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Review

Reimagining the potential of Earth observations for ecosystem service assessments

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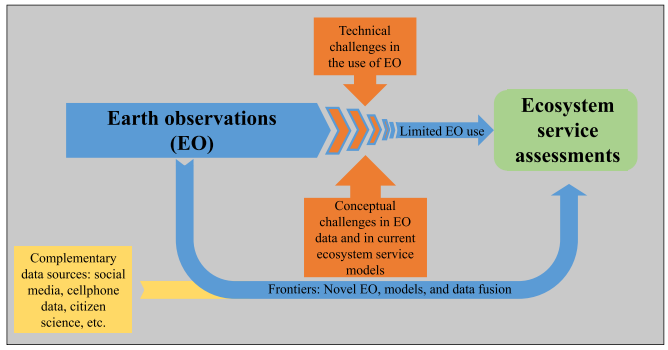
HIGHLIGHTS

- Limited Earth observation (EO) products are used in ecosystem service assessments.
- We identify challenges and solutions to using EO products in ecosystem service models.
- Technical challenges must be addressed systematically by data and model producers.
- Solutions applicable across models address challenges stemming from model structure.
- EO and data fusion offer opportunities to reimagine assessment of ecosystem services.

GRAPHICAL ABSTRACT



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ABSTRACT

The benefits nature provides to people, called ecosystem services, are increasingly recognized and accounted for in assessments of infrastructure development, agricultural management, conservation prioritization, and sustainable sourcing. These assessments are often limited by data, however, a gap with tremendous potential to be filled through Earth observations (EO), which produce a variety of data across spatial and temporal extents and resolutions. Despite widespread recognition of this potential, in practice few ecosystem service studies use EO. Here, we identify challenges and opportunities to using EO in ecosystem service modeling and assessment. Some challenges are technical, related to data awareness, processing, and access. These challenges require systematic investment in model platforms and data management. Other challenges are more conceptual but still systemic; they are byproducts of the structure of existing ecosystem service models and addressing them requires scientific investment in solutions and tools applicable to a wide range of models and approaches. We also highlight new ways in which EO can be leveraged for ecosystem service assessments, identifying promising new areas of research. More widespread use of EO for ecosystem service assessment will only be achieved if all of these types of challenges are addressed. This will require non-traditional funding and partnering opportunities from private and public agencies to promote data exploration, sharing, and archiving. Investing in this integration will be reflected in better and more accurate ecosystem service assessments worldwide.

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1. Introduction

Human dependence on natural systems has frequently been overlooked in decision-making across sectors (Guerry et al., 2015; Rieb et al., 2017; Ruckelshaus et al., 2015). Increasingly, however, both public and private sector decisions strive to account for nature's contributions, including food provision, regulation of freshwater, pollination, and opportunities for recreation; these are often referred to as

ecosystem services (Díaz et al., 2018; TEEB, 2010). Despite these intentions, assessment of ecosystem services in decision making remains limited (Guerry et al., 2015; Rieb et al., 2017). We attribute this to two critical barriers (Fig. 1). First, the scale of decision-relevant information is often mis-matched with existing research and assessment tools. Research quantifying ecosystem services is frequently based on empirical field data, biophysical modeling, economic assessment, or surveys undertaken at the site scale. Using the resulting locally based ecosystem service models in new locations or at different scales requires parameterization, calibration and validation that is often hindered by lack of data. Second, evaluating not just the production of ecosystem goods and services but also the benefits that accrue to specific and relevant beneficiaries is challenging. Most studies of ecosystem services report biophysical values (e.g., tons of sediment retained by vegetation or changes in nutrient discharge) without linking to costs, emotional resonance, health, or safety — information crucial for decision making (Brauman, 2015). Evaluating benefits requires information on human use of ecosystem services, human vulnerability, and access to substitutes, information that biophysical scientists may not have and which is time and labor intensive to collect (Wolff et al., 2015).

Earth observations (EO), collected via remote sensing as well as in situ data, include imagery or raw data (e.g., radar or satellite imagery) as well as products derived through substantial processing (e.g., precipitation, chlorophyll content in water). These data have enormous potential to improve ecosystem service-based decision making, which frequently requires up-to-date information that is globally comparable but locally relevant, because they provide data that are uniform over large areas, available at regular time intervals, and relatively low cost or even free (Cord et al., 2017; Pettorelli et al., 2017). In addition, EO have the potential to improve parametrization of ecosystem service models by providing relevant biophysical data and through fusion with census and other statistical information to provide information about the beneficiaries of ecosystem services. Recent reviews have highlighted opportunities to use EO in ecosystem service assessment, including providing summaries of satellite sensors and associated products that could be used to assess specific ecosystem services (see lists in Andrew et al., 2014; Ayanu et al., 2012; Pettorelli et al., 2017; Xiaoming et al., 2010). The potential value of EO for ecosystem service assessment is also highlighted by several governments and intergovernmental organizations, which have established initiatives to include EO in ecosystem service science (Table 1).

Despite these efforts, the use of EO products in ecosystem service assessments is limited in both number and variety. As of 2013, roughly 5% of the peer-reviewed ecosystem service literature integrated remote sensing and ecosystem services (De Araujo Barbosa et al., 2015), and the EO products used were mostly limited to land use/land cover (LULC) datasets. To a lesser extent, studies used vegetation indices, digital elevation models (DEMs), and surface temperature (Cord et al., 2017; De Araujo Barbosa et al., 2015; Eigenbrod et al., 2010). Given the potential and simultaneous lack of implementation, it is clear that hurdles to integrating EO into ecosystem service assessment exist and must be addressed if EO is to be used more extensively.

Here, we identify key challenges and opportunities for widespread EO uptake in ecosystem service assessments. These challenges and opportunities were identified through a series of workshops (Jan–Jul 2018) bringing together EO scientists, ecosystem service researchers, ecosystem service model users, and decision makers. We delineate where in the process of ecosystem service assessment EO might be used, then lay out a suite of associated challenges. We differentiate technical challenges that require systematic investment in model platforms and data management from conceptual challenges requiring scientific investment to provide solutions and tools relevant across applications. Finally, we highlight frontiers in ecosystem service assessment enabled with EO.

2. Using EO in the process of ecosystem service assessment

2.1. Ways EO can be integrated in ecosystem service modeling

Assessment of ecosystem services includes quantifying the current and future supply of benefits from nature as well as human use of those benefits (often referred to as "demand" in ecosystem service

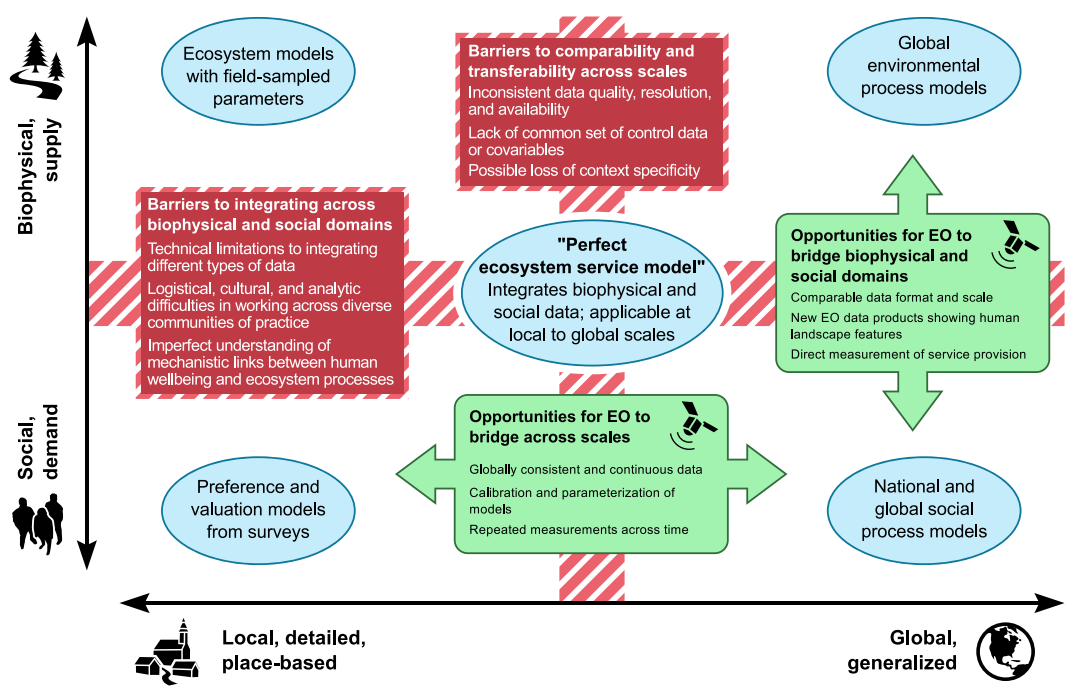

Fig. 1. Opportunities for Earth observations to improve ecosystem service assessments. Ecosystem service models have been applied across scales, from local to global, to quantify ecosystem service supply and demand. Technical and conceptual barriers remain to creating models that effectively integrate social and biophysical systems that are comparable and transferable across geographies. Earth observation data may reduce these barriers by providing new ways to measure ecosystem service drivers that are consistent across time and space.

Table 1
Examples of initiatives aiming to include EO in ecosystem service science.

Target	Initiatives
Creating EO products for measuring and monitoring ecosystem services	Group on Earth Observations ("GEO", 2018) ECOPOTENTIAL (European Union, 2018) Global Pulse (UN, 2018)
Supporting the use of EO data for ecosystem service assessments	Earth Observation for Development (ESA, 2018a) SERVIR Global (USAID, 2018a) SERVIR-Mekong, (USAID, 2018b)
Identifying research priorities in EO for ecosystem service applications	Earth Observations for Ecosystem Valuation (ESA, 2018b) Earth Observations for Ecosystem Accounting (EO4EA, GEO, 2017) National Academies of Sciences, Engineering, and Medicine's decadal survey (NASEM, 2018) Europe's Knowledge Innovation Project on accounting for natural capital and ecosystem services (European Commission, 2018)

literature). Scientists estimate the supply of an ecosystem service with tools ranging from proxy-based models, such as those that associate land use categories (e.g., forest) with certain levels of a service (e.g., biomass production) (Jacobs et al., 2015; Ponette-González et al., 2015), to process-based or mechanistic models (e.g., crop growth) (Bruins et al., 2017; Qiu et al., 2018a; Tallis and Polasky, 2009). Demand for ecosystem services, which integrates preferences and values as well as direct use, is less commonly assessed. A combination of approaches are used to estimate demand, including empirical methods like surveys, participatory research to capture values and preferences, inferred demand (e.g., travel costs associated with specific amenities, cost of irrigation or water treatment as an indication of water demand), and expert-based approaches (Bockstael et al., 2000; Wolff et al., 2015).

In the creation of models of ecosystem service supply and demand, EO can be used in a variety of ways (Table 2). Currently, most ecosystem service supply models are based on thematic LULC maps, often derived from remotely sensed surface reflectance (Cord et al., 2017). Instead, models could use continuous variables from EO products that are more closely tied to ecosystem functions of interest; for example, Leaf Area Index (LAI) has been incorporated in mechanistic models to approximate air quality regulation (Braun et al., 2018). An emerging trend is the use of EO products for quantifying ecosystem structure and functional traits, such as vegetation height and leaf dry matter content, which are better indicators of biomass production than simple cover-based proxies (Díaz et al., 2007; Lavorel et al., 2011). There is also tremendous potential to use EO for calibration and validation of existing or new ecosystem service models. On the demand side, ecosystem service models could be created using EO products representing populations and demographics, which represent where and how people benefit from ecosystem services (Watson et al., 2019). For instance, EO have recently been used to locate human settlements (Elvidge et al., 2017) and to estimate characteristics including social groups and poverty (Watmough et al., 2019; Wurm and Taubenböck, 2018). Poverty can then be used as a proxy for vulnerable populations that rely more heavily on ecosystem services such as access to fresh water and food production.

Table 2
EO opportunities for ecosystem service assessments.

Use type	Example question
Create ecosystem service production functions	How accurate are ecosystem service assessments?
Drive ecosystem service production functions	What is the LULC and where is LULC change happening that could affect ecosystem service supply?
Create ecosystem service demand functions and inform valuation studies	What alternatives do people have to the ecosystem services of interest? How are people using an ecosystem service of interest? To what extent are people's livelihoods impacted by changing/changes to ecosystem services? How far do people travel to access certain ecosystem service amenities? Where does ecosystem service demand occur?
Drive ecosystem service demand functions and inform valuation	How is ecosystem service demand changing over time and space?

EO products can also be used to drive ecosystem service models, providing forcing data and informing parameters. Inputs critical to modeling biophysical processes, such as precipitation and elevation, are globally available EO products, and these could be used to complement and extend local gauge data (Pasetto et al., 2018). Parameter coefficients in ecosystem service models are typically derived from field studies or literature review but could be obtained through statistical regressions of in situ information with remotely sensed data (Ayanu et al., 2012). For example, estimates of cloud water interception could be related to and then predicted from canopy density instead of simple absence or presence of forest in cloudy sites (Brauman et al., 2015; Ponette-González et al., 2015). The use of EO data to quantify how demand for ecosystem services varies over space and time is limited, representing a frontier for ecosystem services modeling.

2.2. Opportunities and roadblocks for EO in ecosystem service decision-support tools

As ecosystem services increasingly inform planning, policy, and decision making (Keeler et al., 2012; McKenzie et al., 2014; Wood et al., 2018), substantial effort has gone into creating accessible decision-support tools to aid assessment. A variety of decision-support tools exist (Bagstad et al., 2013; Grêt-Regamey et al., 2017), including Integrated Valuation of Ecosystem Services Tradeoffs (InVEST, Sharp et al., 2014) and Artificial Intelligence for Ecosystem Services (ARIES, Villa et al., 2014). These tools are widely used in both practice and research to evaluate the impacts of infrastructure development (Arcidiacono et al., 2016; Langridge et al., 2014; McKenzie et al., 2014; Ruckelshaus et al., 2015), agricultural management (Butsic et al., 2017), conservation and restoration prioritization (Mandle et al., 2017; Zhang et al., 2016), flood mitigation (Watson et al., 2016), policy assessment (Qiu et al., 2017), and sustainable sourcing (Chaplin-Kramer et al., 2017).

In general, these tools integrate a suite of ecosystem service production functions and ingest biophysical input data (currently in raster, vector, and tabular format) to derive ecosystem service supply (Fig. 2). Built for usability, decision-support tools currently have limited flexibility for incorporating EO products. Users also frequently apply these tools without calibrating or validating the outputs to a specific site (Ruckelshaus et al., 2015). Ensuring that decision-support platforms can make better use of EO is perhaps the most promising way to integrate EO into ecosystem service assessment more broadly. Below, we summarize several challenges and opportunities for doing so.

3. Technical challenges to using EO in ecosystem service assessment

Any ecosystem service assessment using EO products is likely to face technical challenges that are systematic byproducts of data types, model structure, and data and model management architecture. Such challenges may be overcome by a skilled individual or team with knowledge of EO data and computing support; this is demonstrated by the more frequent use of EO in ecosystem service assessments in developed countries with resources for data acquisition, data processing, cyberinfrastructure (e.g., cloud computing, high speed internet), and technical capacity (De Araujo Barbosa et al., 2015; Grêt-Regamey et al., 2017). These technical barriers must systematically be addressed

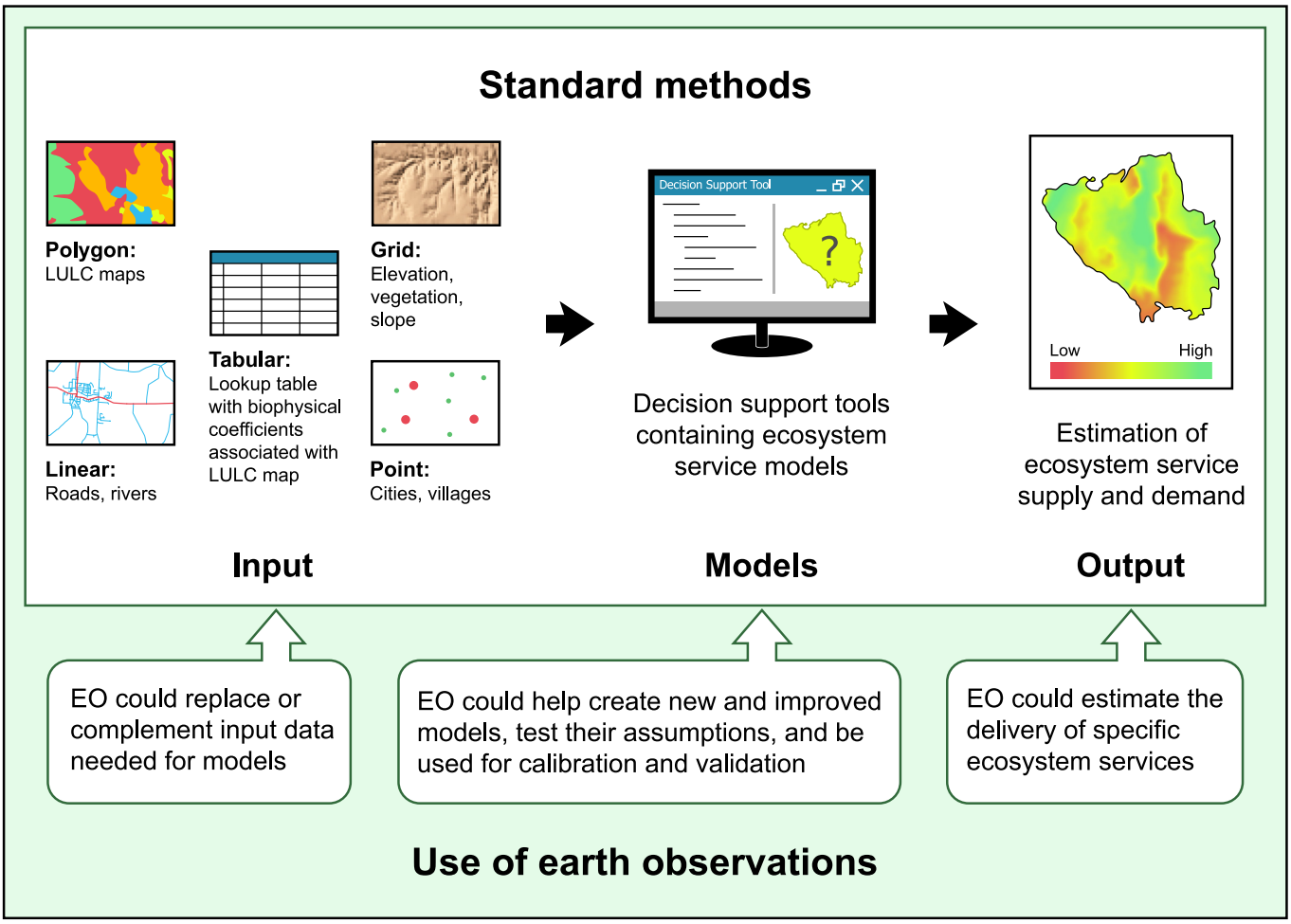

Fig. 2. Illustration of a standard method to estimate ecosystem services. Examples of common data sources used in ecosystem service assessments and how Earth observations can be used in the process.

by data producers and model developers to substantially increase the use of EO in ecosystem service assessments. Though many of these issues have been raised by other authors (Cord et al., 2017; Pasetto et al., 2018; Turner et al., 2003), we highlight them here because they remain major barriers and we emphasize new approaches to overcoming them.

3.1. Knowledge of data and data limitations

Many people assessing ecosystem services have little or no training using EO products (Cord et al., 2017; Pettorelli et al., 2014; Turner et al., 2003), and technical training workshops, though effective, have limited ability to scale. As a result, potential users of EO data may have limited awareness of the range of available products, and once they identify potentially useful data they may be unable to evaluate the benefits and limitations of competing products. For instance, users may be unable to assess whether to use rainfall data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) or the Tropical Rainfall Measuring Mission (TRMM) or when to pick vegetation properties from the normalized difference vegetation index (NDVI) or the enhanced vegetation index (EVI). Analysts may also be reluctant to use EO products without knowing how accurate they are locally (Schaeffer et al., 2013), a particular challenge in regions where field data do not exist or are difficult to obtain (Seppelt et al., 2011), the exact places where EO data products are potentially most appealing.

To address data discoverability issues, data providers have begun developing data sharing platforms (e.g. Giovanni, Acker and Leptoukh, 2007, Google Earth Engine API, Gorelick et al., 2017, Socioeconomic Data and Applications Center, SEDAC, CIESIN, 2018a, and NASA's Distributed Active Archive Centers, DAACs, NASA, 2018a), which ecosystem service decision support tools could link to directly. To help users discern among products, data platforms could include EO metadata with tags like, 'temporally aggregated data,' or 'modeled data.' This type of enhanced metadata featuring semantic annotations would be particularly useful for non-expert users, ensuring better topical and spatiotemporal match between disparate datasets, improving consistency in interpretation, helping reduce language barriers, and making EO data more findable, accessible, interoperable, and reusable (FAIR, Wilkinson et al., 2016). To promote detailed metadata, agencies and other data providers would need to institutionalize it as an expected practice (e.g., U.S. Geological Survey, USGS, and Oak Ridge National Laboratory, ORNL). EO product developers could also provide consensus or ensemble EO data products (e.g., Tuanmu and Jetz, 2014).

3.2. Capacity to process data

Preparing an EO product for use in an ecosystem service model often requires substantial data processing. EO products are available in a wide range of formats (Yang, 2006), including data compression (necessary when EO products are archived), which can be a barrier to novice users (Sivanpillai, 2008). High resolution data are frequently provided

in the form of raw imagery that requires manipulation by the user. Analysts also often need to process EO products with different spatial resolutions (e.g., integrating 500 m LULC, 30 m digital elevation models, and 8 km climatic variables) and temporal resolutions (e.g., static, daily, annual). For example, an ecosystem service model may call for average seasonal values of potential evapotranspiration, a product that is delivered daily, so technical and data processing capacity are needed to manipulate data. Recent advances in cloud computing platforms (e.g., Google Earth Engine API, Gorelick et al., 2017, and NASA NEX, Nemani et al., 2011) are reducing the data processing burden for users but require good programming skills and stable internet access. Data that are pre-processed by EO delivery platforms or ecosystem service decision-support tools will likely see wider uptake. This is already beginning to happen, as decision-support tools and modeling platforms have adapted to incorporate simple data conversion tools (e.g., Moderate Resolution Imaging Spectroradiometer, MODIS, Reprojection Tool to convert projections and data formats, Dwyer and Schmidt, 2006), work with data of different spatial resolutions and projections (e.g., ARIES and Dinamica EGO, Soares-Filho et al., 2013), and serve harmonized time-series data (e.g., NASA MEaSUREs - Making Earth System Data Records for Use in Research Environments, NASA, 2018b). Automated data processing is vital for widespread integration of EO products into ecosystem service modeling.

3.3. Access to data and research results

Once ecosystem service analysts have identified a useful EO product and have the capacity to process it, they may still be unable to access it. Though many remotely sensed EO products, including those from MODIS (250 m+), Landsat (30 m), and Sentinel's Ocean Land Color Instrument (OLCI, 300 m), are freely available, EO data at finer resolutions (<3 m) can be expensive to obtain (Schaeffer et al., 2013). While many assessments can be done at coarser resolutions, high resolution data are important for precise assessments, such as delineating urban canopies. Data producers could collaborate with public agencies to make EO data and products available at low or no cost for non-commercial research purposes. Since Landsat archives were released for free to the public, there has been a dramatic uptake and use of the data worldwide (Engel-Cox et al., 2004; Popkin, 2018; Wulder and Coops, 2014).

Data access may also be limited by restricted use permissions or lack of public availability, particularly derived data products that are not available in data archives. Many new EO products are generated through one-off analyses that are novel (and therefore seen as worthy of publication) but result in data products that quickly become outdated or that cannot be regenerated due to technical and resource limitations. Producing regularly updated EO products requires ongoing funding to operationalize such products and to allow for algorithm and product improvement to meet the continually evolving needs of end users. This does not align with traditional time-limited calls for research innovation, yet in the absence of such funding, the ecosystem services and broader geographic science community loses the value created by initial research outputs. Public-private partnerships may offer a path to data continuity by combining cutting-edge research conducted at public institutions, or in partnership with private corporations, with technical capacity and dedicated maintenance. One example is Climate Engine (Huntington et al., 2017), a partnership between the University of Idaho and Google to create a cloud platform that allows easy reprocessing of climate datasets for researchers.

4. Conceptual challenges to integrating EO products in ecosystem service assessment

There are a range of conceptual and systematic challenges to using EO products in the current generation of ecosystem service models that are generally not unique to a specific data type or model. To avoid reinvention in each subsequent analysis, ecosystem service analysis and associated decision support tools should invest in systematic solutions. Here, we discuss three types of challenges that apply to a range of ecosystem service models and EO data.

4.1. Moving from categorical to continuous conceptualization

Many ecosystem service modeling tools (e.g., InVEST, ARIES) rely on the categorical representation of LULC to predict the supply of an ecosystem service via a production function (reviewed in Seppelt et al., 2011; Tallis and Polasky, 2009). These models thus estimate a set production of an ecosystem service from any particular LULC category. For example, the InVEST carbon storage model estimates carbon sequestration in a landscape by assigning an average biomass value, derived from literature review of plot measurements, to each LULC type (Fig. 3, Sharp et al., 2014). This ignores the spatial heterogeneity of aboveground biomass within LULC types caused by root depth, nutrient availability, slope, climate, soil compaction, and erosion (e.g., Castanho et al., 2013). Calculating biomass with EO has been challenging, but new sensors and techniques are improving the accuracy of measurements (Baccini et al., 2017; Saatchi et al., 2011), and new products are becoming available online (e.g., Global Forest Watch, GFW, 2018). Similarly, in most ecosystem service models, variability within a pixel is not considered, an error that generally becomes progressively worse at coarser spatial resolutions (e.g., percent of imperviousness or percent of agricultural land, Ramankutty et al., 2008). However, properly accounting for spatial heterogeneity is critical for an accurate estimate of ecosystem service supply (Adams et al., 2018; Eigenbrod et al., 2010; Ponette-González et al., 2015), and EO products hold potential to help do so because they are more spatially and temporally continuous than a derived LULC map. However, most ecosystem service models are not currently set up to make use of this information. Updating models to accommodate spatial heterogeneity and within-pixel variability in EO data is a near-term priority.

4.2. Improved estimates of production function parameters

In ecosystem service models, biophysical supply functions rely on static parameters or coefficients distributed using spatially explicit data (e.g., precipitation, slope, biomass). For example, the parameter “C-factor” for retention of sediment by vegetation used in InVEST (Sharp et al., 2014) is currently derived from existing field studies that are often remote from the study region. EO data could allow reasonable extrapolation of these model parameters from “known” to “unknown” geographic regions based on globally distributed EO data and existing local parameter sets to construct predictive relationships via regressions. To make this information transferable across studies, ecosystem service tools would need to incorporate the calculation of parameter prediction relationships in their platforms.

4.3. Scenario assessment

Most decision contexts consider a range of plausible outcomes (scenarios) when implementing resource-management practices (Carpenter et al., 2006). While EO input data can capture critical information about the world as it is, these data need adjustment to account for different potential trajectories of change in the future. For example, an ecosystem service model might incorporate the effects of changes in global temperatures on vegetation productivity (IPCC, 2014) and thus on carbon sequestration. If an EO-derived vegetation index such as NDVI is used in the model to estimate carbon sequestration, then the analyst must find a way to link changes in vegetation productivity to changes in NDVI under a certain scenario, which is not straightforward.

Another example is the challenge of creating scenarios based on changes in LULC. In the current generation of ecosystem service decision-support tools, the analyst provides a current and future LULC

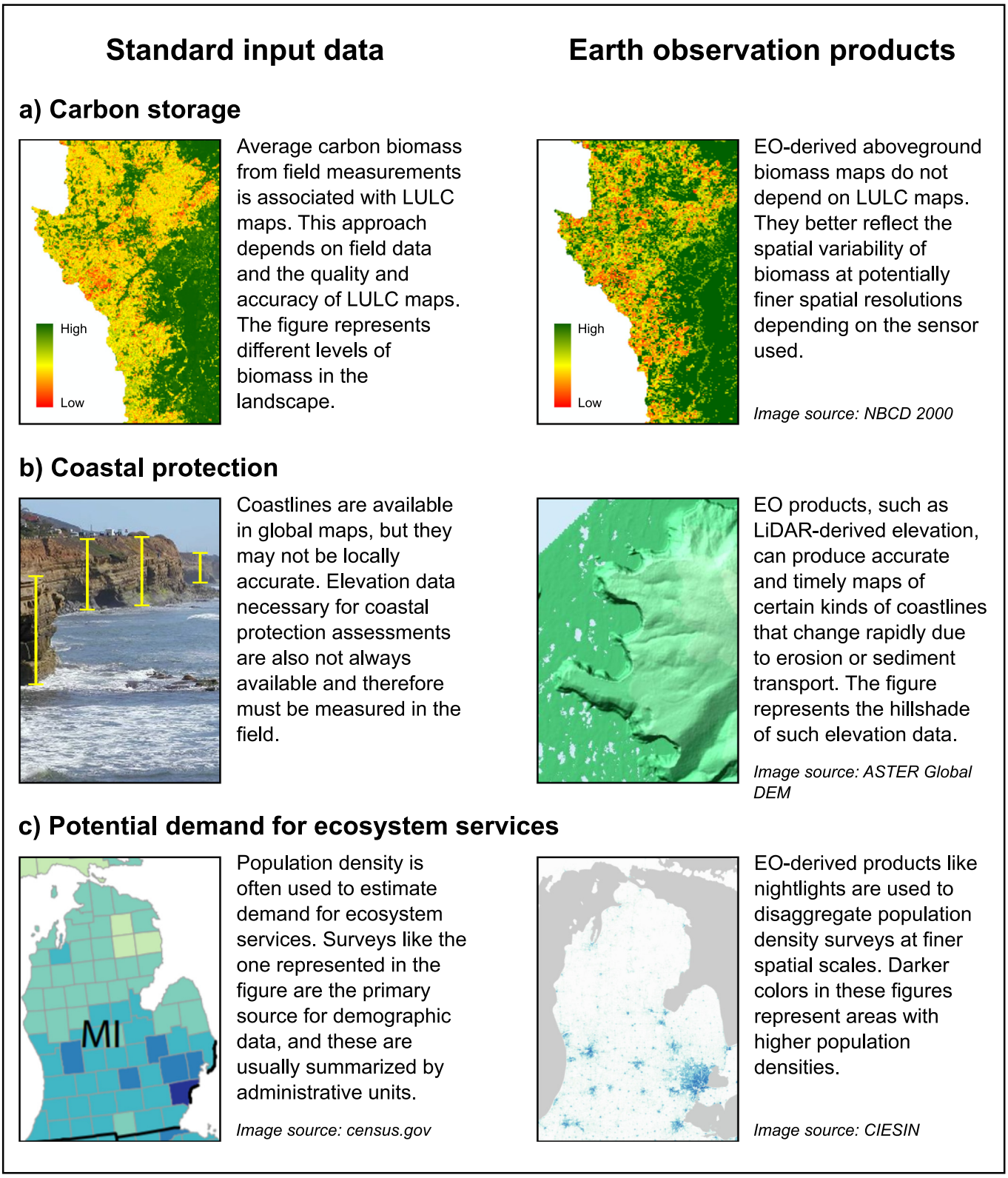

Fig. 3. Example of input variables used in different ecosystem service models and the possible substitute obtained from Earth observations.

map and certain values (e.g., carbon storage) are assigned to each LULC type. If the analyst incorporates an EO product instead, such as EO-derived carbon storage, they can easily calculate carbon storage in the current landscape. However, the EO data cannot be used directly to evaluate scenarios (e.g., converting forest to agriculture, putting in new roads); instead, carbon storage will be simulated through statistical or process-based modeling to properly assess future carbon storage under the scenarios of change. This challenge will arise for every user until it is systematically addressed within ecosystem service decision-support tools. In the absence of a systematic solution, users are likely

to revert to look-up-based parameter values directly linked to productivity or LULC.

5. Frontiers for advancement in ecosystem service assessment through novel uses of EO

Some of the challenges described above may be obviated by development of new data, methods, and models. These will be developed not by finding ways to integrate EO products into existing ecosystem service models and tools but by developing entirely new ways to measure and model ecosystem services that integrate EO products from the first stages of model conceptualization and development (Fig. 2). Many of these new models will be built from data fusion products that combine traditional EO data sources such as satellites and radar with other data sources including social media, mobile phones, and citizen science.

5.1. Improved modeling of demand

Understanding, modeling, and assessing demand for ecosystem services remains limited (Wolff et al., 2015). Traditional methods for evaluating demand are often labor intensive and, depending on the scale of analysis, could require direct interaction through interviews or surveys with potential ecosystem service users at social scales ranging from individuals to households, communities, and beyond (Kenter et al., 2015; Wolff et al., 2015). EO products provide exciting potential to quantify demand in new ways (Ayanu et al., 2012). For example, EO can supplement incomplete or outdated non-EO demographic data, which may only be available quarterly, annually, or with a long lag-time between data collection and publication (Fig. 3). Surveys of economic well-being and inequality based on asset indicators like building materials (McKenzie, 2005) have been updated using EO data to identify roof material types in Uganda (UN, 2018). New ways to quantify non-material ecosystem services such as identity and experience may also be possible with EO data fusion products. Researchers have developed biophysical indicators of some non-material ecosystem services (e.g., Bieling and Plieninger, 2013; Hernández-Morcillo et al., 2013), and EO products could be used to scale-up these approaches or apply them in new regions. For example, sacred sites or large-scale ecosystem-related and culturally significant ceremonies (or their physical footprints) could be identified using EO data, or specific biophysical features could be associated with non-material ecosystem services and EO used to locate those features across the landscape.

Data fusion products hold particular promise for assessment of ecosystem service demand. For example, a number of new, widely used products are based on "nighttime lights" from the Visible Infrared Imaging Radiometer Suite (VIIRS, Elvidge et al., 2017). This nightlight product, in combination with census data, was used to generate global datasets of settlements and to identify urban and rural areas (CIESIN, 2018b) as well as to disaggregate administrative unit-based population and demographic survey data into a gridded format (Sorichetta et al., 2015). Other work combines census, survey, satellite, social media, cellphone, and other spatial datasets to generate world population gridded maps (e.g., WorldPop, Tatem, 2017). To better represent local communities, researchers have used population data disaggregated to the EO-derived settlement level (Amani et al., 2018; Ma et al., 2019). A suite of EO products have been combined with other socioeconomic data to map poverty at a fine scale (Jean et al., 2016). This could help to delineate ecosystem service beneficiaries more vulnerable to future environmental or socioeconomic changes. Emerging applications of machine learning/artificial intelligence (AI) algorithms may also be useful in identifying landscape characteristics such as the location of specific consumers of ecosystem services (e.g., residential areas, specific industries, access points like harbors and docks) to more comprehensively and spatially map and model demand. For example, machine learning has been applied to estimate firewood use in South Africa (Willcock et al., 2018) and to estimate the demographic makeup of neighborhoods across the United States (Gebru et al., 2017). New data fusion products could provide information on where people are (e.g., household location and density), what they are doing (e.g., transportation habits, changes in diets, purchasing power), and what they want (e.g., consuming habits, access to parks), and could therefore be used to develop new and improved models of ecosystem service demand.

5.2. More direct indicators of ecosystem service supply

EO provides an opportunity to assess the delivery of ecosystem services more directly than through production functions (Fig. 2). For example, production functions in ecosystem service models might be bypassed altogether by deriving outputs of interest (e.g., sediment yield) from EO data products (e.g., detecting particles from surface reflectance, Masocha et al., 2017). Similarly, *in lieu* of calculating water balance based on measurements of precipitation and evapotranspiration, hyperspectral imagery, radar, or gravity measurements can be used to directly observe river and floodplain storage, discharge, and groundwater use (Biancamaria et al., 2016; Hess et al., 2003; Solander et al., 2017).

In practice, directly measuring some ecosystem services (e.g., pollination, pest control) is not possible; therefore, many assessments will continue to develop indicators—measurable attributes that capture important aspects of a system. Modeled on the development of the Essential Climate Variables (Bojinski et al., 2014), the Group on Earth Observations Biodiversity Observation Network (GEO BON) developed the concept of Essential Biodiversity Variables (EBVs), recognizing the need for standardized, harmonized, and measurable indicators in the ecological and ecosystem service communities (Pereira et al., 2013). There are now efforts to develop Essential Ecosystem Services Variables (EESVs) and a variety of other bespoke indicators. Better aligning landscape attributes and processes that scientists and society care about (e.g., productivity, species composition and biodiversity, carbon sequestration, ecosystem function, extent of recreational spaces) with actual observational capacity has the potential to both increase the use of EO measurements and derived products for ecosystem service assessment and to improve consistency and comparability across studies.

5.3. Modeling temporal dynamics of ecosystem services

Currently, ecosystem service models are typically used to determine the status of a certain service at a given time (single model run) or to estimate changes over time, either via scenarios or retrospective analyses (model runs representing at least two points in time). These models generally are not designed to address temporal dynamics of driving input data (e.g., weather) or of input data that dictate parameters (e.g., agricultural land management type determines parameters for water infiltration). However, decision-makers frequently need to know how ecosystem service delivery changes over time in a more nuanced way, as well as how tradeoffs and synergies among ecosystem services may evolve over time (Qiu et al., 2018b). Information on ecosystem service changes through time is particularly important to understand time lags, abrupt changes, threshold effects, and feedbacks in ecosystem service management (Rieb et al., 2017) and for setting expectations about policy effectiveness (Ramirez-Reyes et al., 2018).

The next generation of ecosystem service models could take advantage of EO data for dynamic and even near real-time assessments. These assessments could be done in a similar fashion to fire mapping (Justice et al., 2002), forest loss alerts (Hansen et al., 2016), and agricultural rapid monitoring efforts (Becker-Reshef et al., 2010). This requires continuity of EO data (e.g., MODIS, Landsat). Therefore, a data integration and replacement protocol would be required to collect time-series data for a given variable from multiple sources, like the NASA Earth

System Data Records (ESDRs, NASA, 2018c). Given opportunities for retrospective and continuous monitoring of ecosystem services with EO data, policies that address satellite mission continuity and proper data distribution and archiving strategies are essential.

EO products also create potential to incorporate temporal changes in demand for ecosystem services, related to seasonal cultural or religious events, or over longer time periods (Román and Stokes, 2015). For instance, machine learning algorithms could be used to analyze EO imagery for cultural ES assessment by detecting features of interest in social media photographs that appear seasonally (Richards and Tunçer, 2018). The ubiquity of cellphones has made longitudinal studies of human mobility possible (Lu et al., 2016; Phithakkitnukoon et al., 2012; Provenzano et al., 2018). This enables ecosystem service modelers to better parameterize models in space and time using likely ranges of human mobility.

6. Conclusions

While ecosystem services are increasingly considered in decision-making, the potential for wider application remains substantial. One promising path forward is to use EO data to run existing ecosystem service assessment models, particularly in places lacking resources to gather and process local field data. While EO are not a perfect solution for data needs, they have the potential to improve the spatial resolution of assessments anywhere in the world (e.g., Fig. 3). New EO products also create an impetus to develop new approaches to assessing ecosystem services that better capture the temporal dynamics of ecosystem service supply and demand.

As we highlight, EO data products will not be widely incorporated into ecosystem service assessment until technical challenges of data awareness, processing, and access are overcome. These must be addressed systematically and jointly by EO data developers and developers of ecosystem service decision-support tools. Conceptually challenging but systematic barriers also need to be addressed, including adjustment of existing EO data products and ecosystem service models to facilitate use of continuous data, development of new model parameters, and integration of scenario analysis. Many of these adjustments are relevant across different EO products and ecosystem service models, but there has been little investment in them, in part because model modifications are not well addressed by traditional funding opportunities. We highlight several promising pathways for overcoming these key challenges to advance the integration of EO into ecosystem service assessments.

The most exciting frontiers in the integration of EO into ecosystem service assessment will go beyond finding creative ways to feed existing EO data into existing models. EO data products can be used to create improved and new ecosystem service models that advance both our understanding and assessment processes for the complex human-natural systems relationships that ecosystem services represent. Addressing the challenges and opportunities described here will require both systematic investment and interdisciplinary collaboration and creative thinking. Feedback from stakeholders and decision-makers will also be critical in shaping the design of ecosystem service models and data products in the future.

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