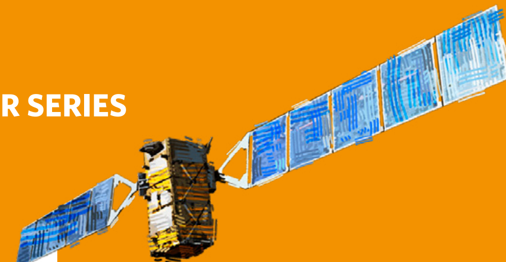
NATURE-BASED CREDIT SCIENCE DECODER SERIES



Remote Sensing

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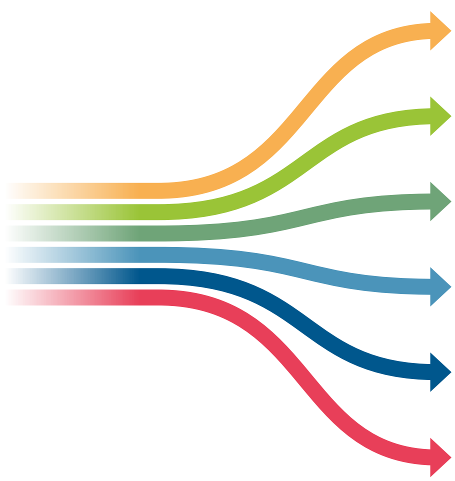
The Nature Conservancy

THE NATURE-BASED CREDIT SCIENCE DECODER SERIES

Carbon accounting methods that center scientific best practices are the backbone of all rigorous approaches to carbon crediting. However, while decades of science have markedly increased the quality of carbon credits to date, research and technology continue to evolve and improve project accounting.

The Nature-based Credit Science Decoder Series is a production of The Nature Conservancy. Each Decoder entry contextualizes current scientific best practices and gaps for carbon projects developed in six emerging Natural Climate Solutions (NCS) pathways*:

Natural Climate Solutions (NCS) Pathways



1. Avoided Conversion of Grasslands and Shrublands (ACoGS)
2. Afforestation, Reforestation and Revegetation (ARR)
3. Agricultural Land Management (ALM)
4. Improved Forest Management (IFM)
5. Reduced Emissions from Deforestation and Degradation (REDD)
6. Wetlands Restoration and Conservation (WRC)

* For a full list of pathways and terms, please refer to the NCS Handbook.

As a supplement to this pathway-based Decoder Series, this guide provides an overview of the latest scientific advancements in **Remote Sensing Technologies** and their applications to NCS project initiation, baseline assessment, and impact monitoring. This summary discusses various concepts, platforms, tools, and data sources to help buyers of high-quality carbon credits evaluate the rigor of carbon markets service providers such as ratings agencies and third-party monitoring services (See Box 1, p. 6). Buyers may also find this resource useful to assess whether carbon markets tools and projects are effectively deploying scientifically sound tools and approaches.

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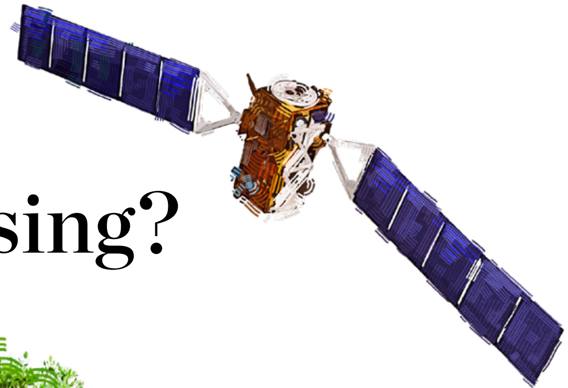


1. What is Remote Sensing?

Remote sensing is a means of efficiently capturing on-the-ground information across large areas. Remote sensing uses vehicles that can be ground-based (e.g., terrestrial laser scanning, geophysical surveys), airborne (aircraft or unmanned aerial vehicles – UAV, or drones), or spaceborne (e.g., NASA's Landsat satellite program). Remote sensing systems can carry various instruments and sensors to collect different types of information about target objects at a distance. Sensors have different resolutions, which determines the amount of detail they can capture. Three types of resolution are important in remote sensing:

- **Spatial resolution.** This refers to the size of the smallest feature that can be detected by the sensor. It is usually reported as a single value representing the cell (pixel) size of the output data. For example, an image with a 30-meter (30 m) resolution will have each pixel measure 30 m by 30 m on the ground.

- **Temporal resolution.** The periodicity, or time, between repeat observations of the same objects by the same sensor. Temporal resolution can vary from minutes to years depending on platform and sensor design.

- **Spectral resolution.** The number and width of spectral bands, where a spectral band is a range of wavelengths on the electromagnetic spectrum (e.g., 0.52-0.60 micrometers for green light) for which the sensor collects information. Multispectral data consists of 3 to 10 bands, hyperspectral data contains hundreds to thousands of narrower bands, while panchromatic data collects information across a single broad band (range) of wavelengths.

After observation, "raw" remotely sensed data must be processed to generate further data products for use by researchers, analysts, or service providers. Data products range in methodological complexity and can include spectral indices (combining spectral bands in some meaningful way), categorical variables (e.g., land cover classifications), or continuous variables (e.g., % forest cover in a pixel). Increasingly, continuous variables are used to describe within-pixel variation in categorical land cover products, reflecting the heterogeny within patches of land cover in highly fragmented mosaic landscapes. Pixel values in these products depict the probabilities or proportions of the pixel belonging to multiple land cover classes.

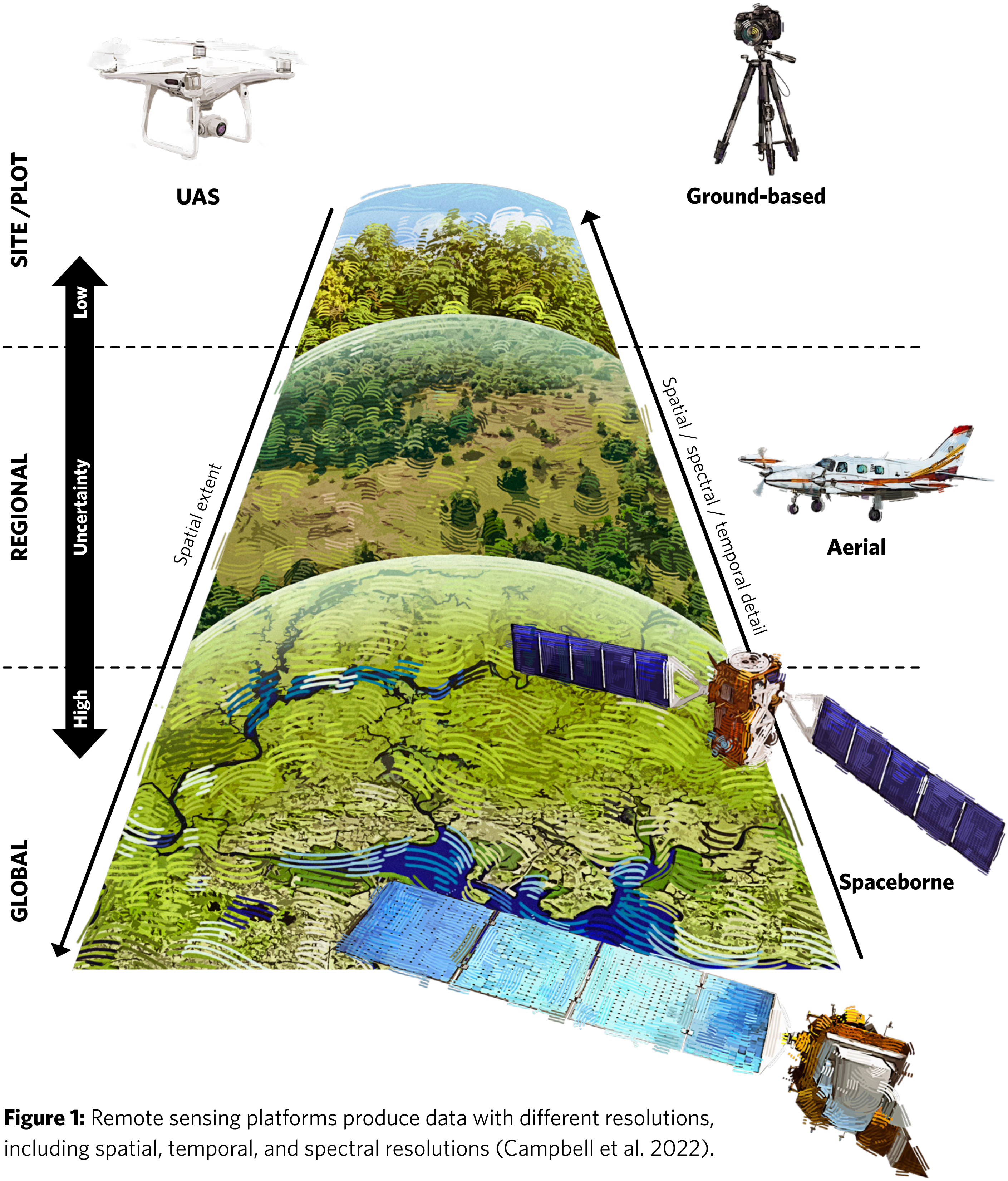


Figure 1: Remote sensing platforms produce data with different resolutions, including spatial, temporal, and spectral resolutions (Campbell et al. 2022).

BOX 1: REMOTE SENSING SERVICE PROVIDERS

In the current voluntary carbon market (VCM), myriad providers are offering technical services for carbon project monitoring, reporting, and verification (MRV), often using remote sensing technologies to produce their offerings. Approaches used by these service providers can vary widely. Or, the precise use of remote sensing within these service offerings may be entirely unclear, due to a lack of transparency in methods. Buyers of these services and of high-quality carbon credits more generally may want to utilize this Decoder to better scrutinize remote sensing techniques used across the VCM. The types of service providers that this guide can be used to evaluate include:

- Project developers – Develop carbon projects
- Brokers – Sell credits from high-quality projects, according to their own assessments
- Ratings agencies – Rate projects according to their own assessments
- Insurance firms – Insure projects based on their own risk assessment of reversal
- Project monitoring firms – Independently monitor projects for buyers after credits are sold
- Project origination firms – Assess project sites with high-quality potential

The service providers mentioned above cover a broad range of offerings catered to buyers in the VCM. The point at which buyers may engage these groups can include origination, monitoring, and/or post-issuance. Regardless, the principles defined in this report can be applied broadly across any of these entities.

BOX 2: REMOTE SENSING TERMINOLOGY

Active vs. passive instruments:

- Active remote sensing refers to sensors that transmit and receive their own source of light or energy. Examples include: radar (Synthetic Aperture Radar - SAR), light detection and ranging (lidar), and sonar. They can operate day or night and can penetrate cloud cover.
- Passive remote sensing refers to sensors that rely on natural sources of light, such as the sun. Examples include optical imagery such as Landsat, MODIS, and VIIRS. Passive remote sensing can produce imagery similar to a camera, making these data easier to interpret than imagery produced using active remote sensing.

Direct measures vs. derived remote sensing products:

- Direct measures refer to vegetation or ground characteristics that are directly observed by remote sensing sensors, without the need for models to enable interpretation. Examples of such measured characteristics include forest canopy height, vegetation extent, or vegetation vigor (greenness). While these measurements require data preprocessing (e.g., location correction/georeferencing, cloud removal/atmospheric corrections, or radiometric/value calibration), they generally do not involve models. Rather, direct measures are typically used as inputs to modeling processes to derive further products. Direct measures can be obtained using both active and passive instruments, including satellite imagery, radar, and lidar.
- Derived products are modeled from direct measures, often by combining remotely sensed direct measures with ground-based observations for model training and validation. Examples of derived products include land use and land cover (LULC) maps, soil organic carbon (SOC) maps, aboveground biomass (AGB) maps, and belowground biomass (BGB) maps of the biomass from roots[1]. Derived products are associated with model uncertainties; more complex models generally have higher uncertainty.
- Figure 2 (p. 13) provides an overview of example workflows associated with the production of map products derived from satellite imagery.

Land cover change vs. degradation:

- Land cover change refers to the extent of habitat that is either gained or lost between two time points that may result in quantifiable carbon stocks changes. These changes can result in either carbon emissions (e.g., forest area lost to anthropogenic fires) or carbon removals (e.g., reforestation).
- Land degradation refers to the decline of the quality or productivity of vegetation or soils without a change in land cover or land use. Degraded lands have diminished capacity to absorb and store carbon, and always lead to reduced carbon sequestration and/or higher carbon emissions. Examples of degradation include persistent reduction of canopy cover and/or carbon stocks due to human activities such as animal grazing, fuelwood collection, or selective logging.

1. Note that while some researchers refer to both SOC and root biomass as "below-ground biomass" (BGB), in this paper we use BGB to refer exclusively to plant biomass in roots.

2. Project Scoping

IDENTIFY POTENTIAL PROJECT SITES

At the onset of the carbon project life cycle, various data sources published in academic literature or online may be consulted to provide geographical information on the potential extent and magnitude of climate change mitigation opportunities. In this context, remote sensing products may be used to assess and compare climate change mitigation potential across regions and NCS pathways. These products are often modelled from remotely sensed data and require little to no technical capacity to interpret and compare potential project regions. Examples of tools that visualize these include Naturebase (naturebase.org), Global Forest Watch (globalforestwatch.org), and Global Mangrove Watch (www.globalmangrovewatch.org).

CONTEXTUALIZE AND PRIORITIZE THE PROJECT SITES

After gaining a rough understanding of the location and magnitude of promising project areas, a prioritization analysis might couple these large-scale opportunity assessments with finer-scale geographic information relevant to specific NCS pathways. This step would include sourcing geospatial data layers that may be derived from remote sensing information. Examples of data types include projections of future sea level rise, aerial imagery, cadastral maps, maps of land tenure type (e.g. government, private, Indigenous), maps of LULC, models of aboveground biomass, soil type, elevation, and crop type or productivity, among others. These data can be employed in automated analyses to quickly determine the most promising project areas and ensure efficient resource use in subsequent project development phases, or be used in participatory mapping efforts to co-identify priority locations among stakeholders.

DETERMINE SITE ELIGIBILITY, SUITABILITY, AND BOUNDARIES

Potential project areas will be further scrutinized for eligibility and suitability. Site eligibility involves ascertaining that an area complies with specific carbon project methodology requirements. For example, proponents of REDD+ projects must determine if the project area meets the forest definition of the country where the project occurs (usually based on minimum canopy cover and/or forest area criteria). In determining project suitability, analysts may use remote sensing data to assess the specifics of the project interventions they wish to propose. This might include building or using species distribution and/or habitat suitability models to determine the appropriate species to use in revegetation projects (e.g., assessing which tree species to use for reforestation) or the specific locations and methods for restoring local hydrology in coastal wetland restoration projects. Remote sensing data will also be used in assessing potential unintended consequences of project activities, such as assessing likelihood of leakage resulting from loss of cropland production or evaluating impacts of rewetting efforts beyond project boundaries. There is also an important role for remote sensing in detailed delineation of project area boundaries. A combination of ground survey (GPS) data and very-high resolution remotely sensed imagery (e.g., satellite or aerial photographs) may be used to generate the project area boundary within which project activities will take place.

PROJECT DURABILITY RISK ASSESSMENT

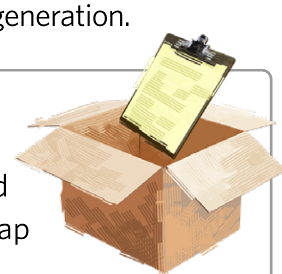
A project proponent may also assess project risks and enabling conditions with remote sensing. Remote sensing data may be employed to perform threat analyses to predict risks to project durability. Some of the factors that could be monitored with remotely sensed data include the incidence of fire, encroachment of agriculture, density of roadworks, and urban/suburban development pressure (e.g., via the intensity of night lights).

RECOMMENDATIONS

1. If using a technical service provider, confirm that they have previous experience in the NCS pathway and ecosystem of interest, the remote sensing datasets and tools being used, and verify their commitment to provide insights on the accuracy of their products.
2. Ensure project area boundaries are accurate and delineated using recent, high-resolution remote imagery (satellite or aerial photographs, categorical land cover maps), sourced from ground survey (GPS) data, or a combination of these. Ensure the project area boundary only includes the land area where project activities will be implemented. Verify project boundaries with recent, high-resolution optical imagery where possible. Ensure any remote sensing imagery has minimal cloud coverage and was obtained during appropriate seasons, as relevant to project implementation.
3. Verify that a projected coordinate system is used when calculating project area and that coordinate systems match between different data sources.
4. Ensure the spatial scale of remote sensing data or derived products is appropriate for the project area. For example, imagery with a resolution of 250 m has a pixel area of 6.25 ha. Data products associated with this imagery may be too coarse to inform important characteristics of a 10-ha project site.
5. Confirm that for all remote sensing data sources, the resolution and minimum mapping unit (the specific size of the smallest feature that can reliably be mapped, generally at least 4 adjacent cells in raster data) complies with requirements set out in the targeted crediting methodology.
6. When verifying land use in project areas before project implementation, ensure the date on which the historic imagery was captured aligns with (predates) the start date of the project.
7. Ensure that categorical land cover maps used during project development are relevant for the proposed project in the proposed location. For example, ensure that they were derived with field verification data from the same geographic region as the project area. Ensure that land cover class definitions (e.g., the percentage of tree cover that counts as forest) align with those used in relevant national legislation and/or the applicable crediting methodology.
8. In offerings of rapid (off-the-shelf) feasibility analyses, ask what data sources are used and question their suitability for the project at hand along with the suggestions laid out above. Ask which threats and permanence risks are assessed. Ask how natural hazards are distinguished from anthropogenic threats to ensure these risks can be overcome by the envisioned project activities.

3. Baselines and Additionality

Another common use of remote sensing data for carbon projects is for establishing systematic baseline information. In particular, when combined with field data, remote sensing can reliably classify local and regional LULC and quantify its change over time and space. At the project scale, satellite imagery or derived maps of LULC dating from the early 2000s or even as far back as the 1980s can provide insights on site history. With remote sensing, land use change within the project area and outside of the project area can be mapped, allowing the project to construct a historic regional average, or dynamic baselines (See Section 5, Innovations in Carbon Market Methodologies, pp. 17–18). For example, for an improved forest management project that proposes to extend harvest rotations beyond a business-as-usual 15-year practice, satellite imagery can support a quantification of business-as-usual harvest rotations by mapping and dating harvest locations within a region. In protect pathways (e.g., avoided coastal impacts, avoided peatland conversion) remotely sensed land cover data might be used to assess historic conversion rates to establish project area baselines and determine whether there is sufficient need for additional conservation action. In restore pathways (e.g., reforestation, revegetation), remotely sensed data could be used to establish natural regeneration rates for target vegetation types, to ensure project activities lead to biomass accumulation beyond natural regeneration.



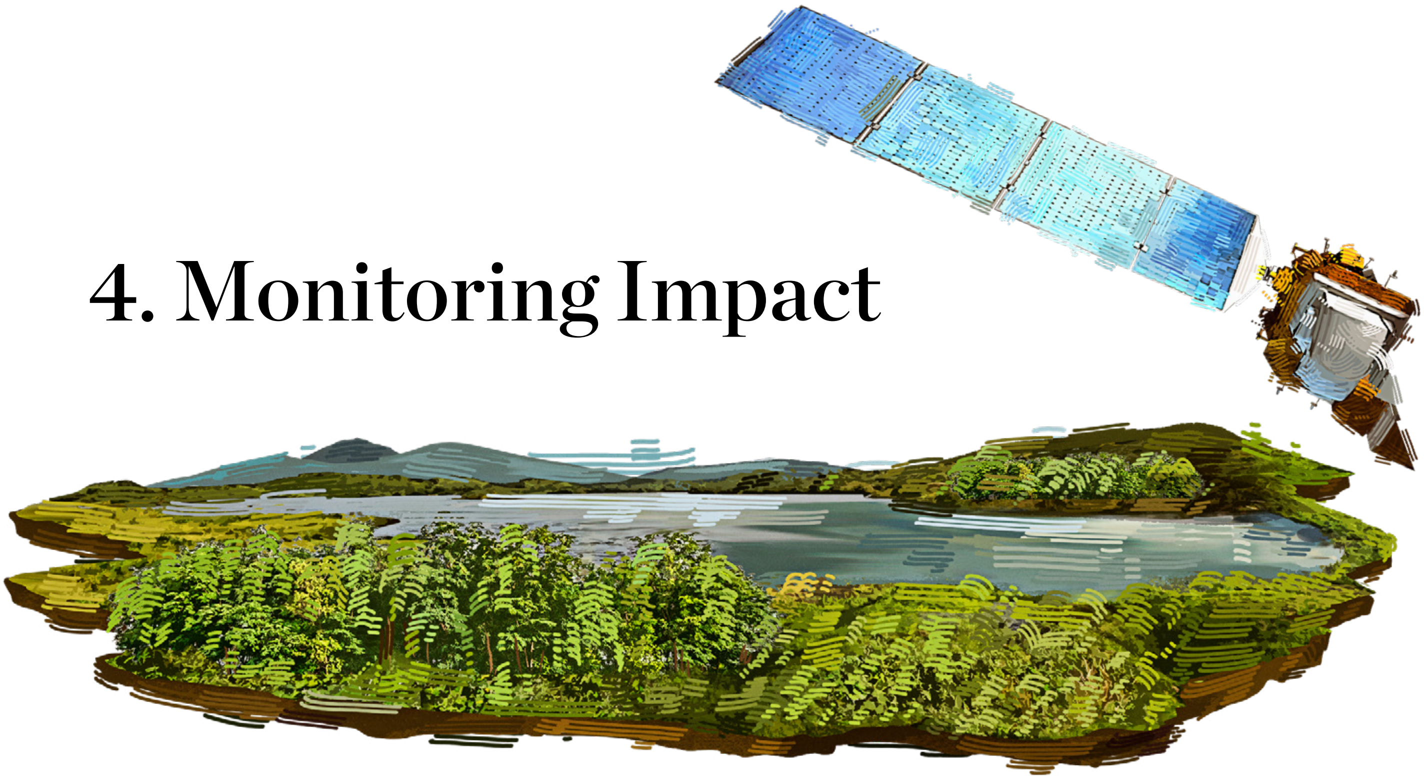
BOX 3: MEASURES OF MAP QUALITY FOR PRODUCTS DERIVED FROM SATELLITE IMAGERY

Map products derived from satellite imagery are typically produced using statistical techniques that require reference data (i.e., real world data from the field) for model training, calibration, and validation.

For categorical map products such as LULC maps, map validation is often presented in the form of overall accuracy, user's accuracy, and producer's accuracy. Overall accuracy reflects the percent of all validation data correctly mapped in the final product, while user's and producer's accuracies are presented for individual map categories. User's accuracy (complementary to the error of commission) indicates the likelihood that a map category will correspond to field conditions. Producer's accuracy (complementary to the error of omission) indicates the likelihood that reference data will be assigned the correct category in the map (See Figure 3, p. 14).

For continuous map products, such as tree cover predictions or biomass estimates, map validation is often presented using common statistical measures, such as standard error or 95% confidence intervals. Large confidence intervals relative to a prediction can indicate poor map performance. For example, a biomass prediction of 100 MgC/ha with a 95% confidence interval of ±80 MgC/ha means we can be 95% confident that the actual biomass at the map location falls between 20 and 180 MgC/ha. This represents a very wide range. Note that map accuracy often decreases with map resolution; finer scale maps are not always better (coarser resolution maps are more accurate). Therefore, there is often an inescapable trade-off between accuracy and resolution.

4. Monitoring Impact



MEASURING CARBON FLUXES

A universally required aspect of carbon projects is effective monitoring and quantification of carbon fluxes over time. While each methodology applies different procedures for monitoring carbon sources, most methodologies allow the use of a combination of remote sensing and field measurements (Glass et al., 2024). There are two main approaches to estimate changes in carbon fluxes (Malerba et al., 2023):

- Stock-difference (or stock change) approach: This assesses changes in the ratio of carbon stocks over successive points in time through field measurements, requiring appropriate sampling designs.
- Gain-loss approach: This assesses the net balance of carbon added or removed in different land-use types by multiplying the area of land impacted by human activities (activity data) by the amount of greenhouse gases emitted or removed (emissions/removal factors). In this approach, activity data are often determined by remote sensing (IPCC, 2006).

For stock-difference approaches, remote sensing can be an effective tool for monitoring carbon stocks throughout the duration of a project, enabling cost-effective, consistent, and timely monitoring of carbon stock changes over large-scale areas to calculate carbon fluxes. For gain-loss approaches, remote sensing can reduce the need for extensive ground-based sampling, allowing for the development of local, regional, or national estimates of carbon budgets. For example, emerging technologies may provide satellite missions the ability to monitor ground-based methane and nitrous oxide emissions from space, potentially driving further transparency and accountability (e.g., Blueflux and MethaneSAT), although these might initially be geared towards high-concentration point-based emissions as opposed to diffuse source emissions.

ASSESSING BIOMASS

Many carbon projects will use a stock-difference approach to carbon accounting. This requires assessment of biomass stocks before and after project implementation. Remotely sensed data can be used to monitor AGB change in shrubs, trees, or other live foliage (UNEP-WCMC), in response to a project intervention. Examples of AGB change include vegetation loss (such as deforestation), vegetation growth (such as reforestation), or shifting agriculture. While advancements in remote sensing technology, such as ground penetrating radar, can be used to directly assess BGB, it is usually estimated indirectly through established root-to-shoot ratios.

Land cover classes with carbon pools of interest that can be monitored with remotely sensed data include mangrove forests, seagrass, tidal marshes (Malerba et al., 2023), terrestrial forests, agricultural lands, and peatlands (Glass et al., 2024). Active remote sensing technology such as lidar and radar transmit and receive signals that travel through vegetation canopies and interact with distinct biomass components, such as tree trunks and branches, providing crucial information on vegetation height and structure (Saatchi, 2011).

Assessing biomass can be achieved through a series of automated or semi-automated models relating carbon variables measured on the ground to passive and active remote sensing data (See Figure 2, p. 13). These predictive biomass models typically involve associating field measurements of biomass to direct remote sensing measures such as canopy height or vegetation indices, and then using those relationships to predict biomass for a study area. In many cases, intermediate models such as allometric equations are used, to predict the final biomass (Figure 2). Allometric equations are models that describe relationships between biomass within broad ecological zones and measurements of vegetation height, stem diameter and wood density.

In the same way remotely sensed land use change detection can be used for monitoring project impact, it can also capture leakage (e.g., when emissions are shifted elsewhere) and reversals (e.g., when a carbon project's emission reductions are released back into the atmosphere).

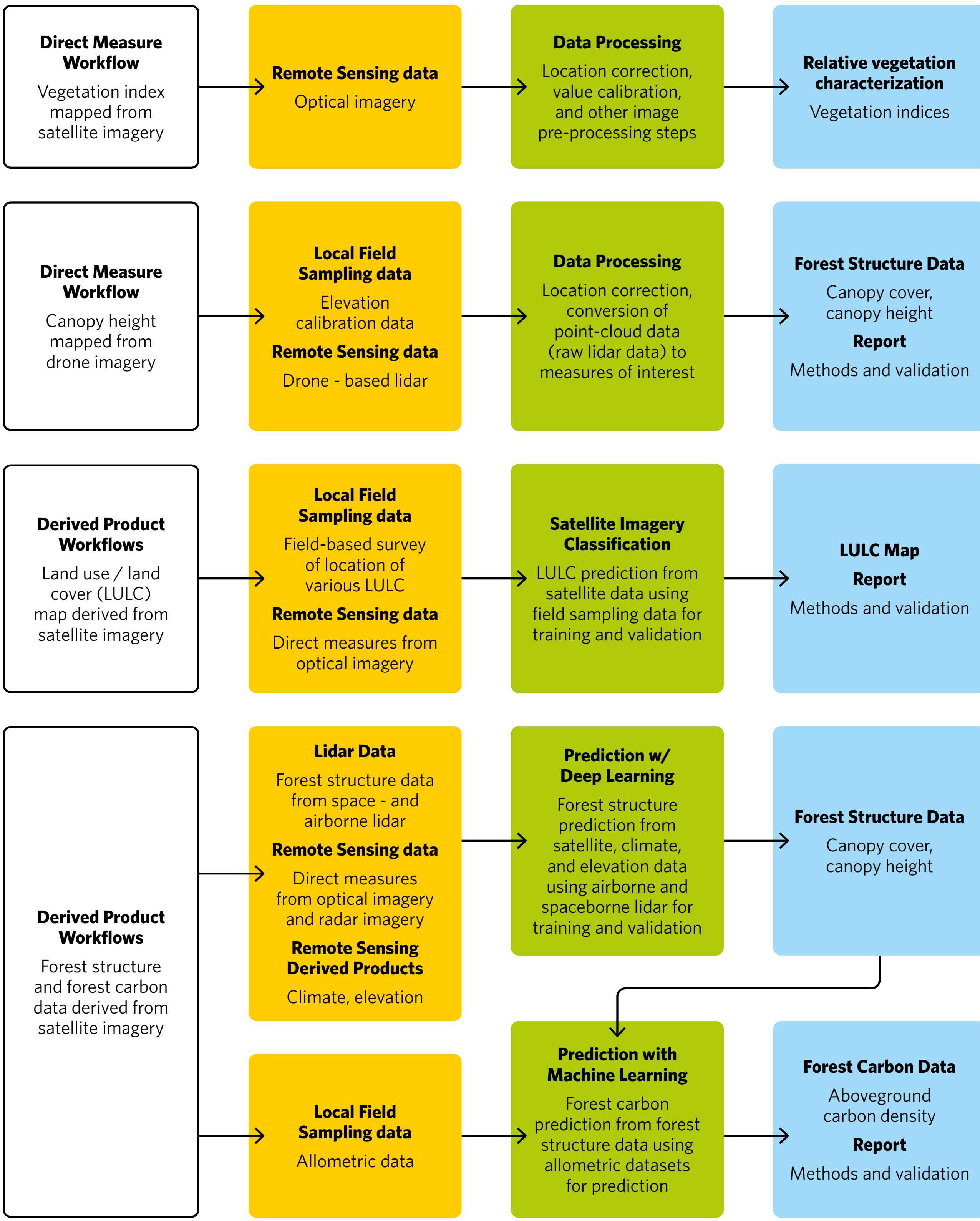
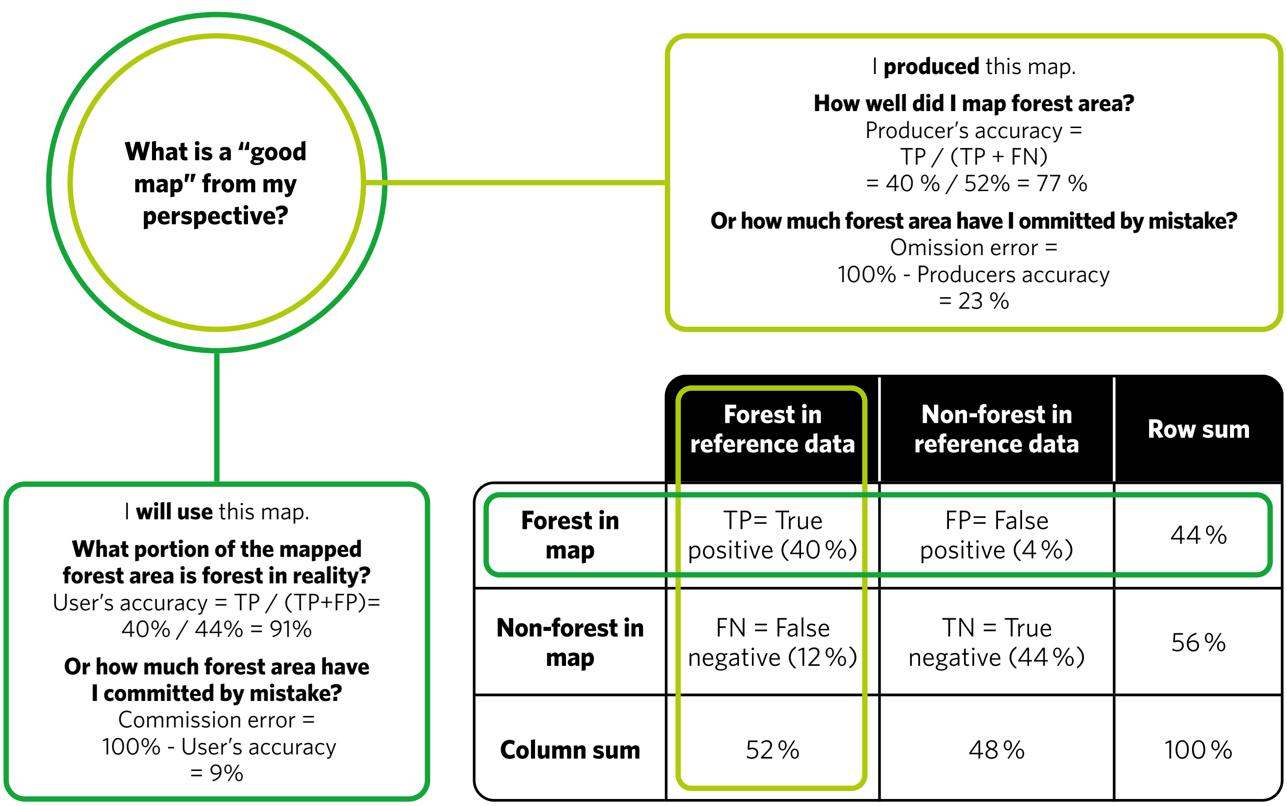


Figure 2: Workflows for producing direct measure and derived product maps from satellite imagery and reference data.

In some circumstances, direct remote sensing measures such as vegetation indices can be useful for characterizing relative vegetation patterns. Vegetation indices are readily calculated from optical imagery. For example, the Normalized Difference Vegetation Index (NDVI) uses red and infrared spectral band information to measure active photosynthesis. NDVI can be positively correlated with biomass in forests (Zhu & Liu, 2015), grasslands (Naicker et al., 2024), and croplands—indicating that higher NDVI values generally indicate higher biomass— and can be used to compare areas of the same land cover type. The relationship between NDVI and biomass breaks down in forests with moderate and high biomass because optical imagery cannot "see" structural complexity below the surface of the canopy. In the remote sensing literature, this is referred to as sensor saturation. Alternative vegetation indices can be less sensitive to sensor saturation. Derived forest structure and forest carbon products often incorporate active remote sensing data along with vegetation indices within their modeling approaches to overcome this issue.

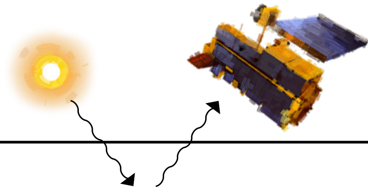
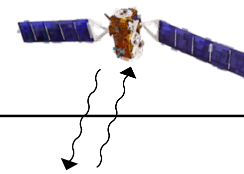
Other carbon pools that can be indirectly measured from remote sensing include BGB root and SOC (See Section 7, Limitations of Remote Sensing Technologies, p. 21). In the case of BGB, it is generally estimated from AGB using a root-to-shoot ratio (R/S) or conversion factors (Mokany et al., 2006; Rovai & Twilley, 2021). For SOC, the most common approach is to correlate on-the-ground patterns with remotely sensed imagery that impact SOC storage, such as vegetation or topography (Angelopoulou et al., 2019).



	Forest in reference data	Non-forest in reference data	Row sum
Forest in map	TP= True positive (40 %)	FP= False positive (4 %)	44 %
Non-forest in map	FN = False negative (12 %)	TN = True negative (44 %)	56 %
Column sum	52 %	48 %	100 %

Figure 3: How to interpret a categorical map accuracy assessment.

Source: (Tyukavina et al., 2024)

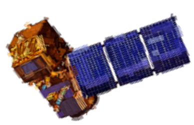
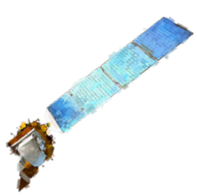
	Passive remote sensing Light or energy does not come from sensor	**Active remote sensing** Sensor transmits and receives light or energy
 Very high spatial and / or spectral resolution airborne remote sensing	**Advantages:** • Very high level of detail and ability to distinguish small features and subtle differences among features **Disadvantages:** • High cost limits footprint and frequency of acquisition • Does not 'see' below forest canopy or through clouds • Large, complex imagery **Example application:** Drone-based hyperspectral imagery used to map trees to species level	**Advantages:** • Very high level of detail and ability to distinguish small features • Can 'see' through canopy allowing for characterization of forest structure **Disadvantages:** • High cost limits footprint and frequency of acquisition • Large, complex imagery **Example application:** Airborne lidar used to map tree canopy elevation, earth surface elevation, and tree canopy height
 High spatial and / or spectral resolution, low temporal resolution satellite remote sensing	**Advantages:** • High level of detail and ability to distinguish small features **Disadvantages:** • Primarily available through commercial providers (moderate cost) • Does not 'see' below forest canopy or through clouds **Example application:** Planet SkySat imagery used to map individual trees in agroforestry setting	**Advantages:** • Can 'see' through clouds and all light conditions, allowing for characterization of forest structure **Disadvantages:** • Emerging technology • Complex data requires extensive pre-processing before use **Example application:** GEDI spaceborne lidar sensor used as training, calibration, and validation data for modeling biomass from other satellite imagery
 Moderate spatial and / or spectral resolution, high temporal resolution satellite remote sensing	**Advantages:** • Global coverage, near real-time monitoring and long historical archives, often freely available or low cost • Well established methods for use **Disadvantages:** • Single pixel in image may include many features or land cover types of interest • Does not 'see' below forest canopy or through clouds **Example application:** Landsat imagery used to establish rates of land cover conversion over long time periods at regional scales	**Advantages:** • Global coverage, near-real time monitoring of disturbances • Can 'see' through clouds and all light conditions, allowing for identification of general vegetation structure **Disadvantages:** • Complex data requires extensive pre-processing before use • Moderate detail **Example application:** Sentinel-1 radar data used to identify forest disturbances in a cloudy, tropical region

Figure 4: Advantages, disadvantages, and examples of active and passive remote sensing.

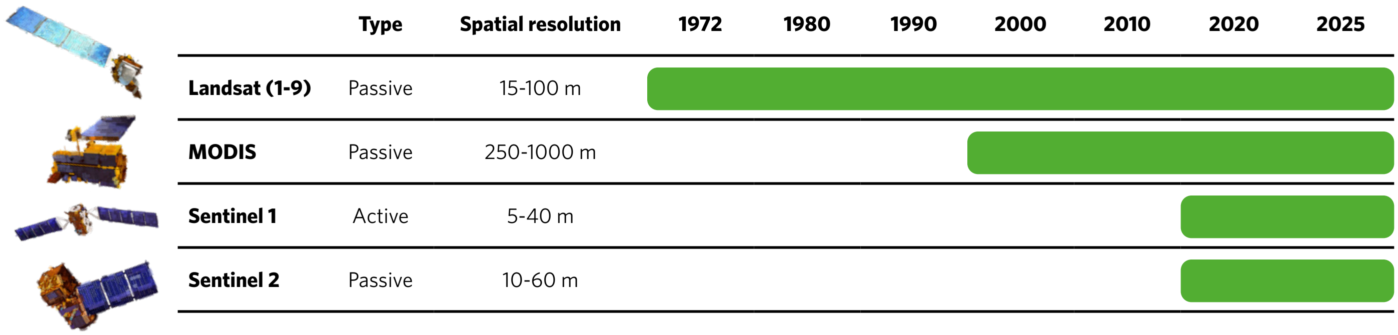


Figure 5: Temporal availability of commonly used, publicly available satellite imagery.

RECOMMENDATIONS

1. Remote sensing products can differ in a multitude of ways. When evaluating change between two time periods, using remote sensing products with similar characteristics, such as spatial resolution, sensor type, and LULC category definitions, can help ensure that changes over time are a function of true on the ground change and not due to product differences. For example, it is not appropriate to map deforestation trends using one dataset derived from 250 m resolution imagery that defines forest as at least 10% tree cover and another dataset derived from 30 m resolution imagery that defines forest as at least 30% tree cover.
2. High-quality remote sensing products will provide detailed methods and report accuracy and uncertainty statistics. Review these materials to understand the biases of the product, such as patterns of under- or over-estimation (producer's and user's accuracy, respectively) associated with particular regions or data ranges, and ensure that the intended use is appropriate. Two common biases in map products derived from optical remote sensing imagery are under-estimation of tree cover where tree cover is sparse, such as in savanna ecosystems, and underestimation of biomass in stands with very high biomass, such as moist tropical forests, where the relationship between remotely sensed signals and biomass saturates.
3. No remote sensing product can directly measure carbon stocks or carbon flux, but remotely-sensed data are often used in conjunction with field sampling or other training and validation datasets to model carbon stock or flux. Model performance is generally best for models derived from passive and active remote sensing data (vs. passive data alone).
4. When using remote sensing products to estimate carbon stock or flux, it is essential to consider the quality and utility of the training and validation datasets for your application. For example, a model trained and validated using biomass data predominantly from tropical forests in Asia may not be useful for an application in low biomass boreal forests in Canada. Relatedly, it is important to consider the uncertainty of the carbon stock model estimates at any point in time relative to the anticipated magnitude of carbon stock change. Small carbon stock changes in a project area may be lost in the 'noise' of the uncertainty of carbon stock products.
5. Remote sensing products will likely have variable quality. In addition to evaluating products individually, look for opportunities to use multiple products derived from different satellites or with different methods to confirm results. Local calibration data from field measurements can provide an additional perspective on product quality.

5. Innovations in Carbon Market Methodologies

COUNTERFACTUALS

Satellite imagery and derived map products are used to evaluate the baseline, or business-as-usual, scenario with increasing frequency. This baseline is often referred to as the "counterfactual" relative to carbon project outcomes, or what would have happened in the project area without project implementation. The counterfactual is difficult to define, because land use dynamics are influenced by many factors, and without experimental or randomized control scenarios, it is impossible to know with certainty what would have happened in alternative project scenarios. Thus, the best approach is to use real world data to model the likelihood of alternative scenarios, and then rely on the most likely to inform a counterfactual. Depending on a project's specific context, most of the early carbon crediting methodologies asked project developers to create relatively simple counterfactuals based on historic flux, existing stocks at the outset of the project, or selection of a reference area with similar initial conditions to the project site, which would be monitored alongside the project area for changes in the absence of project implementation. In recent years, selection of reference sites that poorly represent the project area has become a common critique of carbon projects that use the reference area approach due to its potential to result in over-crediting (e.g., Badgley et al., 2021; Guizar Coutiño et al., 2022; West et al., 2023).

DEFORESTATION RISK MAPS

Innovations in carbon market methodologies, enabled by advances in remote sensing technology, promise robust solutions to these issues. For REDD projects, for example, Verra's VM0048) is a methodology that develops deforestation risk maps from remotely sensed data of known drivers of deforestation, such as distance to the deforestation "frontier," presence of any explicit protected areas, and/or the density of road networks that facilitate increased access to undisturbed forests. The risk map uses these data to develop a spatial representation of how the likelihood of deforestation varies across a landscape, which allows comparison of the amount of deforestation expected to occur with versus without carbon project implementation. The risk map can be used to directly calculate emissions or emissions reductions, or serve as a basis for matching to be used in a dynamic approach.

DYNAMIC BASELINES

Another approach using remote sensing data is to source and monitor counterfactuals from across the broader landscape (e.g., VM0045). Rather than selecting a single reference area, project proponents can instead select a (weighted) combination of reference plots (or pixels/polygons on a map) from a pool of potential control sites. The selection process usually involves some form of statistical matching to balance covariate factors thought to impact the outcome variable (e.g., carbon stocks and fluxes) between the population of treatment and control sites. The covariate data can include remotely sensed variables such as standing forest biomass, forest type, distance to old deforestation, and other environmental and socioeconomic factors affecting land use dynamics. Synthetic controls are another way to balance factors affecting the outcome variable, by using (weighted) combinations of reference plots (or pixels), to obtain a robust assessment of the impact of the project. When project impact is compared to the change in the matched or synthetic controls over time, this is referred to as a dynamic baseline, as it evolves over time. By using dynamic baselines that balance the relevant covariates between matched with-project and control areas, project developers can create more credible, equivalent comparisons that more accurately reflect on the ground changes. One benefit of dynamic baseline methodologies is that they lead to issuing credits only for observed (ex-post) mitigation, rather than using any type of prediction (ex-ante) crediting. Any impactful changes that occur after project start date, such as the implementation of new regulatory frameworks, will also affect with-project and control areas equally, alleviating any need to adjust the counterfactual or invalidate the project.

Also, innovative methodologies are using remote sensing to forecast change in outcome metrics (e.g., carbon stock) in control areas where no field data exists, through relationships calibrated in project areas (e.g., VM0047). In this process, carbon stock density is measured in project areas, and a relationship with a remotely sensed index is derived (e.g., measures of vegetation height, structure, greenness). Changes over time in the value of these remotely sensed metrics in the control units would then be used as a counterfactual against which to compare changes in the same metrics observed in the control. Such a comparison enables evaluation of project impact and additionality, while not requiring on-the-ground access to control units. Solutions like those described here are still under development, and the authors expect to see many new applications of remotely sensed data in this area in the years to come.

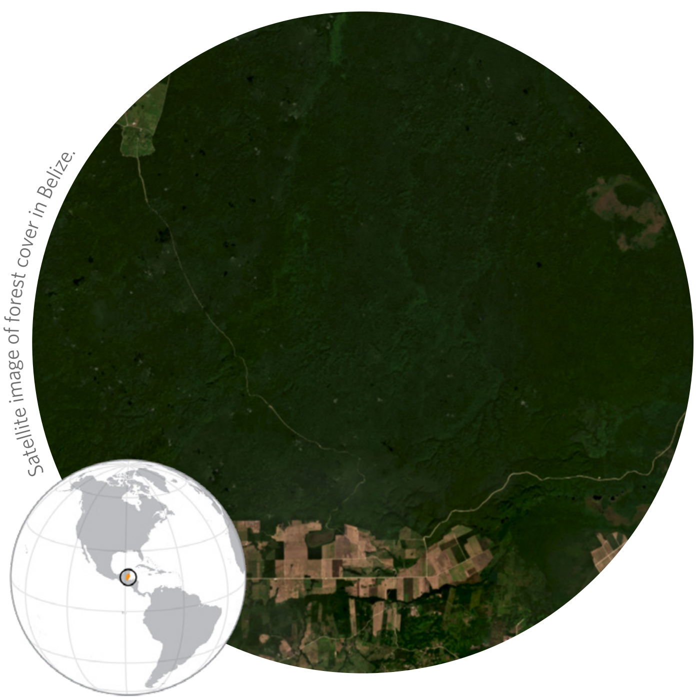
6. Real Examples: How is Remote Sensing Used in Carbon Projects?

EXAMPLE 1: BELIZE MAYA FOREST REDD+ AVOIDED PLANNED DEFORESTATION TO AGRICULTURE PROJECT

Pathway and Carbon pool: Avoided forest conversion. Aboveground and belowground live tree and herbaceous biomass, litter biomass, and soil organic carbon.

Source: https://registry.verra.org/app/projectDetail/VCS/3960

Context: The Belize Maya Forest REDD+ project acquired 87,509 hectares of land that were being offered to sell to agricultural interests in Belize.



Satellite image of forest cover in Belize.

The project will generate 736,688 tCO_2e average annual emission reductions over a 40-year crediting period.

Data acquired: The project used remote sensing data for the following:

- LULC mapping. The project developer used 36 Landsat optical satellite images and topographic products derived from satellite imagery (slope, elevation, aspect) to generate annual LULC maps for 2010–2020 using a machine learning algorithm and training/validation data generated from interpretation of high-resolution optical aerial imagery. The LULC maps were used to 1) delineate areas within the project boundaries where the project is not applicable (non-forest areas during the 10 years prior to project initiation, legally required agricultural setbacks around wetlands) and 2) calculate the annual rate of deforestation (conversion rate of forest to non-forest in LULC time series) and agricultural abandonment (conversion rate of non-forest to forest in LULC time series). Additionally, the project developer provided an accuracy assessment for the LULC map and calculated uncertainty as a 95% confidence interval for the annual rate of deforestation.
- Baseline and additionality. The project developer used elevation and slope

products derived from remote sensing 1) to confirm the project area's vulnerability to agricultural conversion and 2) for matching "proxy parcels" to the project area for calculating the annual rate of deforestation and agricultural abandonment in comparable (control) areas.

- Carbon accounting. A carbon stock assessment (tCO_2e/ha) was conducted in the project area using field plots and multiplied by the estimated annual rate of deforestation in the absence of the project (ha) to estimate the project mitigation potential (tCO_2e).
- Reversal monitoring. Additionally, the project documentation identifies that satellite imagery will be used to monitor the project area for degradation of forest carbon stocks (reversals) due to hurricanes, fires, or other sources of disturbance.

EXAMPLE 2: VIRGINIA COAST RESERVE SEAGRASS RESTORATION PROJECT

Pathway and Carbon pool: Seagrass Restoration. Above-ground non-tree biomass and soil carbon

Source: https://registry.verra.org/app/projectDetail/VCS/2360

Context: This project is located in the Virginia Coast Reserve, a biosphere reserve managed by The Nature Conservancy consisting of 40,000 acres across barrier islands in Virginia, United States. Active seagrass meadow restoration began in 2015 via direct seeding in order to restore the native seagrass vegetation cover. Over a 40-year crediting period the project activity is estimated to generate 28,000 tCO_2e net Greenhouse Gas (GHG) removals.

Data acquired: In this project, aerial surveys using multispectral high-resolution optical imagery beginning in 2015 were conducted to quantify vegetation cover and density in order to calculate initial baseline emissions. Annual surveys were also conducted to quantify seagrass bed change over time for project accounting for the duration of the crediting period, until 2055. Images were acquired annually under the most ideal conditions possible and the boundaries of the seagrass meadows were identified and manually delineated using GIS by experienced analysts using expert knowledge of aquatic grass signatures, distribution of seagrass vegetation from the previous year, ground survey information, and aerial site surveys. Carbon pools of interest directly assessed via remote sensing were above ground biomass while the soil carbon accumulation rate was applied from Oreska et al., 2020 on a per area basis to the restored seagrass beds. Annual monitoring maps from remote sensing data are produced in order to measure change in bed extent and density over time and quantify carbon mitigation.

Satellite image of seagrass cover in Virginia, United States. Google Earth, TerraMetrics, Airbus, 2025.

7. Limitations of Remote Sensing Technologies

While remote sensing is a powerful tool, it is important to also be aware of its limitations.

1. Remote sensing technologies are well-established for mapping land use and land cover changes. Recent applications have resulted in improved prediction of terrestrial AGB. Predictions of BGB and SOC pools cannot be directly assessed from remotely sensed data at scale, and while parameters are advancing, they are currently associated with high uncertainties. Applications in aquatic ecosystems (e.g., seagrass) are hampered by attenuated penetration of longer wavelength radiation, such as near-infrared and shortwave infrared, into the water column. Shortwave infrared radiation benefits from greater depth penetration of water, enhancing remote observations of inter- and sub-tidal ecosystems.
2. The spatial resolution of publicly available remote sensing data (10–30 m) is often coarser than individual tree crowns. This makes it difficult to resolve and monitor individual trees in naturally sparse vegetation types, such as Miombo woodlands and savannas, in addition to smaller habitat patches. For habitats with smaller features such as seagrass, finer scale data is always required.
3. Similarly, ecosystem degradation in denser vegetation types can often not be detected in publicly available data sources. Ecosystem degradation might occur from wood harvest or incidental treefall and might result in small canopy gaps or sub-canopy changes to the forest structure. Radar data is providing some promise in this field (See Box 2, p. 7 and Section 9, Future Directions, p. 23).
4. Carbon project modelling frameworks often track differences in target outputs before and after project implementation. Diurnal, seasonal, and annual variation in carbon pools is often not well accounted for, leaving unknown uncertainty in change estimates. As remote sensing data is increasingly used in monitoring carbon projects, we may expect near-real-time (NRT) or at least sub-annual monitoring to become the norm. Large-scale land cover monitoring is already progressing in this direction.

8. Current Examples of the Use of Remote Sensing in VCM Methodologies

Methodologies, Tools, and Modules	NCS Pathway or Class	Carbon pools that can be detected with remote sensing*					Non carbon applications of remote sensing*
		Above Ground Woody Biomass	Below Ground Woody Biomass	Dead Wood / Leaf Litter	Soil Carbon	Harvested Wood	
VCS (VM0047): Afforestation, Reforestation, and Revegetation, v1.0	Reforestation	C	C	C	C	C	Baseline, monitoring, LULC, performance benchmarks and/or risk assessment and mapping (including either drivers and/or degradation)
VCS (VM0048): Reducing Emissions from Deforestation and Forest Degradation	Deforestation	C	C	C	C	C	
VCS (VT0005): Tool for Measuring Aboveground Live Forest Biomass using Remote Sensing, v1.0	Forests	RS	C	C	C	C	
Gold Standard: Methodology for sustainable management of mangroves v1	Mangrove Mangement	RS	RS	C	C	C	
PlanVivo (PM001): Agriculture and Forestry Carbon Benefit Assessment Methodology	Agroforestry, Reforestation, Mangrove Restoration	RS	RS	C	C	C	
PlanVivo (PU001): Estimation of Baseline and Project GHG Removals by Carbon Pools in Plan Vivo Projects V1.0	Reforestation (terrestrial and mangroves), Agroforestry, Managed Forests	RS	RS	C	C	C	
PlanVivo (PT002): Estimation of Climate Benefits from REDD in Community-Managed Forests	Deforestation	RS	C	C	C	C	
ERS (M001): Quantification Methodology for Terrestrial Forest Restoration	Reforestation	RS	RS	C	C	C	
SC (SCM0008): Methodology for the Restoration of Mangroves	Mangrove Restoration	RS	RS	C	C	C	
UNFCCC (AR-TOOL14): Estimation of Carbon Stocks and Change in Carbon Stocks of Trees and Shrubs In A/R CDM Project Activities	Trees and Shrubs	RS	C	C	C	C	

Table 1: Current examples (as of December 2024) of the use of remote sensing in VCM methodologies for its carbon projects.

RS Directly measured via RS

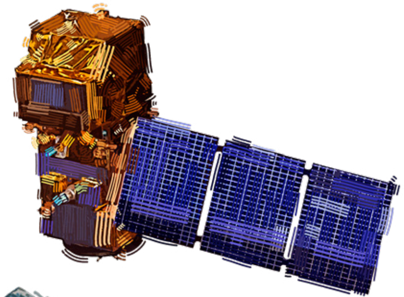
RS Indirectly measured (RS derived)

C Included or optional carbon pool to monitor, however use of RS technology not specified

C Not an included carbon pool in methodology

* Most methodologies recommend that remote sensing technologies be used in combination with field surveys. This list is not exhaustive, and the authors acknowledge that other methodologies also exist

9. Future Directions



On the horizon, the general trend is for a proliferation of new remote sensing technologies. These platforms and their derived products will significantly improve the capabilities of remote sensing, making it an even more powerful tool for monitoring, reporting, and verification in carbon markets. New technologies will provide imagery and data with finer spatial resolution, finer spectral resolution, increased temporal resolution, increased coverage for remote, data-poor areas, and increased availability of active remote sensing data. Combined, these developments will likely result in higher confidence and decreased uncertainty in derived products.

- Finer spatial resolution will enable for the inventory and monitoring of smaller features, such as individual trees or habitat patches.
- Finer spectral resolution will allow for improved or novel classification of map features, such as identifying the species of individual trees based on their distinct spectral profiles.
- Increased frequency of imagery acquisition will enable more rapid detection of changes and provide richer historical baselines. This will also increase the chances of acquiring cloud-free passive imagery, which remains a challenge in cloudy areas.
- An increase in the use of active sensors such as radar and spaceborne, airborne, drone-based, and terrestrial lidar (as terrestrial lidar scanning) will allow for improved estimates of vegetation structure, such as height and volume estimates and sub-canopy changes, which will support improved carbon stock measurement.
- Higher spatial and spectral resolution imagery, including improved availability of radar data across different bands, will also enable detection of smaller scale disturbances in various vegetation types, such as forest degradation. Eventually, these data might also enable further attribution of drivers of habitat loss and degradation such as selective logging activities, fuelwood collection, or mining activities.
- Finally, we expect to continue to see increasing applications of machine learning and other artificial intelligence methods using combinations of the above developments (increased temporal, spatial, and spectral resolution) to improve understanding and prediction of landscape features and changes, and their implications for carbon budgets.

These new developments, along with an increasing push for standardized protocols for the use of remote sensing within accounting methodologies, will likely herald increased use of remote sensing for carbon project monitoring in the future and the evolution of methodologies to incorporate these advancements.

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Carbon projects involve more than just science; they include policy, finance, social, and environmental considerations, to name a few. Through the Decoder Series, our intent is to advise buyers on how to identify best scientific practices in carbon projects. Acknowledging that credit due diligence should extend beyond this scope, we strongly advise readers to adopt these principles in addition to other key project elements.

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