, K., Cramer, W., Mooney, H., Polasky, S., Tietjen, B., Waha, K., Walz, A., & Wolny, S. (2015a). National indicators for observing ecosystem service change. Global Environmental Change, 35, 12–21. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2015.07.014

Karp, D. S., Tallis, H., Sachse, R., Halpern, B., Thonicke, K., Cramer, W., Mooney, H., Polasky, S., Tietjen, B., Waha, K., Walz, A., & Wolny, S. (2015b). National indicators for observing ecosystem service change. Global Environmental Change, 35, 12–21. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2015.07.014

La Notte, A., D'Amato, D., Mäkinen, H., Paracchini, M. L., Liquete, C., Egoh, B., Geneletti, D., & Crossman, N. D. (2017). Ecosystem services classification: A systems ecology perspective of the cascade framework. Ecological Indicators, 74, 392–402. https://doi.org/https://doi.org/10.1016/j.ecolind.2016.11.030

Lavorel, S., Bayer, A., Bondeau, A., Lautenbach, S., Ruiz-Frau, A., Schulp, N., Seppelt, R., Verburg, P., Teeffelen, A. van, Vannier, C., Arneth, A., Cramer, W., & Marba, N. (2017). Pathways to bridge the biophysical realism gap in ecosystem services mapping approaches. Ecological Indicators, 74, 241–260. https://doi.org/https://doi.org/10.1016/j.ecolind.2016.11.015

Lavorel, S., Grigulis, K., Lamarque, P., Colace, M.-P., Garden, D., Girel, J., Pellet, G., & Douzet, R. (2011). Using plant functional traits to understand the landscape distribution of multiple ecosystem services. Journal of Ecology, 99(1), 135–147. https://doi.org/https://doi.org/10.1111/j.1365-2745.2010.01753.x

Lee, H., & Lautenbach, S. (2016). A quantitative review of relationships between ecosystem services. Ecological Indicators, 66, 340–351. https://doi.org/https://doi.org/10.1016/j.ecolind.2016.02.004

Lock, M. C., Skidmore, A. K., van Duren, I., & Mücher, C. A. (2021). Evidence-based alignment of conservation policies with remote sensing-enabled essential biodiversity variables. Ecological Indicators, 132, 108272. https://doi.org/https://doi.org/10.1016/j.ecolind.2021.108272

Mace, G. M., Norris, K., & Fitter, A. H. (2012). Biodiversity and ecosystem services: a multilayered relationship. Trends in Ecology & Evolution, 27(1), 19–26. https://doi.org/https://doi.org/10.1016/j.tree.2011.08.006

Maes, J., Egoh, B., Willemen, L., Liquete, C., Vihervaara, P., Schägner, J. P., Grizzetti, B., Drakou, E. G., Notte, A. La, Zulian, G., Bouraoui, F., Luisa Paracchini, M., Braat, L., & Bidoglio, G. (2012). Mapping ecosystem services for policy support and decision making in the European Union. Ecosystem Services, 1(1), 31–39. https://doi.org/https://doi.org/10.1016/j.ecoser.2012.06.004

Malinga, R., Gordon, L. J., Jewitt, G., & Lindborg, R. (2015). Mapping ecosystem services across scales and continents – A review. Ecosystem Services, 13, 57–63. https://doi.org/https://doi.org/10.1016/j.ecoser.2015.01.006

Martínez-Harms, M. J., & Balvanera, P. (2012). Methods for mapping ecosystem service supply: a review. International Journal of Biodiversity Science, Ecosystem Services & Management, 8(1–2), 17–25. https://doi.org/10.1080/21513732.2012.663792

Masenyama, A., Mutanga, O., Dube, T., Bangira, T., Sibanda, M., & Mabhaudhi, T. (2022). A systematic review on the use of remote sensing technologies in quantifying grasslands ecosystem services. GIScience & Remote Sensing, 59(1), 1000–1025. https://doi.org/10.1080/15481603.2022.2088652

Mitchell, M. G. E., Bennett, E. M., Gonzalez, A., Lechowicz, M. J., Rhemtulla, J. M., Cardille, J. A., Vanderheyden, K., Poirier-Ghys, G., Renard, D., Delmotte, S., Albert, C. H., Rayfield, B., Dumitru, M., Huang, H.-H., Larouche, M., Liss, K. N., Maguire, D. Y., Martins, K. T., Terrado, M., … Dancose, K. (2015). The Montérégie Connection: linking landscapes, biodiversity, and ecosystem services to improve decision making. Ecology and Society, 20(4). https://doi.org/10.5751/ES-07927-200415

Neugarten, R. A., Langhammer, P. F., Osipova, E., Bagstad, K. J., Bhagabati, N., Butchart, S. H. M., Dudley, N., Elliott, V., Gerber, L. R., Gutierrez Arrellano, C., Ivanić, K.-Z., Kettunen, M., Mandle, L., Merriman, J. C., Mulligan, M., Peh, K. S.-H., Raudsepp-Hearne, C., Semmens, D. J., Stolton, S., & Willcock, S. (2018). Tools for measuring, modelling, and valuing ecosystem services: guidance for Key Biodiversity Areas, natural World Heritage sites, and protected areas (C. Groves, Ed.). IUCN, International Union for Conservation of Nature. https://doi.org/10.2305/IUCN.CH.2018.PAG.28.en

Neugarten, R., Langhammer, P., Osipova, E., Bagstad, K., Bhagabati, N., Butchart, S., Dudley, N., Elliott, V., Gerber, L., Gutierrrez, C., Ivanić, K., Kettunen, M., Mandle, L., Merriman, J., Mulligan, M., Peh, K., Raudsepp-Hearne, C., Semmens, D., Stolton, S., & Willcock, S. (2018). Tools for measuring, modelling, and valuing ecosystem services: guidance for Key Biodiversity Areas, natural World Heritage Sites, and protected areas. https://doi.org/10.2305/IUCN.CH.2018.PAG.28.en

O'Connor, B., Secades, C., Penner, J., Sonnenschein, R., Skidmore, A., Burgess, N. D., & Hutton, J. M. (2015). Earth observation as a tool for tracking progress towards the Aichi Biodiversity Targets. Remote Sensing in Ecology and Conservation, 1(1), 19–28. https://doi.org/https://doi.org/10.1002/rse2.4

Pascual, A., Giardina, C. P., Selmants, P. C., Laramee, L. J., & Asner, G. P. (2021). A new remote sensing-based carbon sequestration potential index (CSPI): A tool to support land carbon management. Forest Ecology and Management, 494, 119343. https://doi.org/https://doi.org/10.1016/j.foreco.2021.119343

Pereira, H. M., Ferrier, S., Walters, M., Geller, G. N., Jongman, R. H. G., Scholes, R. J., Bruford, M. W., Brummitt, N., Butchart, S. H. M., Cardoso, A. C., Coops, N. C., Dulloo, E., Faith, D. P., Freyhof, J., Gregory, R. D., Heip, C., Höft, R., Hurtt, G., Jetz, W., … Wegmann, M. (2013). Essential Biodiversity Variables. Science, 339(6117), 277–278. https://doi.org/10.1126/science.1229931

Pettorelli, N., Laurance, W. F., O'Brien, T. G., Wegmann, M., Nagendra, H., & Turner, W. (2014). Satellite remote sensing for applied ecologists: opportunities and challenges. Journal of Applied Ecology, 51(4), 839–848. https://doi.org/https://doi.org/10.1111/1365-2664.12261

Pettorelli, N., Schulte to Bühne, H., Tulloch, A., Dubois, G., Macinnis-Ng, C., Queirós, A. M., Keith, D. A., Wegmann, M., Schrodt, F., Stellmes, M., Sonnenschein, R., Geller, G. N., Roy, S., Somers, B., Murray, N., Bland, L., Geijzendorffer, I., Kerr, J. T., Broszeit, S., … Nicholson, E. (2018). Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. Remote Sensing in Ecology and Conservation, 4(2), 71–93. https://doi.org/https://doi.org/10.1002/rse2.59

Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T. P., Fernandez, M., Lucas, R., Schaepman, M. E., Wang, T., O'Connor, B., Jongman, R. H. G., Kempeneers, P., Sonnenschein, R., Leidner, A. K., Böhm, M., He, K. S., Nagendra, H., Dubois, G., Fatoyinbo, T., … Geller, G. N. (2016). Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. Remote Sensing in Ecology and Conservation, 2(3), 122–131. https://doi.org/https://doi.org/10.1002/rse2.15

Pfeifer, M., Disney, M., Quaife, T., & Marchant, R. (2012). Terrestrial ecosystems from space: a review of earth observation products for macroecology applications. Global Ecology and Biogeography, 21(6), 603–624. https://doi.org/https://doi.org/10.1111/j.1466-8238.2011.00712.x

Ramirez-Reyes, C., Brauman, K. A., Chaplin-Kramer, R., Galford, G. L., Adamo, S. B., Anderson, C. B., Anderson, C., Allington, G. R. H., Bagstad, K. J., Coe, M. T., Cord, A. F., Dee, L. E., Gould, R. K., Jain, M., Kowal, V. A., Muller-Karger, F. E., Norriss, J., Potapov, P., Qiu, J., … Wright, T. M. (2019). Reimagining the potential of Earth observations for ecosystem service assessments. Science of The Total Environment, 665, 1053–1063. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.02.150

Raudsepp-Hearne, C., & Peterson, G. D. (2016). Scale and ecosystem services: how do observation, management, and analysis shift with scale—lessons from Québec. Ecology and Society, 21(3). https://doi.org/10.5751/ES-08605-210316

Remme, R. P., Schröter, M., & Hein, L. (2014). Developing spatial biophysical accounting for multiple ecosystem services. Ecosystem Services, 10, 6–18. https://doi.org/https://doi.org/10.1016/j.ecoser.2014.07.006

Rieb, J. T., Chaplin-Kramer, R., Daily, G. C., Armsworth, P. R., Böhning-Gaese, K., Bonn, A., Cumming, G. S., Eigenbrod, F., Grimm, V., Jackson, B. M., Marques, A., Pattanayak, S. K., Pereira, H. M., Peterson, G. D., Ricketts, T. H., Robinson, B. E., Schröter, M., Schulte, L. A., Seppelt, R., … Bennett, E. M. (2017). When, Where, and How Nature Matters for Ecosystem Services: Challenges for the Next Generation of Ecosystem Service Models. BioScience, 67(9), 820–833. https://doi.org/10.1093/biosci/bix075

Rieb, J. T., Robinson, B. E., & Bennett, E. M. (2023). Substitutability of natural and human capitals: lessons from a simple exploratory model. Ecosystems and People, 19(1), 2281483. https://doi.org/10.1080/26395916.2023.2281483

Rose, R. A., Byler, D., Eastman, J. R., Fleishman, E., Geller, G., Goetz, S., Guild, L., Hamilton, H., Hansen, M., Headley, R., Hewson, J., Horning, N., Kaplin, B. A., Laporte, N., Leidner, A., Leimgruber, P., Morisette, J., Musinsky, J., Pintea, L., … Wilson, C. (2015). Ten ways remote sensing can contribute to conservation. Conservation Biology, 29(2), 350–359. https://doi.org/https://doi.org/10.1111/cobi.12397

Sayyed, T. K., Ovienmhada, U., Kashani, M., Vohra, K., Kerr, G. H., O'Donnell, C., Harris, M. H., Gladson, L., Titus, A. R., Adamo, S. B., Fong, K. C., Gargulinski, E. M., Soja, A. J., Anenberg, S., & Kuwayama, Y. (2024). Satellite data for environmental justice: a scoping review of the literature in the United States. Environmental Research Letters, 19(3), 033001. https://doi.org/10.1088/1748-9326/ad1fa4

Schirpke, U., Ghermandi, A., Sinclair, M., Van Berkel, D., Fox, N., Vargas, L., & Willemen, L. (2023). Emerging technologies for assessing ecosystem services: A synthesis of opportunities and challenges. Ecosystem Services, 63, 101558. https://doi.org/https://doi.org/10.1016/j.ecoser.2023.101558

Schröter, M., Barton, D. N., Remme, R. P., & Hein, L. (2014). Accounting for capacity and flow of ecosystem services: A conceptual model and a case study for Telemark, Norway. Ecological Indicators, 36, 539–551. https://doi.org/https://doi.org/10.1016/j.ecolind.2013.09.018

Schröter, M., Remme, R. P., Sumarga, E., Barton, D. N., & Hein, L. (2015a). Lessons learned for spatial modelling of ecosystem services in support of ecosystem accounting. Ecosystem Services, 13, 64–69. https://doi.org/https://doi.org/10.1016/j.ecoser.2014.07.003

Schröter, M., Remme, R. P., Sumarga, E., Barton, D. N., & Hein, L. (2015b). Lessons learned for spatial modelling of ecosystem services in support of ecosystem accounting. Ecosystem Services, 13, 64–69. https://doi.org/https://doi.org/10.1016/j.ecoser.2014.07.003

Skidmore, A. K., Coops, N. C., Neinavaz, E., Ali, A., Schaepman, M. E., Paganini, M., Kissling, W. D., Vihervaara, P., Darvishzadeh, R., Feilhauer, H., Fernandez, M., Fernández, N., Gorelick, N., Geijzendorffer, I., Heiden, U., Heurich, M., Hobern, D., Holzwarth, S., Muller-Karger, F. E., … Wingate, V. (2021). Priority list of biodiversity metrics to observe from space. Nature Ecology & Evolution, 5(7), 896–906. https://doi.org/10.1038/s41559-021-01451-x

Skidmore, A. K., Pettorelli, N., Coops, N. C., Geller, G. N., Hansen, M., Lucas, R., Mücher, C. A., O'Connor, B., Paganini, M., Pereira, H. M., Schaepman, M. E., Turner, W., Wang, T., & Wegmann, M. (2015). Environmental science: Agree on biodiversity metrics to track from space. Nature, 523(7561), 403–405. https://doi.org/10.1038/523403a

Sumarga, E., & Hein, L. (2014). Mapping Ecosystem Services for Land Use Planning, the Case of Central Kalimantan. Environmental Management, 54(1), 84–97. https://doi.org/10.1007/s00267-014-0282-2

Tallis, H., Mooney, H., Andelman, S., Balvanera, P., Cramer, W., Karp, D., Polasky, S., Reyers, B., Ricketts, T., Running, S., Thonicke, K., Tietjen, B., & Walz, A. (2012). A Global System for Monitoring Ecosystem Service Change. BioScience, 62(11), 977–986. https://doi.org/10.1525/bio.2012.62.11.7

Thierry, H., Parrott, L., & Robinson, B. (2021). Next steps for ecosystem service models: integrating complex interactions and beneficiaries. FACETS, 6, 1649–1669. https://doi.org/10.1139/facets-2020-0116

Topp, S. N., Pavelsky, T. M., Jensen, D., Simard, M., & Ross, M. R. V. (2020). Research Trends in the Use of Remote Sensing for Inland Water Quality Science: Moving Towards Multidisciplinary Applications. Water, 12(1). https://doi.org/10.3390/w12010169

Turkelboom, F., Raquez, P., Dufrêne, M., Raes, L., Simoens, I., Jacobs, S., Stevens, M., De Vreese, R., Panis, J. A. E., Hermy, M., Thoonen, M., Liekens, I., Fontaine, C., Dendoncker, N., Biest, K. van der, Casaer, J., Heyrman, H., Meiresonne, L., & Keune, H. (2013). Chapter 18 - CICES Going Local: Ecosystem Services Classification Adapted for a Highly Populated Country. In S. Jacobs, N.

Dendoncker, & H. Keune (Eds.), Ecosystem Services (pp. 223–247). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-12-419964-4.00018-4

United Nations et al. (2021). System of Environmental-Economic Accounting— Ecosystem Accounting (SEEA EA).

Ustin, S. L., & Middleton, E. M. (2021). Current and near-term advances in Earth observation for ecological applications. Ecological Processes, 10(1), 1. https://doi.org/10.1186/s13717-020-00255-4

Vargas, L., Willemen, L., & Hein, L. (2019). Assessing the Capacity of Ecosystems to Supply Ecosystem Services Using Remote Sensing and An Ecosystem Accounting Approach. Environmental Management, 63(1), 1–15. https://doi.org/10.1007/s00267-018-1110-x

Vaz, A. S., Moreno-Llorca, R. A., Gonçalves, J. F., Vicente, J. R., Méndez, P. F., Revilla, E., Santamaria, L., Bonet-García, F. J., Honrado, J. P., & Alcaraz-Segura, D. (2020). Digital conservation in biosphere reserves: Earth observations, social media, and nature's cultural contributions to people. Conservation Letters, 13(3), e12704. https://doi.org/https://doi.org/10.1111/conl.12704

Vyvlečka, P., & Pechanec, V. (2023). Optical Remote Sensing in Provisioning of Ecosystem-Functions Analysis—Review. Sensors, 23(10). https://doi.org/10.3390/s23104937

Wang, R., & Gamon, J. A. (2019). Remote sensing of terrestrial plant biodiversity. Remote Sensing of Environment, 231, 111218. https://doi.org/https://doi.org/10.1016/j.rse.2019.111218

Wellmann, T., Lausch, A., Andersson, E., Knapp, S., Cortinovis, C., Jache, J., Scheuer, S., Kremer, P., Mascarenhas, A., Kraemer, R., Haase, A., Schug, F., & Haase, D. (2020). Remote sensing in urban planning: Contributions towards ecologically sound policies? Landscape and Urban Planning, 204, 103921. https://doi.org/https://doi.org/10.1016/j.landurbplan.2020.103921Willcock, S., Martinez-Lopez, J., Dandy, N., & Bullock, J. M. (2021). High Spatial-Temporal Resolution Data across Large Scales Are Needed to Transform Our Understanding of Ecosystem Services. Land, 10(7). https://doi.org/10.3390/land10070759

Willemen, L., Veldkamp, A., Verburg, P. H., Hein, L., & Leemans, R. (2012). A multi-scale modelling approach for analysing landscape service dynamics. Journal of Environmental Management, 100, 86–95. https://doi.org/https://doi.org/10.1016/j.jenvman.2012.01.022

Winkler, K. J., Dade, M. C., & Rieb, J. T. (2021). Mismatches in the Ecosystem Services Literature—a Review of Spatial, Temporal, and Functional-Conceptual Mismatches. Current Landscape Ecology Reports, 6(2), 23–34. https://doi.org/10.1007/s40823-021-00063-2

Ziter, C., Bennett, E. M., & Gonzalez, A. (2013). Functional diversity and management mediate aboveground carbon stocks in small forest fragments. Ecosphere, 4(7), art85. https://doi.org/https://doi.org/10.1890/ES13-00135.1

CONNECTING STATEMENT

The comprehensive literature review of ES modelling and EO revealed that there hasn't been a review of EO use in ES models that addresses the calls from the ES community to incorporate EO indicators of ecosystem structure and function in ES models. In Chapter Two, I take a systematic review approach to examine ten years (2012-2021) of ES models. In particular, I aim in Chapter Two to examine: 1) which EO-derived indicators of ecosystem structure and function are currently available at appropriate scales for assessing ES, and 2) which ES modelling studies have used EO-derived ecosystem structure and function data to model which services.

CHAPTER TWO

Note: Manuscript prepared in anticipation of being submitted to *Ecological Indicators*

Earth Observation of Ecosystem Properties in Ecosystem Service (ES) Models: A Systematic Review of ES Literature (2012-2021)

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Abstract: Ecosystem services (ES) are one way to quantify, analyze, and manage the benefits that flow from ecosystems to humans. Yet the capability to assess provision of these services accurately across large spatial extents remains limited. Many current ES models rely on categorical typologies of land-use and land-cover (LULC), with the assumption that all ecosystem properties within a LULC type are identical, and that therefore any area of that LULC type provides the same mix of ES in the same amounts as any other same-sized area of the same LULC. To represent ecosystem heterogeneity more precisely, there have been calls within the ES community to explore modelling approaches that incorporate earth observation (EO) data that are able to capture some ecosystem properties that might vary within a single LULC type. EO might also be able to increase the spatial extent of ES models while maintaining fine temporal and spatial resolutions. In this paper, we systematically reviewed the use of EO data in ES models over ten years (2012-2021), highlighting which EO datasets, at which geographical extents and spatial/temporal resolutions, have been used in ES models, and investigating whether the claims that EO might improve ES models are generally borne out in the literature. Our review of 38 papers, spans all categories of ES models and shows the direct linkages between individual EO datasets and ES models. For example, MODIS Normalized Difference Vegetation Index was the most used EO data input and was used as a proxy for live vegetation cover in 58% of all ES models, and 83% of regulating service models. Our study shows that,

while the promise of increased information resolution has been partially realized for some ES, there are more opportunities still for the ES field.

Keywords: Ecosystem services; earth observation; remote sensing; indicators; social-ecological systems; ecosystem service modelling

1. Introduction

Ecosystems provide benefits that support human well-being and economies, including water purification, sense of place, flood protection, and food production, among many other direct and indirect contributions of nature to people (Daily 1997). These benefits that people obtain from nature are commonly referred to as Ecosystem Services (ES) (MA 2005) or Nature's Contributions to People (NCP) (IPBES 2017). In the decades since ES was first introduced as a concept, continual exploration and development of tools and methods for modelling and monitoring diverse sets of ES (Burkhard et al. 2018; Carpenter et al. 2009; Chaplin-Kramer et al. 2023; Cheng et al. 2019; Costanza et al. 2017; Malinga et al. 2015; Willcock et al. 2023). With this growing ES toolbox, has come a growing number of choices for ES researchers and practitioners who want to design studies to better understand the ES in a place. Among these varied tools and methods, there are unique data requirements, verification schemes, and accuracies/relevancies to specific places and ecosystems (Bagstad et al. 2013).

Despite increasingly publicly available ES information and familiarity with the ES concept more generally, data and information related to ES is still used limitedly in decision-making processes (Mandle et al. 2021). One potential reason for this is a lack of clear consensus around the best data for understanding the relevant social and ecological structure and functions underlying ES at multiple temporal and spatial scales (Lock et al. 2021; Polasky et al. 2015); along with a lack of commonly understood and available approaches and tools for analyzing ES (Ruckelshaus et al. 2015). Understanding, monitoring, and communicating how ecosystem properties and processes affect and underly the provision of ES is critical to assessing the impacts of changing ecosystems, due to natural and human drivers, and the associated impacts of these shifts on human well-being. Further, it is essential to effectively implementing management and policy strategies to establish and meet targets for a more sustainable future (Tallis et al. 2012).

Accurately understanding the dynamics that lead to ES requires a considerable understanding of ecosystem structure and processes (Fu et al. 2013; Notte et al. 2022). However, appropriate data and modelling methods linking biophysical properties and processes of ecosystems to ES over large spatial extents are often lacking (Lavorel et al. 2017). To represent these ecologically meaningful linkages between ecosystem properties and ES more precisely over larger spatial and temporal extents, the ES community has called for exploration of modelling approaches that incorporate Earth Observation (EO) data that are able to capture a variety of ecosystem properties (Cord et al. 2017, 2015; Galaz García et al. 2023; Ramirez-Reyes et al. 2019). For example, different EO technologies, such as the Sentinel-2 constellation of satellites, have the capacity to capture information related to the photosynthetic activity of vegetation in an ecosystem, which in turn can then be related to productivity of vegetation in an ecosystem, which then relates to multiple ES, such as carbon sequestration or air quality regulation (Vargas et al. 2017).

Currently, many ES modelling approaches oversimplify the intrinsic link between ecosystem properties and ES, instead relying on look-up tables that match expert assigned ES value per area of land-use, land-cover (LULC) to LULC maps to quantify service provision (De Araujo Barbosa et al. 2015). These ES modelling methodologies driven by linking LULC to constant ES values miss important linkages between ES and ecosystem properties (Egoh et al. 2012; Martínez-Harms & Balvanera 2012), such as when all forests in a region are assigned a common value for carbon storage per hectare, no matter what type of forest, the age structure of the trees, or how the forest managed, all factors known to impact carbon storage (Ziter et al. 2013; Crockett et al. 2021). Assigning a constant ES value over an entire patch of land, even if it has heterogenous patterns of vegetation or other ecosystem properties within it, runs the risk of over emphasizing the importance of LULC composition while underplaying, or missing altogether, the role of dynamic biophysical processes such as Net Primary Productivity (NPP), that can be derived from EO technologies and are widely understood to contribute to ES potential. While these modelling approaches using a constant value are still used in many ES studies today, new methods have been developed for understanding specific ES by both the ES and EO/RS communities, including precise mapping of services like carbon storage (Pascual et al. 2021).

At the time (2015) of the last review of EO (e.g. satellite, spaceborne, or airborne data) technologies used in ES modelling, LULC was found to be the most used EO-derived data to represent ecosystem processes across ES models, used as the sole remotely sensed data product in 56% of studies (De Araujo Barbosa et al. 2015). This LULC-based modelling approach has its benefits as it is relatively easy to implement where LULC maps exist (Burkhard et al. 2009); however, LULC-based approaches to ES modelling might mask important heterogeneity within and across LULC types that is driven by the underlying biophysical properties of ecosystems, such as properties related to an ecosystems' structure (e.g. ecosystem configuration, habitat structure) or processes/function (e.g. ecosystem phenology, primary productivity, disturbance level). This means that the spatial variability of potential ES supply within landscape patches consisting of a single LULC type will be underestimated and, in many cases, missing all together (Eigenbrod et al. 2010). Not having information about how ES and drivers or ES vary within landscape patches is a critical gap, as that is a level of information particularly relevant to local and regional scales for land management and engagement with land stewards (Maes et al. 2012).

EO technologies are one important and useful tool for closing the data gap in the assessment of ecosystem properties, processes, and ES across temporal and spatial scales. EO provide a broad view of Earth's properties with regular and repeated observations over time that are cost effective for monitoring across large (remote and inaccessible) areas (Anderson 2018; Ustin and Middleton 2021). EO information is collected from remote sensors, such as the Sentinel-2 constellation of satellites, and then raw data from a satellite is processed through established and tested algorithms to develop EO-derived indices, such as NDVI. This processing of information from EO sensors can produce maps of ecosystem properties and processes, such as NPP. As well, with many of these EO ecosystem indicators, there has been a shift over the last decade away from the transformation of “raw” imagery to the provision of analysis ready data and data products.

The expanding range of EO sensors and information that can be derived from remote sensors provide unique opportunities for ES research to explore methods that might fill existing knowledge gaps in the linkages between structure, function, and ES across large spatial and temporal extents. Different remote sensors capture information with different levels of detail (from the spatial and temporal resolution to the number of bands that can be used to derive information) and different algorithms can be used for mapping ecosystem properties and functions (that range from LULC categorization to vegetation indices, such as NPP, to water quality indicators and other earth surface properties (Pfiefer et al. 2011)). Once EO information is processed, this transformed data of EO-derived indicators have been used to quantify through ES models, which encompass a range of services from food and freshwater provisioning, climate regulation, erosion regulation, outdoor recreation, and many more (De Araujo Barbosa et al. 2015).

EO-derived indicators relating to ecosystem properties are most often used to assess the capacity of an ecosystem to provide ES through use as an input in spatially explicit models of individual ES. These ES models and assessments typically provide a snapshot of ES dynamics; with assessments typically undertaken at one spatial scale and at a single location. Because EO technologies can observe at relatively fine resolution regularly over large areas, they provide an opportunity to overcome data limitations, including by complementing field surveys and less regularly updated spatial datasets, such as national LULC maps (Andrew et al. 2015; Crossman et al. 2013). Given that EO can provide quality assured regular and repeatable coverage of spatial information that is consistent over both space and time, there is great potential for it to support ES modelling across a range of spatial and temporal resolutions. Furthermore, there is hope EO can make ES assessment more scalable across space and time; moving the field away from either one-time national assessments that don't provide fine scale results relevant to local contexts or localized field-based assessments that can't be scaled up to larger landscape or national contexts.

Braun et al. (2018) identified four key gaps in the ES field that could be better addressed with EO information integrated into ES models. First, the authors pointed to a lack of studies in the ES field that consider the dynamics of multiple ES together across multiple scales of space and time. Second, a large proportion of ES studies that do integrate observations of ecosystem properties and processes are undertaken at small scales and are not being scaled up to larger (e.g. national or global levels). Third, a large proportion of ES studies are mono-temporal, or cover 10 years or less, providing limited understanding of dynamics through time. And finally, in ES studies that do span larger temporal and spatial scales, ES estimates are most often derived from LULC estimates, contributing to a lack of understanding to the mechanisms that drive ES dynamics at these larger scales and masking local heterogeneity.

A systematic review that encompasses the many new EO sensors and ES models launched and created in the last 10 years to understand ES is lacking. Thus, we have undertaken a review of the last ten years of multi-service ES modelling papers that are incorporating EO-derived indicators of ecosystem properties. Through a review of ten years (2012-2021) of ES modelling papers, we have coded 38 publications (with 138 included models of individual ES within them) to show: 1) what EO sensors and derived indicators of ecosystem structure and function are currently used for assessing ES, 2) what ES modelling studies have used EO indicators of ecosystem structure and function to model which services, and 3) at what spatial-temporal scales is this work currently being done. This paper aims at providing a synthesis of both established and emerging linkages between EO technologies and ES models over the last 10 years (2012–2021).

2. Methods

To examine the current state of EO integration in ES modelling studies, we conducted a systematic review (Figure S3.1). To start, we searched for peer-reviewed publications in the Scopus and Web of Science databases. We used the search string (“ecosystem service*” OR “ecological service*” AND “model*” OR “map*” OR “assessment*” AND “earth observation*” OR “remote sensing”) to search for peer-reviewed publications in English, with the search keywords found in the title, abstract, or keywords. We limited the search to articles published between 2012 and 2021 to capture the latest trends in how ES are being modelled. The initial search produced 1831 publications (Figure S3.1.).

Next, we screened titles and abstracts of the initial collection of publications. Publications were excluded from inclusion from this review if they (1) were not related to ES modelling, (2) were not original research papers (i.e. reviews, conference papers and abstracts), (3) focused on methodological developments of a single ES model rather than application of EO indicators across models of multiple ES, or (4) did not include at least one ES within the publication that was modeled with an EO-derived indicator of ecosystem structure or ecosystem function as an input (beyond LULC) (see supplemental text for description of how we defined ecosystem structure and function). This resulted in 274 eligible articles that were downloaded in PDF format.

Finally, we screened the full texts of the narrowed down publication list, applying the same selection criteria as above, resulting in 38 publications included in the final review (supplementary material Fig S3.1.). The final publications included in this review were not evenly distributed over the review period (Fig 3.1.), with 82% of the publications used in this review being published in the last five years of the review period.

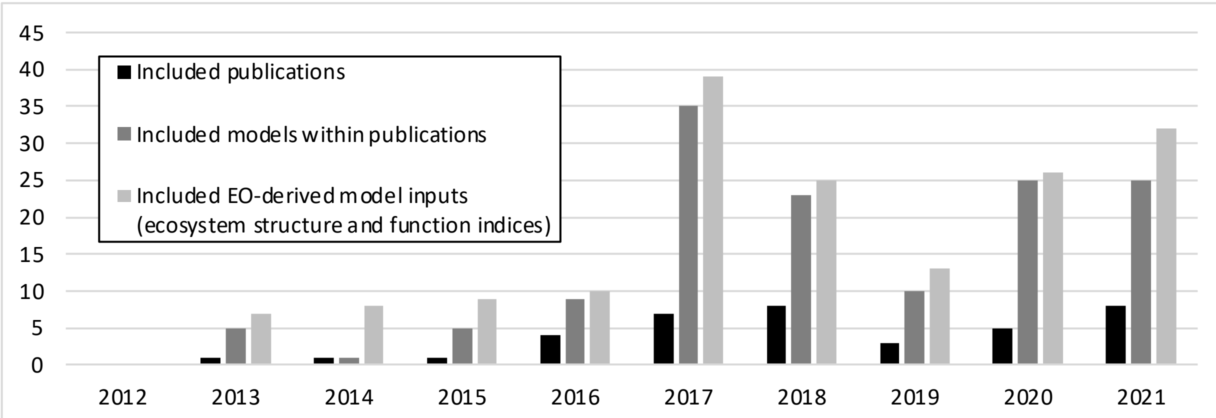

Fig 3.1. Frequency of publications (black), included models within publications (gray), and included EO-derived model inputs (light gray) per year. Note that no publications from 2012 met our inclusion criteria and figures throughout the rest of publications will start at 2013.

From these publications, we extracted three levels of information related to the: publication/study, ES models within each publication, and EO-derived input within each model. At the publication level, we coded variables, such as geographic location/extent of study, ecosystem types covered, resolution of ES models (e.g. 100m), and temporal dimensions of study (e.g. frequency and range of ES modelled). We then coded the models that used an EO-derived indicator of ecosystem structure and function as an input. At the individual model level, we then coded variables such as individual ES modelled, ES category of the model, methodological approach, and listed all model inputs/sources. Finally, at the ES model input level, we coded resolution of the EO indicators, data source and EO sensor, and indicator class (using ecosystem structure and function categorization described above and in Skidmore et al. 2022). We then synthesized the findings of the review, providing a snapshot of how EO is being integrated with ES, along with discussing important questions moving forward for the ES community that have emerged from undertaking this review.

3. Results

In this section, we first give an overview of the ES-EO literature included in this review before presenting an overview of which EO sensors are being used to derive indicators related to ecosystem structure and function and, in turn, which ES models are being developed to use these indicators of ecosystem structure and function. Finally, we discuss the spatial and temporal aspects of how the literature and ES models reviewed.

3.1 Literature characteristics

We found that EO data and methods used for ES modelling in various journals and across a variety of geographical settings. Our review contains publications from 24 journals covering a range of research topics, although generally journals were focused more on ecological rather than remote sensing/earth observation topics. The most common journals were *Ecological Indicators* (7 papers) and *Ecosystem Services* (6 papers), with no other journals publishing more than two publications included in this review.

Studies included in this review addressed ES on six continents and 19 countries, with one global and three multi-country studies. China was the most commonly appearing study country; and Asia was the most common continent of study, followed closely by Europe. Africa was the most underrepresented continent in the review, with three studies included from South Africa and one from Ethiopia. Studies were nearly evenly split between those that used ecological boundaries (e.g., a watershed) (56%) versus administrative boundaries (e.g., a country boundary) (44%) in designing their ES models.

3.2 Sensor technologies and derived indicators of ecosystem structure and function

We found that a variety of EO sensors were used to derive indicators used in ES models (Fig. 3.2.). The most frequent source of EO data in this review is data from satellite sensors, making up 97% of the reviewed data. Airborne imagery from aircrafts and drones made up the remaining 3% of data sources we found in our review. Our review, which focuses on multi-service literature, is likely biased towards studies that use satellite data which capture information over wider extents that contain multiple ecosystem types and thus a varied set of ES.

In terms of specific sensors, MODIS sensors were the most widely used, representing 33% of all sensors, followed by Sentinel sensors (22%), with Landsat sensors (e.g. OLI, TM) representing 14% of all sensors in the review. Landsat and MODIS were the two most consistent sensor, showing up in every year of reviewed papers. However, the relatively recently launched (in 2015) and released data from the European Sentinel satellites showed a significant uptake in studies published starting in 2019 and was the most frequently occurring data source over the last two years of the review. New sensors bring new possibilities, likely explaining the growth of Sentinel-2 constellation data, which has a finer spatial resolution and temporal frequency than many historically popular satellite sensors, such as Landsat. However, the long-term consistency (and existing verification schemes) of older, popular sensors (Landsat, MODIS) means that they may remain commonly used for a longer period of time (although MODIS end of life is December 2025), as existing ES models and pre-processed datasets are already established and readily available. Initiatives, such as NASA's Harmonized Landsat and Sentinel-2 program, may increase the speed at which transitions occur to using data from newly launched sensors.

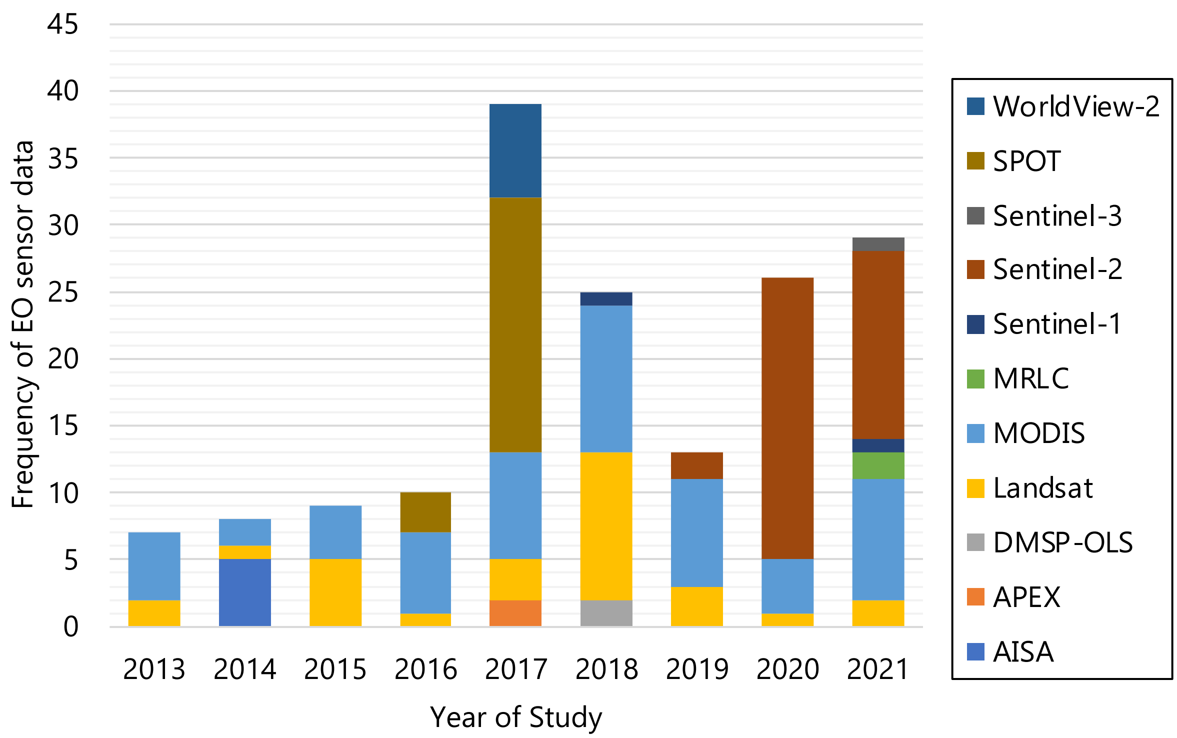

Figure 3.2. EO sensors used to derive inputs in ES models between 2011 and 2021. Different colors refer to different EO sensors and frequency refers to number of times information derived from the sensor appeared in a reviewed ES publication. A sensor can be counted multiple times per ES model. For example, if a MODIS sensor was used to derive NDVI and canopy gap width and both indicators were used together to model water regulation, it would appear twice under one year.

Raw, or unprocessed, data from EO sensors is then processed (through established algorithms and calibration/validation schemes) into indicators. In this review we do not focus on the methodological details of index development, but on the broader picture of which indicators are derived from which sensors, and then subsequently how these indicators are being used within ES models. Taking Skidmore et al. 2022's publication and organization of EO indicators into ecosystem structure and ecosystem function categories as a reference (see Supplemental Table S3.1.), we organized the indices developed from EO sensors into ecosystem structure and function indicator classes, with three sub-indicator classes for both structure and function (Table 3.1.).

Indicator class	Indicator sub-class	EO-sensor	EO-derived indicator	Times found in ES models
Ecosystem structure	Live Cover Fraction	Landsat	Bare Soil Index	1
		Sentinel-2	Crown Cover	5
		Sentinel-2	Gap Width	1
		AISA	Green Biomass	1
		Landsat	Green Vegetation	2
		AISA	Litter Mass	1
		MRLC	Tree Cover	2
		Sentinel-2	Vegetation Type	4
	Ecosystem distribution	Sentinel-2	Colour Diversity	3
		Landsat	Colour Intensity	1
		Sentinel-2	Landscape Heterogeneity	2
		AISA	Species Diversity	1
		Sentinel-1	Vegetation Structural Diversity	1
	Ecosystem Vertical Profile	Sentinel-2	Canopy Height	3
		Sentinel-2	NDI45	1
		MODIS	NDVI	23
		Landsat	NDVI	11
		Sentinel-2	NDVI	9
		SPOT	NDVI	19
		Worldview-2	NDVI	13
Ecosystem function	Primary productivity	AISA	Crude Protein Content	1
		Sentinel-1	Ecosystem soil moisture	1
		MODIS	EVI	2
		MODIS	FPAR	1
		APEX	GPP	2
		Sentinel-2	IRECI	2
		MODIS	LAI	7
		Sentinel-3	LAI	1
		Sentinel-2	MTCI	3
		MODIS	NPP	14
		AISA	Soil Carbon Content	1
	Ecosystem phenology	MODIS	Phenology	1
	Ecosystem disturbance	Landsat	Burn Ratio	1
		Landsat	NDWI	8
		Sentinel-2	NDWI	4
		DMSP-OLS	Nighttime Stable Lights	2

Table 3.1. EO-derived indicators of ecosystem structure and function used within ES models reviewed. From left to right, we show the class of indicators (ecosystem structure/ecosystem function), the sub-class of indicators, the EO sensor used to derive the indicators (colors

correspond to the sensor colors from Fig 3.2.), the title of the indicators used in an ES model, and the number of times that each specific indicator was found in the ES models reviewed.

Our review found that EO-derived indicators of ecosystem structure were used nearly 2.5 times more frequently than indicators of ecosystem function, with 102 occurrences of ecosystem structure indicators found used in reviewed studies as opposed to 40 occurrences of ecosystem function indicators. Broken down further, ecosystem vertical profile as a sub-indicator of ecosystem structure, or the standing biomass in an ecosystem (e.g. NDVI), was the most used data input in ES models and relates to the vegetation structure. While indicators related to primary productivity (e.g. NPP, LAI, GPP), made up the majority of ecosystem function indicators. The vast majority of the indicators highlighted in this review (Table 3.1.) are associated with assessing vegetation presence, condition, and functioning (86% of indicators found in this review; e.g. LAI, NDVI and NPP). NDVI, the most popular indicators found in this review, accounted for 52% of all indicators reviewed in total.

Within the indicators sub-classes of ecosystem structure, we also found, in addition to ecosystem vertical profile mentioned above, multiple indicators used to model ES using information on ecosystem distribution (all related to heterogeneity and diversity of biophysical structures) and live cover fraction (all related to vegetation coverage or lack thereof). In terms of ecosystem function sub indicators, we found only one study that used phenology to map seasonal ES change, while water quality indicators (8% of indicators found in this review; e.g. NDWI) and damage impacts (3% of indicators found in review; e.g. fire, human disturbance) were used to address the effects of ecosystem disturbance on ecosystem function and thus ES potential of a particular area. Most ecosystem function indicators related to primary productivity, as mentioned above.

Interestingly, the majority of primary productivity indicators were derived from MODIS, which has a larger spectral range as compared to Landsat, however these data are at a coarser resolution (250, 1000m as opposed to 10, 30m with Landsat or Sentinel-2). Landsat (TM, OLI) and Sentinel-2 data was most commonly linked to sub-indicator classes of ecosystem structure and configuration (e.g, live cover fraction, ecosystem distribution, ecosystem vertical profile) and one sub-class of ecosystem function, ecosystem disturbance, through the NDWI index.

The reviewed studies did not exclusively use EO-derived indicators as the sole source of information used to models ES, and a variety of non-EO data was used alongside EO-derived data in the analyzed studies including social, physical, and ecological datasets. Common data we found paired with EO-derived indicators to assess ES included: LULC and built infrastructure data, social-demographic and socio-economic data, and meteorological data. Other key data sources that were used to validate (or ground truth) EO indicators relations to specific ES included *in-situ* biological data, such as plant traits, soil measurements, and species maps. Carbon sequestration, carbon storage, and timber production models were the only cases we found of an ES being modelled exclusively using EO indicators as input data.

3.3 Earth observation indicators used to model ecosystem services

EO-derived indicators of structure and function (Table 3.1.) have been used in models of cultural, regulating, and provisioning ES (Fig. 3). NDVI was by far the most frequently occurring index, used as an input in 52% of models overall and 70% of the regulating service models (Table 3.1.). This was followed by other vegetation indices (LAI, EVI) used in 12% of models and water quality measures (NDWI) used in 6% of models. The use of different individual indicators was not found to be proportional within models of different ES (Fig. 3.3.). For example, models of cultural services were the only category of models to include ecosystem distribution indicators, while we found a high proportion of primary productivity indicators used to model provisioning services, relative to its proportion in cultural and regulating service studies. Breaking Figure 3.3 down from right to left, with the exception of ecosystem distribution and phenology, EO data relating to all sub-classes of ecosystem structure and function are used to model all three types of services (cultural, regulating, provisioning).

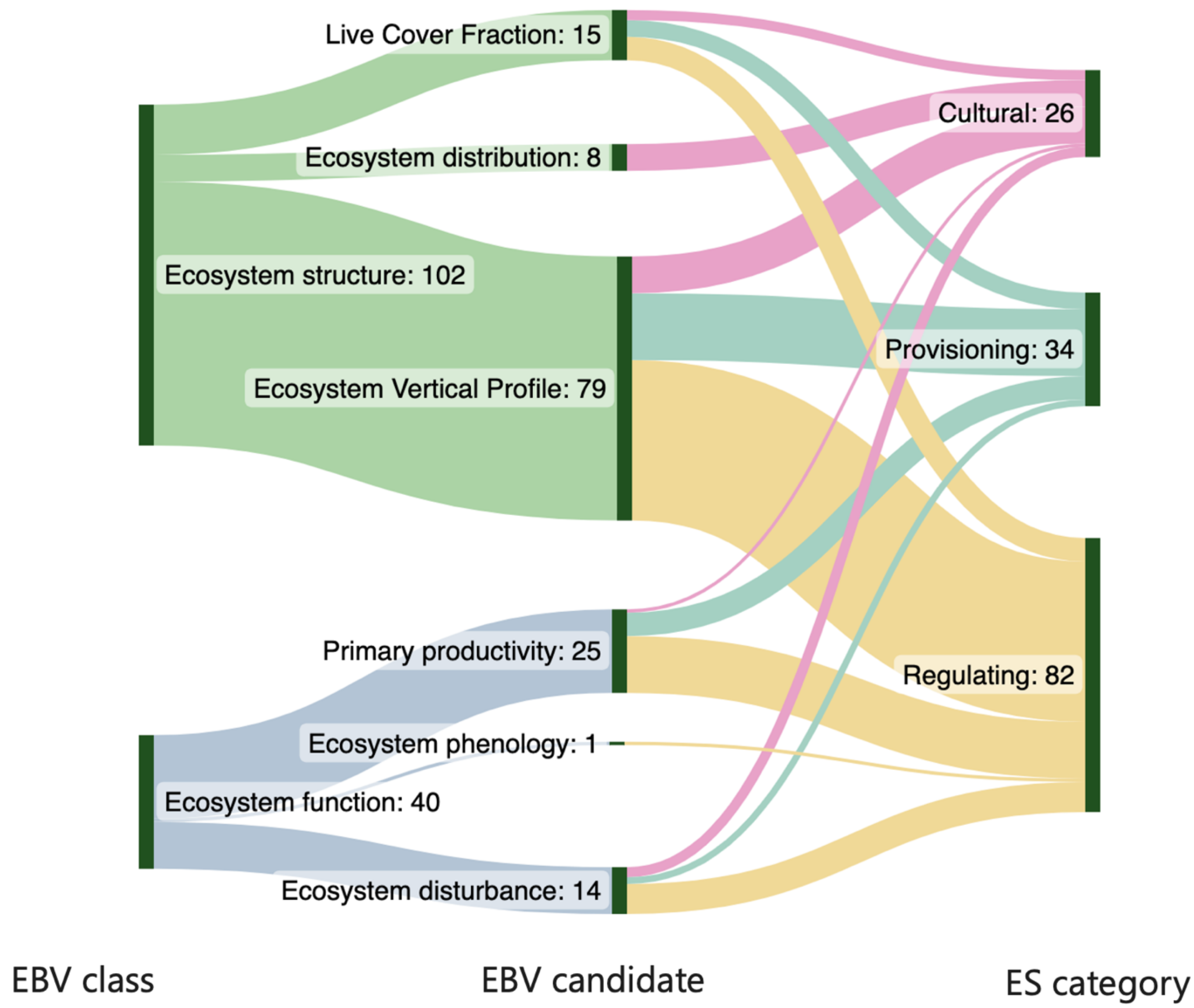

Figure 3.3. Earth observation indicators used to model ecosystem service models by type, the numbers refers to the count of individual EO-derived data-products that are found with single ES models. From left to right this figure shows the indicator class of EO-derived model inputs, then the indicator sub-class, then the category of ES service it was used to model.

Breaking down the ES that are being modelled with EO indicators further, we found that 30 unique ES were mentioned in the included articles, with a total of 138 models of an ES that utilized at least one EO-derived indicator of ecosystem structure or function to model these 30 ES (Figure 3.4.). Most of the ES models reviewed (61%, 15 unique services) were modelling regulating services, including the top three most frequently modelled individual ES, which were carbon sequestration (14%), soil retention (13%), and water flow regulation (10%). Provisioning services made up 23% (9 unique services modelled) of the total ES models reviewed, followed by cultural services, which accounted for 17% of the models reviewed (6 unique services modelled). The most common provisioning service and cultural services modelled were food production and outdoor recreation, respectively.

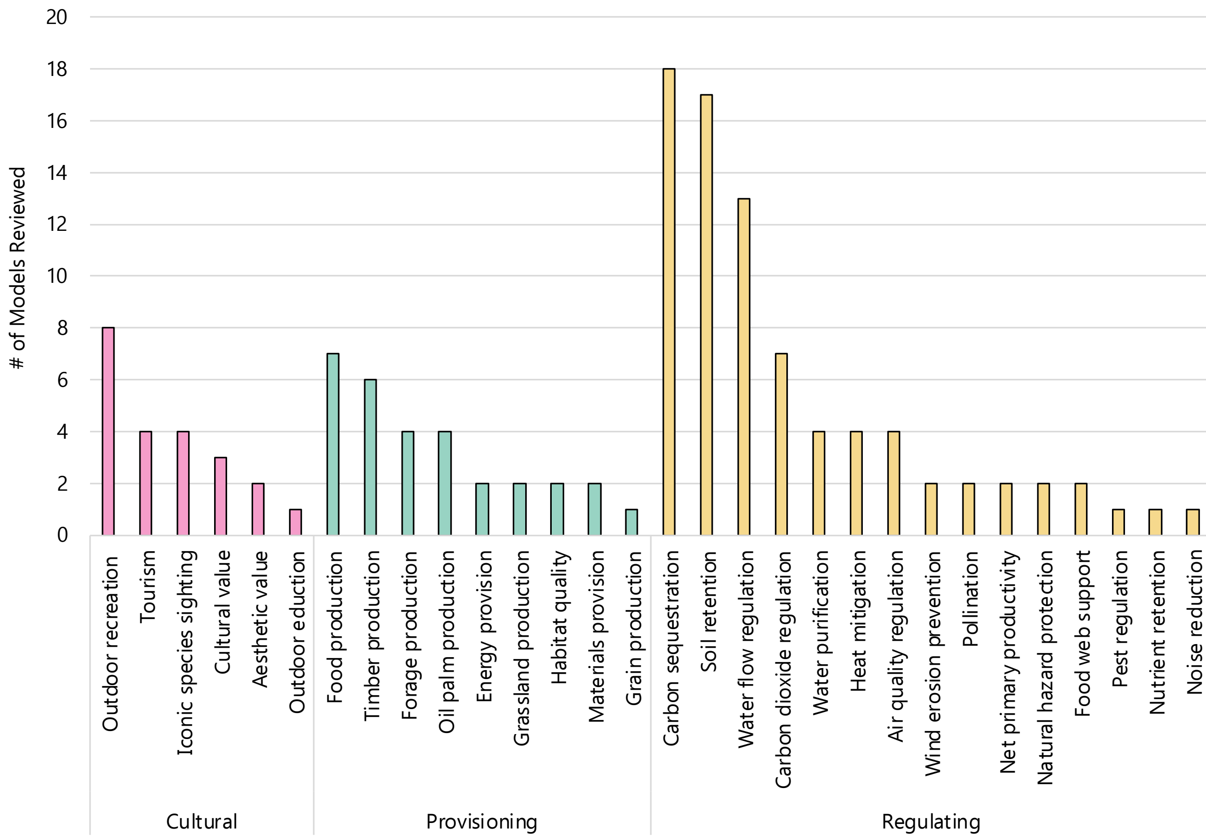

Figure 3.4. The frequency of times that an ES was modelled using an EO indicator to assess in reviewed papers. For example, we found that outdoor recreation was modelled in 8 of the reviewed papers using an EO indicator as an input, but this does not mean that we found 8 unique models (e.g. InVest, ARIES, …) used to model outdoor recreation. Cultural services are presented in pink, provisioning services in blue, and regulating services in yellow.

With linkages between individual EO-sensors used to derive specific indicators used to model individual ES (Fig. 3.5.), we have started to identify less frequently appearing and potentially emerging methodologies from the literature. In Figure 5, we identify the connection between ecosystem structure and function indicator classes, individual indicators derived from EO sensors, and three sets of models for individual ES (outdoor recreation, food production, and soil retention). We identified a disproportionately high use of ecosystem distribution indicators (i.e. the spatial configuration of elements of an ecosystem) to model cultural services, which could be due to the geographic proximity between people and nature that needs to occur for cultural services to be realized. Food production models were the only type of model that used drone imagery to derive EO indicators, which may relate to drones as an emergent tool in smart agriculture practices. Finally, in soil retention models, all but one EO indicator used was NDVI, which might point towards a more established methodology that has emerged to model sediment retention.

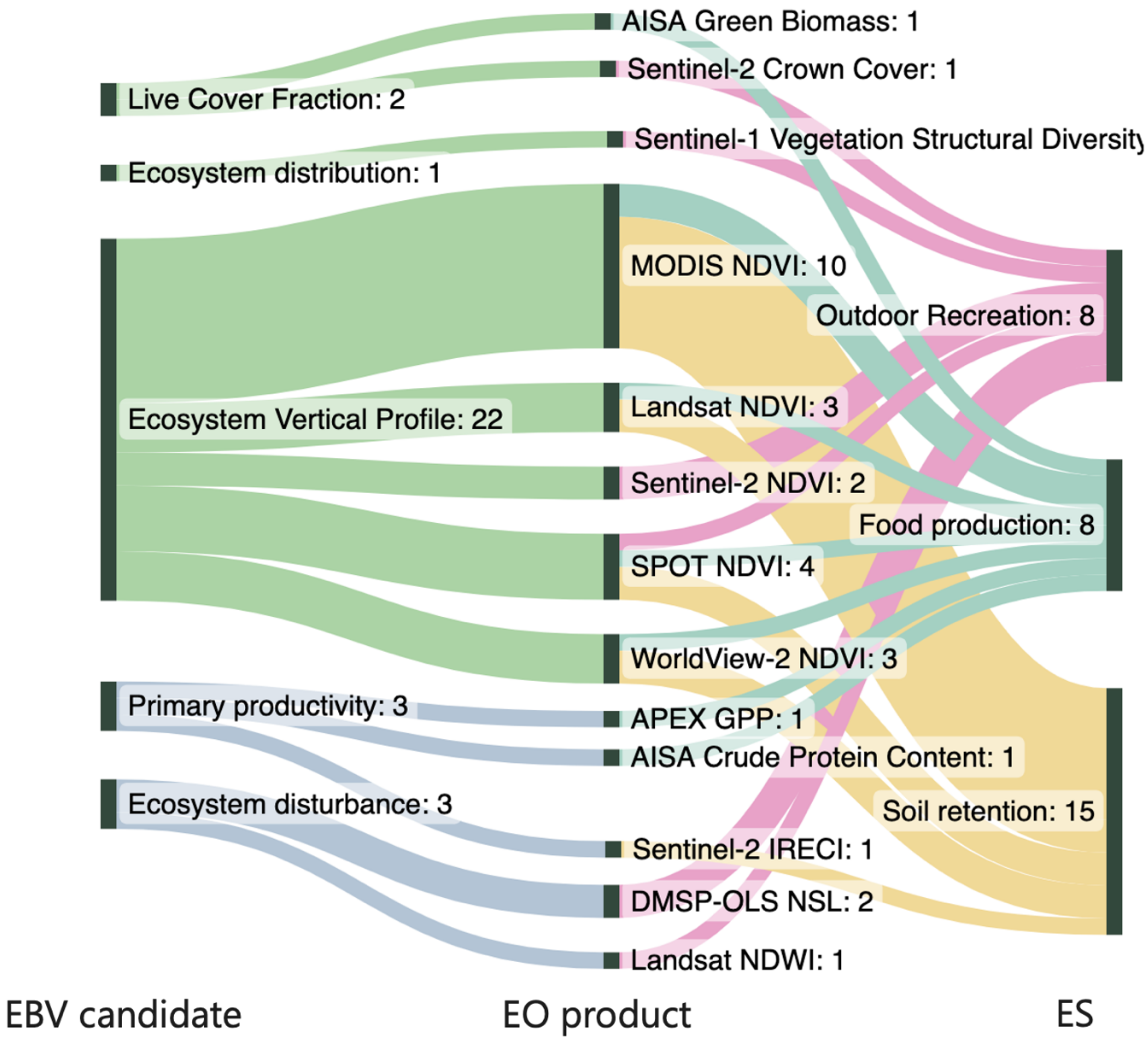

Figure 3.5. Earth observation indicators found in ES models of outdoor recreation, food production, and soil retention. From left to right, we highlight the connection between ecosystem structure and function indicators classes, individual indicators derived by EO sensors, and three sets of ES service models (outdoor recreation, food production, and soil retention).

3.4 Spatial and temporal resolution of ES models

Despite many of the most commonly used EO sensors (i.e., Landsat, Sentinel-2, and MODIS) having worldwide coverage at multi-annual time steps, few ES studies included in our review were carried out at the national (20%) or global scale (1 study). Further, only 32% of studies were carried out across multiple time steps (32%). We additionally found that ES model results were often aggregated to coarse spatial and temporal resolution, even though most EO data inputs have fine temporal and spatial resolution. For example, although Landsat data has a 30m spatial resolution and temporal image frequency of ~16 days, the final ES models were often 1 km models at an annual timestep. The literature consistently points to the advantage of EO sensors providing an opportunity to have finer resolution information in which to understand ES, yet we've found that most papers are taking that finer resolution input data and not using it to deliver finer resolution results.

3.5 Trends through 2012-2021

The variety of ES modelled utilizing EO technologies is ever evolving. Figure 3.6 highlights how the proportion of ES models from cultural, provisioning, and regulating service categories changed over time in the literature identified for this review. The last three years (2019, 2020, 2021) had the most even distribution of ES service models of the entire study period, indicating a potential increased exploration of EO applications to different service types. This, alongside the changes in sensors being used in these studies throughout the last ten years (Figure 3.2.), indicate that the ES field is still in a period of methodological testing and development, exploring what data can be linked to ES through which models.

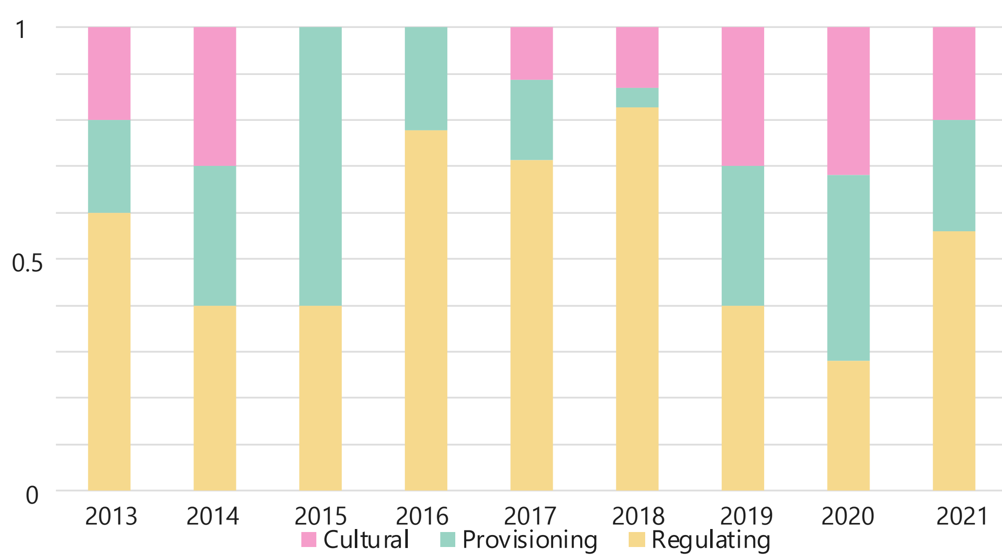

Figure 3.6. The proportion of cultural, provisioning, and regulating ES models that utilized earth observation to assess ecosystem services per year (2013-2021) of review.

4. Discussion and conclusion

In this review, we have identified a growing body of ES modelling literature demonstrating that EO is being used integrate information on ecosystem properties, including properties of ecosystem structure and function, into ES models. We found that an increasingly diverse set of EO sensors are being used to derive information that is being used in ES models; with historically popular sensors (Landsat, MODIS) being consistently used over the last ten years, while emerging sensors (Sentinel-2 constellation) are starting to play an increasingly important role in providing information. EO indicators derived from these sensors highlighted in this review are associated with highly-tested indicators of vegetation structure and function (86% of indicators found in review; e.g. LAI, NDVI and NPP), water quality function indicators (8% of indicators found in review; e.g. NDWI), ecosystem disturbance (3% of indicators found in review; e.g. fire, human disturbance), and changes in ecosystem function across seasons (1% of indicators found in review; e.g. phenology). These EO indicators were found to be most used in models of regulating services across the entire review period; yet we found EO indicators applied across ES models of cultural, provisioning, and regulating services.

There is a link between developments in the EO and ES fields. One example highlighted by this paper is the shift in 2019 to the use of Sentinel-2 data in ES models, just as this satellite constellation's data was first made available publicly. As the breadth of EO data publicly and privately available continues to expand, it is expected that there will continue to be additional EO indicators that are tested and used across varying ES models. These shifts in the ES field driven by shifting EO technology are important to continually "take stock" of through time. Furthermore, an open library of tested and verified EO-indices of ecosystem structure and ecosystem function across specific locations and ecosystem types is critical going forward. That is, the accuracy of an NDVI measure is going to be different in forests in China and Canada, and the accuracy will vary by shifts in forest types, from beech forests to hardwoods.

With many in the ES field concerned with monitoring of environmental trends through time, it is important for ES modelers to consider which new EO information is consistent with existing EO data. Furthermore, clear communication in the literature is critical moving forward. Research projects that are explicit about which component of the system is being proxied with EO data, and subsequently which ES is then being modelled from the data is key for improving the consistency and replicability of how ES are modelled into the future (Pettorelli et al. 2017). Furthermore, in reading papers for this review there was often a lack of specificity in model design and EO, such as TM or OLI Landsat not being specified in multiple studies. This lack of specificity makes reproducibility difficult and might even point to a gap in understanding on the part of ES research community using EO data and technologies.

One goal of this review was to test whether EO indicators could be organized into structure and function classifications, which we found to clarify certain trends in the field, such as finding that advancements in EO indicators of ecosystem spatial distribution has been particularly important in advancing the latest cultural service models over the period of review. Communication of the linkages the authors were making between the data used to model ES and its relevancy to the production of each particular service was not always clearly communicated. Expanding on that point further, communication in the literature review of testing, calibration, and validation of EO data to ES models was rarely presented in the papers or associated supplemental materials.

It is important to note that EO data is only just one component of the shifts in the sources of data being used to understand interaction between nature and people. While LULC remains an important data source, EO indicators of structure and function are increasingly becoming key data sources used in assessing ES as well, both with and without LULC; roughly 30% of studies in this review did not use LULC in their models. Shirpke et al.'s review (2023) additionally shows that the use of data collected from mobile devices (e.g. smartphones and tablets) is proliferating in ES studies, especially those focused on cultural ES (in which EO use was found least frequently, as found in this review). This incorporation of multiple data sources (including

EO, but also data from mobile technologies, field surveys, and social-economic datasets) is key for understanding the spatial variation and drivers of ES from *both* ecological and social processes.

While the primary research question addressed by this review related to whether EO is being used as a tool to incorporate linkages from the biological processes that influence the capacity of ecosystems to provide ES over broad scales, this is just one of the key gaps that EO can potentially address. Another promise of using EO for ES assessments is to allow the ES community to increase the spatial extent of work while maintaining fine temporal and spatial resolutions (in addition to maintaining information resolution about ecosystems by avoiding loss through classifying to LULC). This study shows that while the promise of expanded extent has been partially realized for some ES, there are more opportunities still to be realized, as only 10% of studies utilized EO to examine ES over a wide extent (e.g. global or national scale) *and* over multiple time steps; as opposed to 58% of studies which assessed ES at a limited spatial extent and at a single point in time. One limiting factor in these cases may be the use additional datasets to model ES, such as socio-demographic data, which are not available at the same fine resolution as EO. Finally, while it is anticipated that EO will allow for analysis of interactions between multiple ES across spatial and temporal extents in which there has not previously been the capacity to run those types of analyses, we saw limited uptake of these large-scale analyses in the literature that looked at interactions between the multiple ES modelled at a global, or even national scale.

We recognize that at the current stage of ES modelling research, there are tradeoffs in the aspects of complexity that a single study can truly account for. For example, to look at how ES changes across time, a study might simplify the modelling process to run the model based on current, past, and simulated future LULC maps. Or, in a study that does comprehensive field surveying to calibrate and verify EO indicators used for modelling ES, the researchers may limit the number of ES considered. We generally found in our review there was a tradeoff between the complexity of the data sources/modelling approach used, the range of ES considered, and a multi-scale examination of study outputs over space and time. To this point, one key limitation of this review is that it includes only studies assessing multiple ES and the most advanced work on EO integration may be found in literature that is focused on modelling development of a single ES, such as the growing body of literature around heat mitigation in urban areas or estimating carbon stocks within single forest stands. Further still, many of the EO indicators that came up in this study may be missing where the EO field is currently, and perhaps there could be major gains to be made if more modern EO data and approaches were to be applied in the ES context; this would require increased dialogue between ES and EO scholars and practitioners.

While the increasingly fine spectral, temporal, and spatial resolution of EO indicators is expanding the opportunities for integration into ES models, other research frontiers in ES modelling exist and should continue to be explored as well; including mixed-data studies that incorporate EO data with socio-economic data (Hodbod et al. 2019). ES assessment is ultimately of a place and there should not be an abandonment of participatory approaches and ecological field surveys that compliment remote assessments, allowing researchers can get an on-the-ground understanding of the social-ecological systems that they are located within**.** There is no 'one right method' to model ES in every place and to answer every research/policy/decision-making question. There is exciting new research on using "model ensembles" that opens the possibility of a future in which diverse modelling techniques are used together to improve our measurements and understanding of ES as well (Willcock et al. 2020, 2023). EO technologies will remain an important tool for the ES community moving forward and should be used in conjuncture with multiple methods and knowledge systems for understanding the human-nature relationship (Cole et al. 2023).

The literature analysis presented here illustrates that the ES modelling field is continuing to evolve, utilizing existing and emerging EO technologies to ES models across a range of cultural, regulating, and provisioning services. As new technologies emerge and continue to increase the capacity of the ES community to study and understand dynamic processes across greater extents of time and geographic space, some of the most pressing questions that have emerged from undertaking this review are:

- How can the ES community most effectively keep up with changing EO technology, while maintaining consistency required for long-term monitoring of ecosystems across large temporal and spatial extents?

- At what scale and resolution of assessment do EO technologies provide the most “accuracy improvement”? As opposed to using coarser datasets, such as LULC, across large extent studies or more place-based field observations applied to local studies.

- How can the ES community test and validate emerging EO indicators of ecosystem structure and function across different geographic locations and ecosystem types? Is there an effective way that field observations and remote EO can be used together across larger extents?

- How can we facilitate and improve communication between ES modelling experts and EO/remote-sensing experts to increase adoption rates of EO use to improve ES modelling studies going forward?

- How can the ES community leverage the use of other forms of information (e.g., participatory maps, social survey data) and other emerging technologies (e.g., mobile data, AI) with EO technologies to provide more holistic understanding of ES in the future?

5. References

Andrew, M. E., Wulder, M. A., Nelson, T. A., & Coops, N. C. (2015). Spatial data, analysis approaches, and information needs for spatial ecosystem service assessments: a review. GIScience & Remote Sensing, 52(3), 344–373. https://doi.org/10.1080/15481603.2015.1033809

Assessment, M. E. (2005). Ecosystems and human well-being: wetlands and water. World Resources Institute.

Bagstad, K. J., Semmens, D. J., Waage, S., & Winthrop, R. (2013). A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosystem Services, 5, 27–39. https://doi.org/https://doi.org/10.1016/j.ecoser.2013.07.004

Braun, D. (2017). Remote sensing of ecosystem services. University of Zurich.

Braun, D., Damm, A., Hein, L., Petchey, O. L., & Schaepman, M. E. (2018). Spatio-temporal trends and trade-offs in ecosystem services: An Earth observation based assessment for Switzerland between 2004 and 2014. Ecological Indicators, 89, 828–839. https://doi.org/https://doi.org/10.1016/j.ecolind.2017.10.016

Burkhard, B., Kroll, F., Müller, F., & Windhorst, W. (2009). Landscapes' capacities to provide ecosystem services - A concept for land-cover based assessments. Landscape Online, 15. https://doi.org/10.3097/LO.200915

Burkhard, B., Santos-Martin, F., Nedkov, S., & Maes, J. (2018). An operational framework for integrated Mapping and Assessment of Ecosystems and their Services (MAES). One Ecosystem, 3, e22831. https://doi.org/10.3897/oneeco.3.e22831

Carpenter, S. R., Mooney, H. A., Agard, J., Capistrano, D., DeFries, R. S., Díaz, S., Dietz, T., Duraiappah, A. K., Oteng-Yeboah, A., Pereira, H. M., Perrings, C., Reid, W. V, Sarukhan, J., Scholes, R. J., & Whyte, A. (2009). Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proceedings of the National Academy of Sciences, 106(5), 1305–1312. https://doi.org/10.1073/pnas.0808772106

Chaplin-Kramer, R., Neugarten, R. A., Sharp, R. P., Collins, P. M., Polasky, S., Hole, D., Schuster, R., Strimas-Mackey, M., Mulligan, M., Brandon, C., Diaz, S., Fluet-Chouinard, E., Gorenflo, L. J., Johnson, J. A., Kennedy, C. M., Keys, P. W., Longley-Wood, K., McIntyre, P. B., Noon, M., …

Watson, R. A. (2023). Mapping the planet's critical natural assets. Nature Ecology & Evolution, 7(1), 51–61. https://doi.org/10.1038/s41559-022-01934-5

Cheng, X., Van Damme, S., Li, L., & Uyttenhove, P. (2019). Evaluation of cultural ecosystem services: A review of methods. Ecosystem Services, 37, 100925. https://doi.org/https://doi.org/10.1016/j.ecoser.2019.100925

Cole, B., Bradley, A. V, Willcock, S., Gardner, E., Allinson, E., Hagen-Zanker, A., Calo, A. J., Touza, J., Petrovskii, S., Yu, J., & Whelan, M. (2023). Using a multi-lens framework for landscape decisions. People and Nature, 5(4), 1050–1071. https://doi.org/https://doi.org/10.1002/pan3.10474

Cord, A. F., Bartkowski, B., Beckmann, M., Dittrich, A., Hermans-Neumann, K., Kaim, A., Lienhoop, N., Locher-Krause, K., Priess, J., Schröter-Schlaack, C., Schwarz, N., Seppelt, R., Strauch, M., Václavík, T., & Volk, M. (2017). Towards systematic analyses of ecosystem service trade-offs and synergies: Main concepts, methods and the road ahead. Ecosystem Services, 28, 264–272. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.07.012

Costanza, R., de Groot, R., Braat, L., Kubiszewski, I., Fioramonti, L., Sutton, P., Farber, S., & Grasso, M. (2017). Twenty years of ecosystem services: How far have we come and how far do we still need to go? Ecosystem Services, 28, 1–16. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.09.008

Crockett, E. T. H., Vennin, S., Botzas-Coluni, J., Larocque, G., & Bennett, E. M. (2021). Bright spots of carbon storage in temperate forests. Journal of Applied Ecology, 58(12), 3012–3022. https://doi.org/https://doi.org/10.1111/1365-2664.14042

Crossman, N. D., Bryan, B. A., de Groot, R. S., Lin, Y.-P., & Minang, P. A. (2013). Land science contributions to ecosystem services. Current Opinion in Environmental Sustainability, 5(5), 509–514. https://doi.org/https://doi.org/10.1016/j.cosust.2013.06.003

Daily, G. C. (1997). Introduction: what are ecosystem services. Nature's Services: Societal Dependence on Natural Ecosystems, 1(1).

de Araujo Barbosa, C. C., Atkinson, P. M., & Dearing, J. A. (2015). Remote sensing of ecosystem services: A systematic review. Ecological Indicators, 52, 430–443. https://doi.org/https://doi.org/10.1016/j.ecolind.2015.01.007

del Río-Mena, T., Willemen, L., Tesfamariam, G. T., Beukes, O., & Nelson, A. (2020). Remote sensing for mapping ecosystem services to support evaluation of ecological restoration interventions in an arid landscape. Ecological Indicators, 113, 106182. https://doi.org/https://doi.org/10.1016/j.ecolind.2020.106182

Eigenbrod, F., Armsworth, P. R., Anderson, B. J., Heinemeyer, A., Gillings, S., Roy, D. B., Thomas, C. D., & Gaston, K. J. (2010). The impact of proxy-based methods on mapping the distribution of ecosystem services. Journal of Applied Ecology, 47(2), 377–385. https://doi.org/https://doi.org/10.1111/j.1365-2664.2010.01777.x

Fu, B., Wang, S., Su, C., & Forsius, M. (2013). Linking ecosystem processes and ecosystem services. Current Opinion in Environmental Sustainability, 5(1), 4–10. https://doi.org/https://doi.org/10.1016/j.cosust.2012.12.002

Galaz García, C., Bagstad, K. J., Brun, J., Chaplin-Kramer, R., Dhu, T., Murray, N. J., Nolan, C. J., Ricketts, T. H., Sosik, H. M., Sousa, D., Willard, G., & Halpern, B. S. (2023). The future of ecosystem assessments is automation, collaboration, and artificial intelligence. Environmental Research Letters, 18(1), 011003. https://doi.org/10.1088/1748-9326/acab19

Hodbod, J., Tebbs, E., Chan, K., & Sharma, S. (2019). Integrating Participatory Methods and Remote Sensing to Enhance Understanding of Ecosystem Service Dynamics Across Scales. Land, 8(9). https://doi.org/10.3390/land8090132

Lavorel, S., Bayer, A., Bondeau, A., Lautenbach, S., Ruiz-Frau, A., Schulp, N., Seppelt, R., Verburg, P., Teeffelen, A. van, Vannier, C., Arneth, A., Cramer, W., & Marba, N. (2017). Pathways to bridge the biophysical realism gap in ecosystem services mapping approaches. Ecological Indicators, 74, 241–260. https://doi.org/https://doi.org/10.1016/j.ecolind.2016.11.015

Lock, M. C., Skidmore, A. K., van Duren, I., & Mücher, C. A. (2021). Evidence-based alignment of conservation policies with remote sensing-enabled essential biodiversity variables. Ecological Indicators, 132, 108272. https://doi.org/https://doi.org/10.1016/j.ecolind.2021.108272

Maes, J., Egoh, B., Willemen, L., Liquete, C., Vihervaara, P., Schägner, J. P., Grizzetti, B., Drakou, E. G., Notte, A. La, Zulian, G., Bouraoui, F., Luisa Paracchini, M., Braat, L., & Bidoglio, G. (2012). Mapping ecosystem services for policy support and decision making in the European Union. Ecosystem Services, 1(1), 31–39. https://doi.org/https://doi.org/10.1016/j.ecoser.2012.06.004

Malinga, R., Gordon, L. J., Jewitt, G., & Lindborg, R. (2015). Mapping ecosystem services across scales and continents – A review. Ecosystem Services, 13, 57–63. https://doi.org/https://doi.org/10.1016/j.ecoser.2015.01.006

Mandle, L., Shields-Estrada, A., Chaplin-Kramer, R., Mitchell, M. G. E., Bremer, L. L., Gourevitch, J. D., Hawthorne, P., Johnson, J. A., Robinson, B. E., Smith, J. R., Sonter, L. J., Verutes, G. M., Vogl, A. L., Daily, G. C., & Ricketts, T. H. (2021). Increasing decision relevance of ecosystem service science. Nature Sustainability, 4(2), 161–169. https://doi.org/10.1038/s41893-020-00625-y

McDonough, K., Hutchinson, S., Moore, T., & Hutchinson, J. M. S. (2017). Analysis of publication trends in ecosystem services research. Ecosystem Services, 25, 82–88. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.03.022

Notte, A. La, Czúcz, B., Vallecillo, S., Polce, C., & Maes, J. (2022). Ecosystem condition underpins the generation of ecosystem services: an accounting perspective. One Ecosystem, 7, e81487. https://doi.org/10.3897/oneeco.7.e81487

Pascual, A., Giardina, C. P., Selmants, P. C., Laramee, L. J., & Asner, G. P. (2021). A new remote sensing-based carbon sequestration potential index (CSPI): A tool to support land carbon management. Forest Ecology and Management, 494, 119343. https://doi.org/https://doi.org/10.1016/j.foreco.2021.119343

Pettorelli, N., Schulte to Bühne, H., Tulloch, A., Dubois, G., Macinnis-Ng, C., Queirós, A. M., Keith, D. A., Wegmann, M., Schrodt, F., Stellmes, M., Sonnenschein, R., Geller, G. N., Roy, S., Somers, B., Murray, N., Bland, L., Geijzendorffer, I., Kerr, J. T., Broszeit, S., … Nicholson, E. (2018). Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. Remote Sensing in Ecology and Conservation, 4(2), 71–93. https://doi.org/https://doi.org/10.1002/rse2.59

Pfeifer, M., Disney, M., Quaife, T., & Marchant, R. (2012). Terrestrial ecosystems from space: a review of earth observation products for macroecology applications. Global Ecology and Biogeography, 21(6), 603–624. https://doi.org/https://doi.org/10.1111/j.1466-8238.2011.00712.x

Polasky, S., Tallis, H., & Reyers, B. (2015). Setting the bar: Standards for ecosystem services. Proceedings of the National Academy of Sciences, 112(24), 7356–7361. https://doi.org/10.1073/pnas.1406490112

Ramirez-Reyes, C., Brauman, K. A., Chaplin-Kramer, R., Galford, G. L., Adamo, S. B., Anderson, C. B., Anderson, C., Allington, G. R. H., Bagstad, K. J., Coe, M. T., Cord, A. F., Dee, L. E., Gould, R. K., Jain, M., Kowal, V. A., Muller-Karger, F. E., Norriss, J., Potapov, P., Qiu, J., … Wright, T. M. (2019). Reimagining the potential of Earth observations for ecosystem service assessments. Science of The Total Environment, 665, 1053–1063. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.02.150

Ruckelshaus, M., McKenzie, E., Tallis, H., Guerry, A., Daily, G., Kareiva, P., Polasky, S., Ricketts, T., Bhagabati, N., Wood, S. A., & Bernhardt, J. (2015). Notes from the field: Lessons learned from using ecosystem service approaches to inform real-world decisions. Ecological Economics, 115, 11–21. https://doi.org/https://doi.org/10.1016/j.ecolecon.2013.07.009

Schirpke, U., Ghermandi, A., Sinclair, M., Van Berkel, D., Fox, N., Vargas, L., & Willemen, L. (2023). Emerging technologies for assessing ecosystem services: A synthesis of opportunities and challenges. Ecosystem Services, 63, 101558. https://doi.org/https://doi.org/10.1016/j.ecoser.2023.101558

Skidmore, A. K., Coops, N. C., Neinavaz, E., Ali, A., Schaepman, M. E., Paganini, M., Kissling, W. D., Vihervaara, P., Darvishzadeh, R., Feilhauer, H., Fernandez, M., Fernández, N., Gorelick, N., Geijzendorffer, I., Heiden, U., Heurich, M., Hobern, D., Holzwarth, S., Muller-Karger, F. E., … Wingate, V. (2021). Priority list of biodiversity metrics to observe from space. Nature Ecology & Evolution, 5(7), 896–906. https://doi.org/10.1038/s41559-021-01451-x

Tallis, H., Mooney, H., Andelman, S., Balvanera, P., Cramer, W., Karp, D., Polasky, S., Reyers, B., Ricketts, T., Running, S., Thonicke, K., Tietjen, B., & Walz, A. (2012). A Global System for Monitoring Ecosystem Service Change. BioScience, 62(11), 977–986. https://doi.org/10.1525/bio.2012.62.11.7

Ustin, S. L., & Middleton, E. M. (2021). Current and near-term advances in Earth observation for ecological applications. Ecological Processes, 10(1), 1. https://doi.org/10.1186/s13717-020-00255-4

Vargas, L., Willemen, L., & Hein, L. (2019). Assessing the Capacity of Ecosystems to Supply Ecosystem Services Using Remote Sensing and An Ecosystem Accounting Approach. Environmental Management, 63(1), 1–15. https://doi.org/10.1007/s00267-018-1110-x

Wellmann, T., Lausch, A., Andersson, E., Knapp, S., Cortinovis, C., Jache, J., Scheuer, S., Kremer, P., Mascarenhas, A., Kraemer, R., Haase, A., Schug, F., & Haase, D. (2020). Remote sensing in urban planning: Contributions towards ecologically sound policies? Landscape and Urban Planning, 204, 103921. https://doi.org/https://doi.org/10.1016/j.landurbplan.2020.103921

Willcock, S., Hooftman, D. A. P., Blanchard, R., Dawson, T. P., Hickler, T., Lindeskog, M., Martinez-Lopez, J., Reyers, B., Watts, S. M., Eigenbrod, F., & Bullock, J. M. (2020). Ensembles of ecosystem service models can improve accuracy and indicate uncertainty. Science of The Total Environment, 747, 141006. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.141006

Willcock, S., Hooftman, D. A. P., Neugarten, R. A., Chaplin-Kramer, R., Barredo, J. I., Hickler, T., Kindermann, G., Lewis, A. R., Lindeskog, M., Martínez-López, J., & Bullock, J. M. (2023). Model ensembles of ecosystem services fill global certainty and capacity gaps. Science Advances, 9(14), eadf5492. https://doi.org/10.1126/sciadv.adf5492

Willcock, S., Martinez-Lopez, J., Dandy, N., & Bullock, J. M. (2021). High Spatial-Temporal Resolution Data across Large Scales Are Needed to Transform Our Understanding of Ecosystem Services. Land, 10(7). https://doi.org/10.3390/land10070759

Ziter, C., Bennett, E. M., & Gonzalez, A. (2013). Functional diversity and management mediate aboveground carbon stocks in small forest fragments. Ecosphere, 4(7), art85. https://doi.org/https://doi.org/10.1890/ES13-00135.1

Supplemental information

Figure S3.1. Figure of PRISMA search protocol for review

Table S3.1. Terminology translation table listing EO products and their relationship with the GEO BON Ecosystem Structure and Ecosystem Function EBVs

Acknowledgments

We acknowledge the support of the Natural Sciences and Engineering Research Council of Canada (NSERC), funding reference number NSERC NETGP 523374-18. [Cette recherche a été financée par le Conseil de recherches en sciences naturelles et en génie du Canada (CRSNG), numero de référence CRSNG NETGP 523374-18].

Author contributions

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Declaration of interests

The authors declare no competing interest.

Chapter Two Supplemental Materials

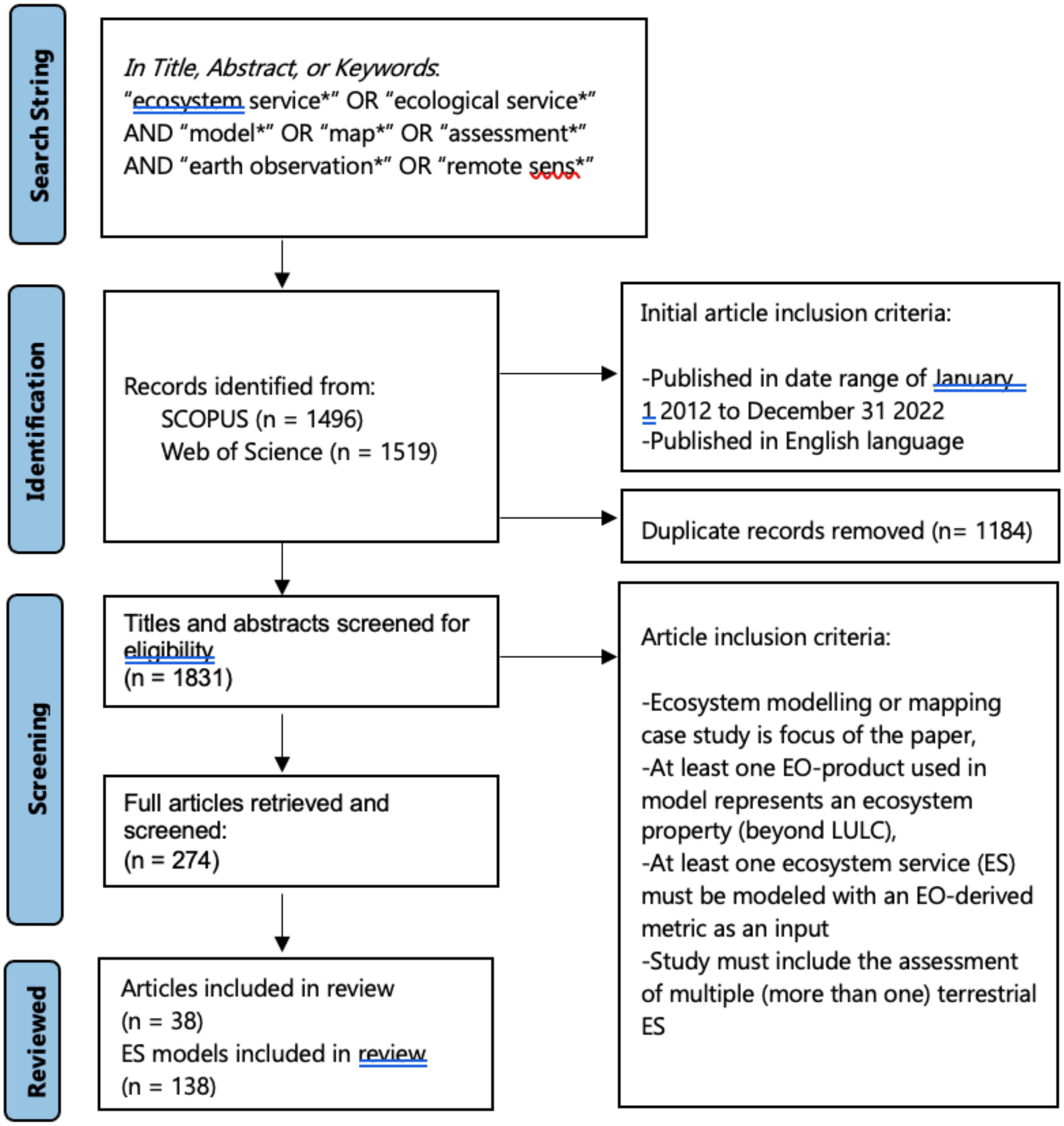

Figure S3.1. PRISMA flow diagram for literature review

Table S3.1. Terminology translation table listing EO products and their relationship with the GEO BON Ecosystem Structure and Ecosystem Function EBVs, as well as typical EO product terminology (Adapted from Supplemental Table 1 from Skidmore et al. (2021))

EBV class	Candidate EBVs (GEO BON)	Example of the candidate EBVs (GEO BON)	Typical remote sensing enabled biodiversity variable name	Remote sensing biodiversity products
Ecosystem Function	ecosystem phenology	timing, such as day of year of onset of ecosystem energy pulses	ecosystem phenology	land surface peak (max of season)
				land surface green-up (start of season)
				land surface senescence (end of season)
	primary productivity	gross primary productivity	ecosystem physiology	gross primary productivity
		net primary productivity		net primary productivity
		net ecosystem exchange		leaf area index
				specific leaf area
				foliar N/P/K content
				evapotranspiration
				fraction of absorbed photosynthetically active radiation
				ecosystem soil moisture
				carbon cycle (sequestration)
				carbon cycle (below ground biomass and carbon)
	ecosystem disturbance	pulse rate, recovery rate, pulse magnitude	ecosystem disturbance	biological effects of fire disturbance (direction, duration, abruptness, magnitude, extent, frequency)
				biological effects of pest and disease outbreak
Ecosystem Structure	ecosystem distribution	presence-absence of ecosystem types	spatial configuration	ecosystem structural variance
		fraction of horizontal cover per ecosystem type		ecosystem fragmentation
	live cover fraction	cover fraction of living forms	habitat structure	land cover (vegetation type)
				fraction of vegetation cover
		Plant area index		plant area index profile (canopy cover)
	Ecosystem Vertical Profile	biomass (e.g. in kg/m2) at different heights or depths		above-ground biomass
				leaf area index
				urban habitat
				ice cover habitat
				deadwood habitat
				vegetation habitat
				habitat structure
				biological effects of fire disturbance (direction, duration, abruptness, magnitude, extent, frequency)
				biological effects of irregular inundation

Supplemental text on defining indicators of ecosystem structure and function:

Building on Skidmore et al. (2022) in this publication helps demonstrate how existing literature can be synthesized and organized within a standardized and monitorable framework aimed at providing guidance around potential data sources for this future ES model development. In synthesizing these findings using this existing framework, we hope to contribute to efforts being developed to establish common definitions in the ES monitoring field, such as the current efforts to select Essential Ecosystem Services Variables (EESVs) by the GEO BON initiative. The raw coded data from this review, not organized around structure and function, showing direct links from EO sensor to EO-derived indicators to ES models.

SCHOLARLY DISCUSSION and CONCLUSION

The ES modelling field has evolved rapidly since the concept was first introduced. In that time, there has been considerable testing and developments of methods for modelling and monitoring multiple ES (Burkhard et al. 2018; Carpenter et al. 2009; Chaplin-Kramer et al. 2023; Cheng et al. 2019; Costanza et al. 2017; Malinga et al. 2015; Willcock et al. 2023). As this ES toolbox for understanding, studying, and communicating about ES has grown, there has also been a growing number of choices for ES researchers and practitioners who want to design studies to better understand ES in specific locations. Among these varied tools and methods, there are unique data requirements, verification schemes, accuracies, and relevancies to specific places, ecosystems, and environmental management decisions (Bagstad et al. 2013).

Chapter One of this thesis aimed to synthesize much of the work that has been done in the landscape-scale ES modelling field over the past 20 years and connecting these developments to ES monitoring schemes around the globe, from Canada's Census of the Environment to GEOBON's work developing Essential Ecosystem Service Variables. In particular, Chapter One focused on three of the most critical choices in modelling and monitoring design for ES: 1) the choice of input data and, subsequently, model complexity, 2) the spatial dimensions of ES considered, and 3) the temporal dimensions of ES considered.

This comprehensive literature survey shows that EO data has since the beginning played a critical role in ES modelling and monitoring design because it impacts these three choices mentioned above. EO can influence the complexity of models because it is used to produce indicators related to a wide range of properties of ecosystem structure and function. EO can influence the spatial dimensions of a study because many EO indicators can be created at relatively fine resolution spatial grain across broad spatial extents. And EO can contribute to tracking change through time because many EO sensors, such as satellites, provide information over regular, repeated intervals. However, continued advancements have occurred in EO technologies, and, over the last ten years, there have been numerous calls from the ES community to continue exploring the diverse potential uses of EO data in ES models (Braun et al. 2018; del Río-Mena et al. 2019; Ramirez-Reyes et al. 2019).

Chapter Two identified, through a systematic review, a growing body of ES modelling literature demonstrating how EO is being used integrate information on ecosystem properties, including properties of ecosystem structure and function, into ES models. Chapter Two shows that an increasingly diverse set of EO-sensors are being used to derive information related to various properties of ecosystem structure and function that are then being used in ES models. Historically popular sensors (Landsat, MODIS) have remained consistently used over the last ten years, while emerging sensors (Sentinel-2) are starting to play an increasingly important role in providing information for ES models. EO indicators derived from these sensors highlighted in this review were associated with highly-tested indices of vegetation structure and function (86% of indicators found in review; e.g. LAI, NDVI and NPP), water quality function indicators (8% of indicators found in review; e.g. NDWI), ecosystem disturbance (3% of indicators found in review; e.g. fire, human disturbance), and changes in ecosystem function across seasons (1% of indicators found in review; e.g. phenology). These EO indicators were found to be most used in models of regulating services across the entire review period; yet we found EO data used in ES models across all three categories (cultural, provisioning, and regulating services).

Many of the recommendations that emerged from Chapter Two involve the need for clear communication and knowledge brokering between disciplines, as illustrated by the open questions at the end of the manuscript, restated here:

- How can the ES community most effectively keep up with changing EO technology, while maintaining consistency required for long-term monitoring of ecosystems across large temporal and spatial extents?

- At what scale and resolution of assessment do EO technologies provide the most "accuracy improvement"? As opposed to using coarser datasets, such as LULC, across large extent studies or more place-based field observation applied to local studies.

- How can the ES community test and validate emerging EO-indices of ecosystem structure and function across different geographic locations and ecosystem types? Is there an effective way that field observations and remote EO can be used together across larger extents?

- How can we facilitate and improve communication between ES modelling experts and EO/remote-sensing experts to increase adoption rates of EO use in ES modelling studies going forward?

- How can the ES community leverage the use of other forms of information (e.g., participatory maps, social survey data) and other emerging technologies (e.g., mobile data, AI) with EO technologies to provide more holistic understanding of ES in the future?

Some recommendations related to these questions that have emerged from studying and thinking about this topic for my MSc, include the need for continued:

- Development of generalizable ES models that can produce results over large spatio-temporal extents. These types of models need to be able to incorporate data from multiple EO sensors, in addition to incorporating socio-economic data and other forms of data relevant to understanding ES dynamics.

- Communication in models and data dashboards about where ES occur, but also the dynamic processes of ecosystem change that underpin ES, such as, tracking of Net

Primary Productivity of different ecosystems across seasons and changing climatic conditions.

- Dialogues between EO and ES experts are needed to better understand how the technology is changing and what opportunities may emerge in the future as a result.

- Emphasis on science communication from the ES community to increase uptake of the use of these ES data in decision-making, from the local level to global agreements.

As a researcher, my background is rooted in the landscape ecology discipline as opposed to EO, and, therefore, much of the search terms and literature analysis in this thesis is biased towards the ecological aspects of EO application. This precludes much of the EO literature, for example developments of EO to monitor and study species diversity, soil properties, wildfire, and many more specific use cases. However, by limiting the search in this way, it is clear that some of the more modern approaches and outcomes of EO research are not showing up in ES work at a landscape-scale, and the ES field may be disconnected, or "falling behind," from where the EO community is. While there is a potential danger in promoting outdated methods, there is also potential danger in moving forward with new EO data and models without strong understanding of the technology. Breaking down disciplinary barriers and increasing dialogues between those working on ES and those working on EO could facilitate major gains in the uptake in use of more modern data and modelling approaches being used in ES work, while reducing errors that can be caused by misunderstanding the data and technologies (Alix-Garcia and Millimet 2023).

In addition to these limitations caused by a disconnect between the ES and EO fields, there are limitations caused by silos within the larger ES community. For example, review papers have shown major advancements in urban ES studies using EO (Wellmann et al. 2020) and water quality studies using EO (Topp et al. 2020) over the last decade, but many of these advancements were not mirrored in (or scaled up to) the macro-scale, multi-service ES studies examined in Chapter Two that include water quality or urban ES models. Within studies on localized places or on modelling single ES there are often more advanced data sources being explored, such as LiDAR, yet these EO data rarely appeared in the literature tied to large-scale studies. This lack (or lag-time) in the scalability of these advancements might be the cause of macro-scale ES models being "behind the times," further causing a disconnect between ES researchers and potential partners in the EO community, but also showing a disconnect between silos of the larger ES community. Increased dialogue is imperative between ES researchers working across scales and places.

When taking the two chapters of this thesis together, a key takeaway is that assessing ES involves people making choices around the indicators and data that are used. The results of this MSc project help to document what EO-derived indicators and proxies are currently being used to assess ES and how these choices are incorporating ecological connections between ecosystem structure, function, and ES across broad scale assessments. This work also points to a lack of standardization currently present in ES models, from a lack of transparency in validation and clear definitions of how EO data was being used. This is all part of a larger current conversation around developing common frameworks for monitoring ecosystems in a continuous, consistent manner, whilst filling gaps in the spatial and temporal coverage of field-based observations. Larger projects and networks that this work closely aligns with, include NSERC ResNet, GEOBON, and StatsCan Census of Environment, which are all networks of researchers and practitioners coming together with aims to create more systematic monitoring schemes for ES. This thesis has shown that early choices made about the data used in designing an ES model or monitoring scheme influence: 1) the components and drivers of ES that can be linked to final ES, 2) the spatial extent and resolution of outputs and the ability for those outputs be used across different scales of decision-making, and 3) the temporal extent and resolution outputs used to track trends through time. To ensure a sustainable future of the planet, it is critical to not just look at outputs, but to understand that data choices need to be made with critical thought and consideration.

REFERENCES

Alix-García, J., & Millimet, D. L. (2023). Remotely Incorrect? Accounting for Nonclassical Measurement Error in Satellite Data on Deforestation. Journal of the Association of Environmental and Resource Economists, 10(5), 1335–1367. https://doi.org/10.1086/723723

Bagstad, K. J., Semmens, D. J., Waage, S., & Winthrop, R. (2013). A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosystem Services, 5, 27–39. https://doi.org/https://doi.org/10.1016/j.ecoser.2013.07.004

Braun, D., Damm, A., Hein, L., Petchey, O. L., & Schaepman, M. E. (2018). Spatio-temporal trends and trade-offs in ecosystem services: An Earth observation based assessment for Switzerland between 2004 and 2014. Ecological Indicators, 89, 828–839. https://doi.org/https://doi.org/10.1016/j.ecolind.2017.10.016

Burkhard, B., Santos-Martin, F., Nedkov, S., & Maes, J. (2018). An operational framework for integrated Mapping and Assessment of Ecosystems and their Services (MAES). One Ecosystem, 3, e22831. https://doi.org/10.3897/oneeco.3.e22831

Carpenter, S. R., Mooney, H. A., Agard, J., Capistrano, D., DeFries, R. S., Díaz, S., Dietz, T., Duraiappah, A. K., Oteng-Yeboah, A., Pereira, H. M., Perrings, C., Reid, W. V, Sarukhan, J., Scholes, R. J., & Whyte, A. (2009). Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proceedings of the National Academy of Sciences, 106(5), 1305–1312. https://doi.org/10.1073/pnas.0808772106

Chaplin-Kramer, R., Neugarten, R. A., Sharp, R. P., Collins, P. M., Polasky, S., Hole, D., Schuster, R., Strimas-Mackey, M., Mulligan, M., Brandon, C., Diaz, S., Fluet-Chouinard, E., Gorenflo, L. J., Johnson, J. A., Kennedy, C. M., Keys, P. W., Longley-Wood, K., McIntyre, P. B., Noon, M., … Watson, R. A. (2023). Mapping the planet's critical natural assets. Nature Ecology & Evolution, 7(1), 51–61. https://doi.org/10.1038/s41559-022-01934-5

Cheng, X., Van Damme, S., Li, L., & Uyttenhove, P. (2019). Evaluation of cultural ecosystem services: A review of methods. Ecosystem Services, 37, 100925. https://doi.org/https://doi.org/10.1016/j.ecoser.2019.100925

Costanza, R., de Groot, R., Braat, L., Kubiszewski, I., Fioramonti, L., Sutton, P., Farber, S., & Grasso, M. (2017). Twenty years of ecosystem services: How far have we come and how far do we still need to go? Ecosystem Services, 28, 1–16. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.09.008

Malinga, R., Gordon, L. J., Jewitt, G., & Lindborg, R. (2015). Mapping ecosystem services across scales and continents – A review. Ecosystem Services, 13, 57–63. https://doi.org/https://doi.org/10.1016/j.ecoser.2015.01.006

Ramirez-Reyes, C., Brauman, K. A., Chaplin-Kramer, R., Galford, G. L., Adamo, S. B., Anderson, C. B., Anderson, C., Allington, G. R. H., Bagstad, K. J., Coe, M. T., Cord, A. F., Dee, L. E., Gould, R. K., Jain, M., Kowal, V. A., Muller-Karger, F. E., Norriss, J., Potapov, P., Qiu, J., … Wright, T. M. (2019). Reimagining the potential of Earth observations for ecosystem service assessments. Science of The Total Environment, 665, 1053–1063. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.02.150

Topp, S. N., Pavelsky, T. M., Jensen, D., Simard, M., & Ross, M. R. V. (2020). Research Trends in the Use of Remote Sensing for Inland Water Quality Science: Moving Towards Multidisciplinary Applications. Water, 12(1). https://doi.org/10.3390/w12010169

Wellmann, T., Lausch, A., Andersson, E., Knapp, S., Cortinovis, C., Jache, J., Scheuer, S., Kremer, P., Mascarenhas, A., Kraemer, R., Haase, A., Schug, F., & Haase, D. (2020). Remote sensing in urban planning: Contributions towards ecologically sound policies? Landscape and Urban Planning, 204, 103921. https://doi.org/https://doi.org/10.1016/j.landurbplan.2020.103921

Willcock, S., Hooftman, D. A. P., Neugarten, R. A., Chaplin-Kramer, R., Barredo, J. I., Hickler, T., Kindermann, G., Lewis, A. R., Lindeskog, M., Martínez-López, J., & Bullock, J. M. (2023). Model ensembles of ecosystem services fill global certainty and capacity gaps. Science Advances, 9(14), eadf5492. https://doi.org/10.1126/sciadv.adf5492