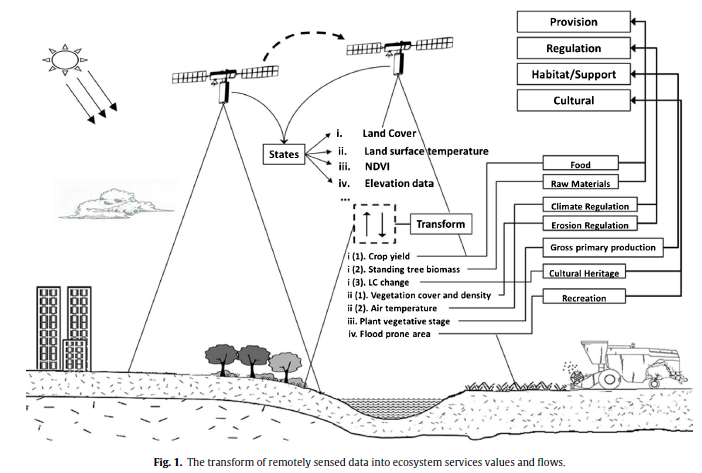
Literature Review of Earth Observation Data for Ecosystem Accounting

# Introduction

Earth observation (EO) satellites are important and useful tools for rapid assessment of ecosystem properties and functions as they provide a synoptic view of the Earth’s surface, regular and repeatable observations over multi-annual time periods and are highly cost effective for monitoring remote and inaccessible areas. Therefore the use of satellite remote sensing in global environmental monitoring and ecosystem mapping is becoming widespread. In this regard, the spatial mapping of ecosystem extent, condition and services supply and use is fundamental to the generation of ecosystem accounts. These three themes of extent, condition and services are the core bio-physical accounts established by the System of Environmental-Economic Accounting - Experimental Ecosystem Accounting (SEEA-EEA) framework. Therefore, there is significant potential for EO data to address the requirements for bio-physical ecosystem accounting.

To date a number of different mapping methodologies have been developed to support the compilation of these types of accounts - using both direct and indirect observations. Where *In-situ* data is unavailable or incomplete, satellite imagery is now commonly used, in conjunction with in-situ data, for land cover mapping and for land cover change analysis. There is a significant legacy on the use of remotely sensed land cover data for informing land management in Europe (e.g., via the Corine Land Cover products) and internationally (e.g., based on the FAO Land Cover Classification System). Such data on land cover characteristics can also act as proxies for the assessment of ecosystem characteristics. Parameters such as soil type, climate, vegetation, water availability, elevation, productivity and other biophysical information can also be collected using EO approaches for different time periods. These can integrated with land cover or ecosystem extent data to support the compilation of ecosystem condition accounts and provide useful input data for estimating and modelling ecosystem services supply and use accounts, as shown in Figure 1.



**Figure 1:** The generation of remotely sensed data into ecosystem service values and flows (De Araujo Barbosa *et al.*, 2015)

# Earth Observation for Ecosystem Accounting

Given the possibilities of Earth Observation (EO) techniques for providing readily available, low cost spatial data on ecosystem assets, it is often an essential data source for ecosystem accounting. This is especially true for data poor regions. Box 1 provides such an example for the use of EO data to inform ecosystem accounting in Orinoco River Basin, Colombia.

In order to gain a fuller understanding of the potential of EO data to inform ecosystem accounting, it is necessary to look beyond the limited number of accounting applications and also into the wider ecosystem assessment literature. This section provides such a review, focusing on the use of EO data for assessment of the key ecosystem accounting themes of extent, condition and services.

**Box 1: Example for the application of earth observation to data to ecosystem accounting in Orinoco River Basin, Colombia.**

Vargas *et al.* (2017) investigated how remote sensing could be used to analyse ecosystem assets in the Orinoco River Basin, Colombia. The study assessed ecosystem assets through extent, condition and capacity to supply four specific ecosystem services, in line with the core bio-physical accounts set out in the SEEA- EEA framework. Two Ecosystem Accounting Areas were specified: a large-scale natural area spanning the geographical boundaries of the Orinoco River Basin; and, the protected areas estate within this area, comprising national parks and indigenous reserves.

In order to measure ecosystem extent, data acquired via the Moderate Resolution Imaging Spectroradiometer (MODIS, a sensor on board the Terra and Aqua satellites), was used to generate land cover maps. These maps generated 17 land cover types, which were subsequently reclassified into 6 Ecosystem Types. MODIS data were chosen as they support spatial accounting and exclusively cover large geographic areas for whole river basins and administrative boundaries. Maps were generated at different spatial resolutions (250, 500 and 1000m). Data was processed for a 10 year time span from 2003 - 2013. To assess the ecosystem extent, the changes in extent was compared between 2003 and 2013 using ArcGIS, i.e. the number of pixels in km2 covering each ecosystem type.

For measuring ecosystem condition, the MODIS Enhanced Vegetation Index (EVI) and the Normalised Difference Water Index (NDWI) were used. EVI was used to gather information on vegetation photosynthetic activity and vegetation type based on the relationship between EVI and leaf area. NDWI was used for information on canopy water status. In addition, Land Surface Temperature (LST) was used to generate information on top canopy temperature. Four multiband images were stacked for 2003 and 2013 for each indicator (EVI, NDWI, day LST, night LST), and clipped with the map of ecosystem extent to monitor changes.

Capacity to supply ecosystem services was measured using accumulated Net Primary Productivity (NPP) from the MODIS data. NPP is an indicator of energy and carbon being accumulated by plants, generated through plant photosynthesis. Net Ecosystem Productivity (NEP) was also used an indicator of the carbon sequestration: while NPP accounts for the organic matter left after plant respiration once both chemical and solar energy are converted into plant biomass, NEP includes respiration for both plant (autotroph) and heterotrophs.

## Using EO for Ecosystem Extent Assessment

Several pilot or experimental applications of the SEEA-EEA provide useful illustrations of the role of EO for supporting ecosystem accounting. A common approach in these applications has been to draw on satellite based observation of land cover as a proxy for delineating ecosystem extent. For example, Phil-WAVES (2016) for Southern Palawan provides a set of pilot ecosystem accounts grounded in EO data on land cover for 2003, 2010 and 2014, based on the FAO Land Cover Classification System. These land cover data were used to inform ecosystem extent accounting for coastal / marine ecosystems, via an unsupervised classification process.[[1]](#footnote-1) Monitoring data could then be integrated with the extent of different ecosystem types (e.g., the composition of mangrove species assemblages). However, the study notes that inadequate ground validation in 2003 may mean change estimates from this period could be inaccurate. In addition, the potential for paddy fields under water to be interpreted as open water, rather than crops, may also lead to overestimation of the extent of ‘open water’ ecosystems. This emphasises the importance of primary or ground-truthing data to validate the use of satellite and other remote observations in ecosystem assessment and accounting.

As Driver *et al.* (2015) observe, whilst land cover classes may align with ecosystem types in some cases, land cover is also an artefact of its historical and current use. This implies land cover classes may not always be ecologically meaningful representations of ecosystems. As such Driver *et al.* (2015) present an integrated land cover and ecosystem extent accounts using the SEEA framework for KwaZulu-Natal province in South Africa. In their application, they integrate satellite derived land cover maps with a vegetation map for the province. Changes in the extent of natural ecosystems (i.e., extent of vegetation classes) are then derived from the intersection of the historic baseline of the distribution of biomes or vegetation class (c.1840) with ‘Natural’ classes as presented in time series maps of land cover. UNEP-WCMC (2017) also provide a similar application, using recent EO data on land cover change and data on natural vegetation distributions derived from aerial imagery from the 1950s to calculate natural ecosystem extent accounts for Uganda.

Using a high spectral resolution EO land cover data can make this separation of different potential ecosystem types easier (Carrao *et al.*, 2008). For instance, the MODIS sensor at 500 m resolution is effective at creating coarse global land cover maps, whilst medium resolution sensors such as Landsat or SPOT may be more appropriate to obtain the detailed land cover characteristics required for ecosystem extent accounting using land cover data at country and regional scales (Fuller *et al.*, 1994; Tiede *et al.*, 2010). Vargas et al (2017) and Kleindl *et al.*, (2015) also identify misclassification of land cover type as a common source of error that may affect ecosystem extent accounting (as also ted in Phil-WAVES, 2016). These types of errors may be mitigated with further information (e.g. field observations or high resolution images). Landscape structure can also cause challenges - increasing habitat complexity and heterogeneity increases number of classification types, and makes differentiation difficult via EO.

## Using EO for Ecosystem Condition Accounting and Assessment

There are a number of applications of EO data for informing on ecosystem condition in the literature. In some cases, EO data can be used to show, in limited cases, the distribution of certain species (Andrew & Ustin, 2009). Plant species, for instance, have been mapped directly from EO data, which infers that the underlying ecosystem service provided by that species may be mapped. However there are challenges in applying this method, as the majority of plant species have similar spectral characteristics, and as such it is difficult in distinguishing different species in image data. Small differences in leaf properties, pigment composition, water content and structure, canopy architecture, leaf area index and leaf angle distribution can be used to aid differentiation. Very high spatial resolution can be used to survey a number of animal species, such as cattle (Begall *et al.*, 2008), flamingos (Groom *et al.*, 2011), elephants (Vermeulen *et al.*, 2013), whales (Fretwell *et al.*, 2014) and penguins (Fretwell *et al.,* 2012). Changes in phenology can also be monitored through EO and used to assess pressures on ecosystem condition that drive habitat / vegetation community changes (Rödder et al., 2016).

Airborne Laser Scanning (ALS) uses LiDAR (Light Detection and Ranging) to calculate the distance between the sensor and the target, collecting 3D points from the area beneath an aeroplane or helicopter. Parallel flight lines can be flown to obtain full coverage of a target area, and this can be used (amongst other applications), to measure forest structure (Vihervaara *et al.*, 2015). The study by Vihervaara *et al.* (2015) used ALS data to calculate 14 structural forest parameters, such as height, density and intensity metrics, to provide a representation of forest structure. This data was then combined with citizen-science collected bird data, which provided indication of ecological condition. Birds are useful indicators of ecological condition as they combine the effects of abiotic stressors on species at lower trophic levels (O’Connell *et al.*, 2000). The Vihervaara *et al.*, (2015) study highlights the possibilities of using EO data.in combination with primary data collection to undertake an ecosystem assessment at the landscape scale.

Using remote sensing techniques in ecosystem service assessments are also summarised across a number of studies by Andrew *et al.* (2014). This study finds EO data can be used to assess a number of different processes and variables: plant traits (Schneider *et al.*, 2017) – chemical traits such as nitrogen (Martin *et al.,* 2008) and water content (Cheng *et al.,* 2008), structural traits such as biomass or vegetation height; vegetation conditions – for example habitat degradation or plant stress (Price *et al.*, 2010), ecological integrity (Burkhard *et al.*, 2009); ecological processes – biogeochemical processes such as nutrient, carbon and water cycles (Frankenberg *et al.*, 2011), phenology (Cleland *et al.*, 2007; Verbesselt *et al.*, 2010), disturbance using spatial soils, vegetation and climate data (Lorz *et al.,* 2010); soil properties, soil moisture (Khanna *et al.*, 2007), soil carbon and texture (Mulder *et al.*, 2011), soil reflectance (Okin & Painter, 2004); hydrological variables – water stocks such as snow water (Derksen *et al.*, 1998), ground water (Tiwari *et al.*, 2009), surface water (Pekel *et al.*, 2016) or water quality (Ritchie *et al.*, 2003)

Recent literature focuses on the use of EO data for analysing ecosystem function, where ecosystem function is described as the attributes related to one of more multiple ecosystem processes (Lovett *et al.,* 2006). For example, the provision of food for all organisms, as opposed to the provision of food for humans, which would be considered an ecosystem service (Pettorelli *et al.,* 2017). As discussed in Pettorelli *et al.* (2017) ecosystem functions can be measured through indicators, and associated proxies, which often need to be combined with *in situ* data or process measurements in the laboratory, to provide accurate representation. A number of open-access remote sensing data products can contribute towards the monitoring of ecosystem function. For example, amongst other measurements, MODIS sensors provide measurements of land and sea surface temperatures, which act as a proxy for the temperature regulation indicator. Therefore any changes in the land and sea surface temperatures, provide an indication of the ecosystem condition of the area. This indicator helps to monitor climate regulation.

Ecosystem function indicators can also be used to measure the risk of ecosystem collapse over a specified time frame (Keith, 2015). As discussed in Murray *et al.* (2018), such risk assessments requires information on the geographic distribution of an ecosystem, and changes in spatial extent and ecosystem function over time. For example, changes in land extent combined with loss of tree cover and reduced biomass are symptoms of increasing collapse risk, driven by drivers such as over exploitation, habitat loss, and pollution. These indicators can be measured through vegetation indices such as LAI and NDVI and land cover maps derived from EO.

## Using EO for Ecosystem Services Accounting and Assessment

Ecosystem service assessment can be relatively simply undertaken through analysis of land cover maps. Burkhard *et al.* (2014), use land cover maps to create matrices of ecosystem service potential supply. The study developed three matrices, which scored ecosystem service potential, ecosystem service flows and ecosystem service demands of different land cover types against a range of ecosystem services. UNEP-WCMC (2017) develop his type of approach, using expert knowledge approach to specify the suitability of different land cover and vegetation types (and their extent) for supporting species delivering economically important provisioning ecosystem services (e.g., Shea butter) and cultural services (e.g., wildlife watching for tourism). However, a key issue with this approach is the absence of on-the ground data to support the assertion that habitat is of suitable condition for these species and that they actual occur at these locations.

Schröter *et al.* (2014) test possibilities for ecosystem service accounting for the Telemark County in northern Norway. The study investigated 9 key final ecosystem services, including provisioning, regulating and cultural services based on the CICES classification. Each of the ecosystem services were modelled spatially using a land cover data representing 25 different vegetation types. A range of approaches were employed for modelling ecosystem services, drawing on multiple data sources such as: look-up tables for different land cover types (e.g., for carbon storage by vegetation type); subnational statistics disaggregated by land cover type (e.g., number of mouse hunted disaggregated to their preferred habitats) and using a range of different satellite based measurements (e.g., Net Primary Production for modelling carbon sequestration) and direct in-situ measurements (e.g., forest inventories). Ecosystem accounts were developed for capacity (potential ecosystem service supply) and flow (actual ecosystem service supply and use) for the annual flow of ecosystem services across 25 vegetation types.

Cord *et al.* (2017) also provide a framework for using EO data to measure ecosystem services supply and use. They illustrate how such data can be to provide direct measurements of water quality (used to assess the water regulation - a regulating service). In addition, applications combining EO data with wider socio-economic and other data are highlighted (e.g. for outdoor recreation). Cord *et al.* (2017) also illustrate how information on ecosystem service demand (use) can be derived from EO. For example, data on the demand for non-timber forest products (a provisioning service), can be generated through information on accessibility – through gathering information on roads and fluvial networks. The study emphasises the benefit of using multiple different methods (different types of satellite products) as well as other types of information (e.g. socio-economic). Cord et al. (2015) also show that demand for outdoor recreation, can be assessed using geocaching data. Geocaching is an outdoor activity, where participants locate ‘geocaches’ through Global Positioning Systems (GPS), drawing similarities to a more worldwide game of ‘hide and seek’. GPS coordinates and visit rates of geocaches were combined with an online survey to gather stated and revealed preferences. From this, the demand for outdoor recreation could be analysed.

The Phil-WAVES (2016) project also employed wider EO data beyond land cover for estimating ecosystem services flows. These included EO data on land surface evapotranspiration data derived from MODIS data and digital elevation data derived from the Shuttle Radar Topography Mission (SRTM) as useful geomorphological indicators for ecosystem characteristics. These were used, in combination with other EO data (e.g., from weather stations) and factors, to model ecosystem services for water regulation and avoided sediment loading in the watershed. In addition, accounts for carbon storage and sequestration services were then developed using forestry inventory data and factor assumptions for the different forest land cover classes in the land account (Closed forest; Open forest; Other Wooded Land; and, Mangrove).

Braun *et al.* (2018) review the role of EO data in ecosystem services assessment. They identify the following gaps in using EO for measuring ecosystem service flows:

1. Land use and land cover based on the assumption of the same biophysical values per land cover class are still the most commonly used EO information for estimating ecosystem service flows. These underlying assumptions often results in errors in ES supply and use estimates (Eigenbrod *et al.*, 2010).
2. There is a lack of approaches that quantify ES based on ecosystem processes observations at large spatial scales (Lavorel *et al.*, 2017).
3. A large proportion of EO data are mono-temporal, or cover 10 years or less.
4. There is a lack of studies using multiple ES at different temporal and spatial scales.

With respect to point 1, Vargas et al., (2017) also encountered issues when allocating ecosystem services to ecosystem types. For example timber harvest services were sometimes allocated to open water or agricultural land, due to misclassification of the satellite imagery and temporal land cover dynamics. Other challenges involved modelling of ES flow (rather than capacity), which required the presence of a beneficiary. For timber harvesting this was overcome by excluding forested areas that are accessible only at high economic cost, and where beneficiary is likely to be absent. The above observation reflects the complications of modelling Ecosystem Services where beneficiaries exist across different scales.

# Stock-take of EO for Ecosystem Accounting

In order to enhance the use of earth observation data in ecosystem accounting, the Earth Observation for Ecosystem Accounting (EO4EA) initiative was set-up under the auspices of the Group on Earth Observations (GEO). The EEA hosted a workshop for this initiative in 2017, where a number of practitioners presented experimental work in this area. Key applications of note includes:

1. Results from Canada based on using look up tables for ecosystem services (and their values) for different land cover classes produced significantly different results depending on the land cover product used.
2. The EEA is the currently compiling accounts of ecosystem extent at the EU scale using Corine Land Cover data (CLC) but is moving towards a more habitat based approach. With respect to ecosystem condition earth observation data on NPP, Phenology, Vegetation characteristics and phenology is available and improving.
3. The Satellite-based Wetland Observation Service (SWOS) identifies the use of Chlorophyll a estimates as potential indicator for ecosystem condition
4. Conservation international identified the use of earth observation data for informing on land use and cover; ecosystem productivity (NPP) and data on ecosystem condition that can inform ecosystem service modelling in conjunction with wider statistical data for a sub-national approach in Peru
5. For Essential Biodiversity Variables, the Zoological Society of London identified the role of remote sensing for observing changes in ecosystem function (via disturbance (observations of fire / thermal anomalies), NPP and secondary production) and ecosystem structure (based on land cover and ecosystem extent).
6. The Joint Research Council of the European Commission have been developing ecosystem service accounting approaches drawing on earth observation data. This includes the use of land surface temperature for microclimate regulation; leaf area index for air purification; imperviousness level for flood control in urban areas and Normalised Difference Vegetation Index (NDVI) for soil erosion control
7. The Statistics Office of Poland identified the use of NDVI to support spatial estimations of crop yields, in conjunction with *in-situ* data
8. The Joint Nature Conservation Committee (JNCC) in England have been using Sentinel 1 radar data and inspection data for training the classification (Sentinel 2 provides verification). They also produce the NDVI and the Normalised Difference Water Index (NDWI)

# Key Messages

Given earth observations can provide robust, quality assured regular and repeatable coverage of spatial data that is consistent over both space and time, there is much potential for it to support ecosystem accounting at a range of spatial resolutions in multiple countries (both in the Europe and beyond). Furthermore, these data are increasing becoming freely available.

The above review identifies the common application of remotely sensed land cover data as a pragmatic approach for inferring trends in ecosystem extent and providing important input data for modelling / estimating ecosystem services. Earth observation has a demonstrable track record in successfully supporting the production of ecosystem extent accounts based on remote land cover observations, although some issues with respect to misclassification are identified. However, the need for ground-truthing and the potential for the selection of different land cover products to affect findings in the same study area is identified. An important point with respect to monitoring trends in ecosystem extent is that land cover classes provide limited information on ecosystem structure. Whilst, this should not preclude the use of land cover as a good starting point for ecosystem extent accounting, further work is required to move to more ecologically meaningful ecosystem extent accounting (e.g., integrating data on altitude and vegetation). The availability of high resolution remote sensing data would also increase the potential to capture more detailed information on ecosystem structure.

Several studies identify the potential for earth observation to inform on ecosystem condition, including functional characteristics. However, by their nature, satellite observations require condition characteristics to be visible. As such they are likely to be focused on condition indicators associated with vegetation (e.g., leaf surface index, NDVI and NPP), geomorphological indicators (e.g., slope and elevation), damage impacts (e.g., fire), water quality indicators (e.g., chlorophyll a concentrations and NDWI) and pressure indicators (e.g., temperature and phenology shift from climate change). However, there is the potential for modelling further condition parameters based on these data and information on land cover (e.g., evapotranspiration, soil loss, flood and landslide susceptibility). Alternative, ground-based remote sensing approaches (such as weather stations) also provide important information that can support assessment and accounting for ecosystem condition (e.g., with respect to water availability / precipitation). There is likely to remain a number of condition parameters (e.g., species diversity and soil quality) that will require *in-situ* monitoring data. In this respect, Vargas et al. (2017) suggest an optimal approach for ecosystem accounting would combine both remote sensing and primary data collection. Nonetheless, in combination with such measurement, there is clear potential for earth observation data assist interpolations and modelling to extend the inferences that can be drawn from such data across wider areas and scales. An important observation in the literature is how to link changes in condition to risk of ecosystem collapse,

The studies reviewed identify that ecosystem service modelling is often grounded in interpretations of land cover. For example, via the use of look up tables or factors and co-efficient (e.g., for carbon storage / sequestration by land cover type), using land cover as an indicator for disaggregating data (e.g., for hunting or viewing species based on land cover as a proxy for habitat preferences) or in combination with other data in spatial modelling approaches (e.g., using elevation data for water regulation services, NPP for biomass provision services and leaf surface index for air purification). Incorporating the use of other datasets (including earth observations) provides an opportunity for the detection of more spatial variation in the estimation of biophysical values for ecosystem services and avoid the issue of constant values per land cover class. Importantly, this should also capture how ecosystem service flow varies with respect to the location of beneficiaries. The use of geocaching was identified in one study as a good possibility to demonstrate recreational ecosystem service use. Nonetheless, estimating cultural ecosystem service flows needs more research, (Shröter *et al.*, 2012).

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1. Unsupervised classification involves categorization of digital image data by computer processing based solely on the image statistics without the availability of training samples [↑](#footnote-ref-1)