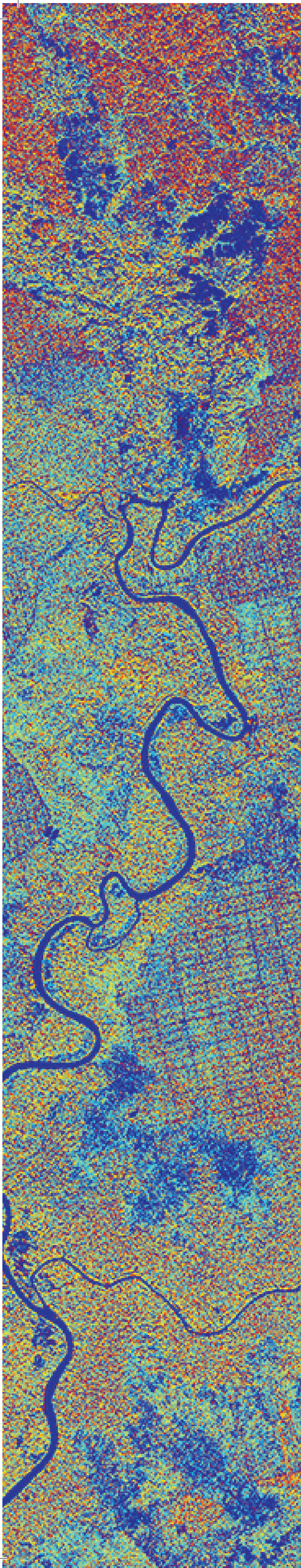

THE UNIVERSITY of EDINBURGH
School of GeoSciences

THE HECTARES INDICATOR:

A Review of Earth Observation Methods for Detecting and Measuring Forest Change in the Tropics

Edward Mitchard

ecometrica

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This document describes current and emerging earth observation technologies based on satellites and other aerial data sources and an assessment of how these can be used to map forests and forest changes.

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Summary

This document provides an introduction to the different types of Earth Observation (EO) data, and the different ways in which they can be used to map forests and forest change. EO data is divided into optical, radar and LiDAR, which are discussed in turn. A wide range of peer reviewed studies are discussed in order to assess the utility and accuracy of different methods in different circumstances. The review shows that optical data is the most widely used, radar next, and LiDAR last. This is precisely the opposite of their data content, with LiDAR being the richest data source, providing full cross sectional information on forests, radar potentially providing some of these data, and optical viewing only the top of the tree canopy and thus providing almost no three dimensional information. Decisions on which data type to use is clearly related far more to data availability, cost, and the complexity of the required analysis, than to which system would provide the most comprehensive information about a forest.

The main results and guidance can be found in Tables 3 and 9, which present the optimum methods for mapping forest characteristics at a single time point, and mapping change in forest characteristics through time, respectively. The optimum method is defined as the method that best balances three factors: accuracy, cost (of both data and analysis), and maximum potential monitoring frequency.

For forest characteristics mapping, high-resolution (<30 m pixels) optical data appears the most useful, with radar data potentially having a role, especially in combination with optical data for classifying forest into many forest types, or for its ability to see through clouds. For mapping forest change the picture is more complex, with optimal products depending on the forest type, proportion of time the study area is under cloud, the required temporal and spatial resolution, and whether the target of change detection is deforestation, degradation, or biomass change. Current, systematically produced and free-of-charge products are useful for low cost deforestation monitoring of moist or wet tropical forests, but are not useful in drier savanna ecosystems due to confusion by grass and tree deciduousness, nor for mapping degradation or biomass change. High resolution optical data is useful for degradation mapping, but only in areas with low to medium cloud cover. In areas with high cloud cover, or for drier ecosystems, radar is the most useful tool. Biomass mapping will normally need custom data collected from LiDAR on unmanned aerial vehicles or aircraft, as satellites that can provide suitable information are planned but not yet launched, and will have a coarse (>100 m) resolution regardless.

It seems likely there will be a switch in the coming years from a reliance on US satellites for most forest monitoring (Landsat, MODIS), towards new satellites funded by the European Commission (Sentinel-1/2/3), due to increased temporal/spatial resolution and data provision guarantees. The potential from ever cheaper UAVs is discussed, with it being predicted that UAVs have much to offer for collecting reference data, while the potential from the launch of cheap and small satellites (e.g. cubesats) by private companies or governments is seen as more limited, but potentially significant in the future.

Contents

Glossary of Terms and Acronyms

AGB	*Above Ground Biomass*, the biomass of trees per unit area, usually given in Mg ha^{-1} (also tonnes/ha, which is identical)
ALOS PALSAR	*Advanced Land Observing Satellite Phased Array L-band SAR*, a widely used L-band radar satellite operated by JAXA. Followed by ALOS-2 PALSAR-2.
Commission error	The proportion of pixels within a class in a classified map that in fact belong to a different class according to the reference data. It is the complement of User's accuracy.
Deforestation	An anthropogenic disturbance to a forest area, that results in that area no longer meeting the relevant forest definition
Degradation	There is no consensus on how forest degradation is defined. In this review it is considered as an anthropogenic disturbance to a forest area, that reduces its aboveground biomass, but after which it still meets the relevant forest definition
EO	*Earth Observation*, remotely sensed data from a satellite, aircraft or UAV platform
ESA	*European Space Agency*
ETM+	*Enhanced Thematic Mapper+*, the main sensor on Landsat 7. Similar bands to TM, but with additional 15 m resolution panchromatic band.
JAXA	*Japanese Space Exploration Agency*
LiDAR	*Light Detection and Ranging*, an EO method involving sending many short pulses of laser light and detecting the time taken for them to return, giving the distance between the sensor and various forest elements, as well as the ground.
Machine learning	A data analysis and prediction technique involving a computer developing an algorithm itself, normally from a multi-dimensional dataset, without explicit programming.
MRV	*Measurement, Reporting and Verification,* normally discussed in the context of the monitoring and reporting requirements for countries to take part in the UNFCCC's REDD+ scheme
MSS	*Multi-Spectral Scanner*, the main sensor used on Landsat 1-3, also present on Landsat 4/5
NASA	the US *National Aeronautics and Space Administration*
Neural network	A widely used type of machine learning technique
OLI	*Operational Land Imager*, the main sensor used on Landsat 8. Similar bands and resolution to ETM+, but much higher dynamic range (pixel values from 0-4095 rather than 0-255).
Omission error	The proportion of the reference data for a class that is allocated to a different class. It is complement to the producer's accuracy.
Producer's accuracy	The proportion of reference data from a class correctly allocated to that class in an output map. It is the complement of omission error.
Radar	A method of imaging using pulses of microwave radiation. Unlike optical data, usually only a single wavelength is used, named by single letters (e.g. L-band, C-band, X-band).
Random forest	A machine learning technique often employed in remote sensing classification and regression.
REDD+	*Reducing Emissions from Deforestation and forest Degradation, in developing countries, and the role of conservation, sustainable management of forests, and enhancement of forest carbon stocks in developing countries*, a part of the UNFCCC agreements.
SAR	*Synthetic Aperture Radar*, a type of radar that uses the flight of a travelling sensor (e.g. in a satellite) to simulate a far larger antenna than exists, allowing high resolutions from a distance.
TM	*Thematic Mapper*, the main sensor on Landsats 4 and 5
UNFCCC	*United Nations Framework Convention on Climate Change*
User's accuracy	The proportion of all reference data assigned to a particular class in a classified map that are truly that class in the ground truth dataset. It is the complement of commission error.

1 Introduction

1.1 The challenge of mapping forests and forest change

The woody vegetation of the tropics is highly diverse in its species composition and structure, and is changing fast. This change is a result of human actions (for example felling trees, setting fires, and damming rivers), recovery from past disturbance, and climate change.

Woody vegetation varies in many different ways. Some of these axes of variation are continuous parameters, for example percentage canopy cover, maximum tree height, or carbon storage per unit area. Others are more discrete, for example the presence or absence of a grass layer, the presence of a certain tree species, or whether a forest was planted by humans or developed naturally.

Policy makers, companies, non-governmental organisations and civil society all have their own motivations for wishing to know how these parameters are distributed across the landscape of their interest, and how these are changing. Normally they cut up these continuous distributions into distinct classes (dividing a landscape into say intact forest, secondary forest and 'other wooded land' based on canopy cover thresholds), and look at the rate of change from one class to another through time. Increasingly however they are also interested in changes within forest classes, for example rates of forest degradation or regeneration in terms of changes in carbon storage per hectare. It is important to these users that such data are available with high and consistent accuracy, little time delay, to a guaranteed schedule, and at minimal cost.

Unfortunately, mapping forest characteristics in space and through time is challenging using any method. Large budgets cannot necessarily produce good forest change maps: for some parameters the methodologies necessary for producing maps at scale have not yet been developed or validated (for example biodiversity mapping), and it is impossible to retroactively collect new datasets from the past. Mapping change therefore often relies on the analysis of suboptimal historical satellite datasets, and mapping some modern day characteristics may involve active research, rather than applying existing methodologies. There is often a disconnect between the data that users would like, and what can actually be mapped with high accuracy, especially within, what might be considered, an acceptable budget for the user.

The standard tool for quantifying forest characteristics is the forest inventory plot. In these, all the trees within a fixed area, often a hectare (100m x 100m), have their trunk diameter measured, their species determined, and potentially other measurements made such as their height. From these plots it is possible to differentiate different forest types, based for example on the dominant tree species, and to estimate aboveground biomass (the mass of carbon stored in the trunk and branches of the trees). For logistical and financial reasons however, it is only possible to sample a very small proportion of any forested landscape directly through plots: it may take an experienced team up to a week to set up a single one hectare plot in tropical forest. Therefore, plots are used typically to make initial, high fidelity estimates that are then scaled up to the landscape scale using Earth Observation (EO) data. Such EO data, from satellites, manned aircraft, or Unmanned Aerial Vehicles (UAVs), will have an imperfect ability to map the characteristics of interest, but will cover a far larger area than would be possible using field plots alone. A further advantage to the EO data is that a survey can be repeated frequently using the same sensor, often at zero cost to the user.

It is possible to remeasure field plots every few years in order to directly quantify how the forest is changing: for example a set of hundreds of such plots across the tropics have been remeasured every few years to show that intact tropical forests are increasing in carbon storage (Pan *et al* 2011). However, this is only appropriate for diffuse changes that are occurring across large areas. Plots are a very poor way of mapping changes that affect only a small proportion of the forest each year. For example, with deforestation or disturbances such as selective logging, it may be that 1 % of a forested area is deforested each year, but by coincidence none of the say fifty plots set up inside a forest are actually cleared during five years of monitoring. In fact, plots have been shown to be an especially poor method for monitoring clearance, as the plot corners and the trees themselves tend to be permanently marked, and people know that the plot is monitored, meaning that these people are less likely to clear the trees in the plot than those in the surrounding area.

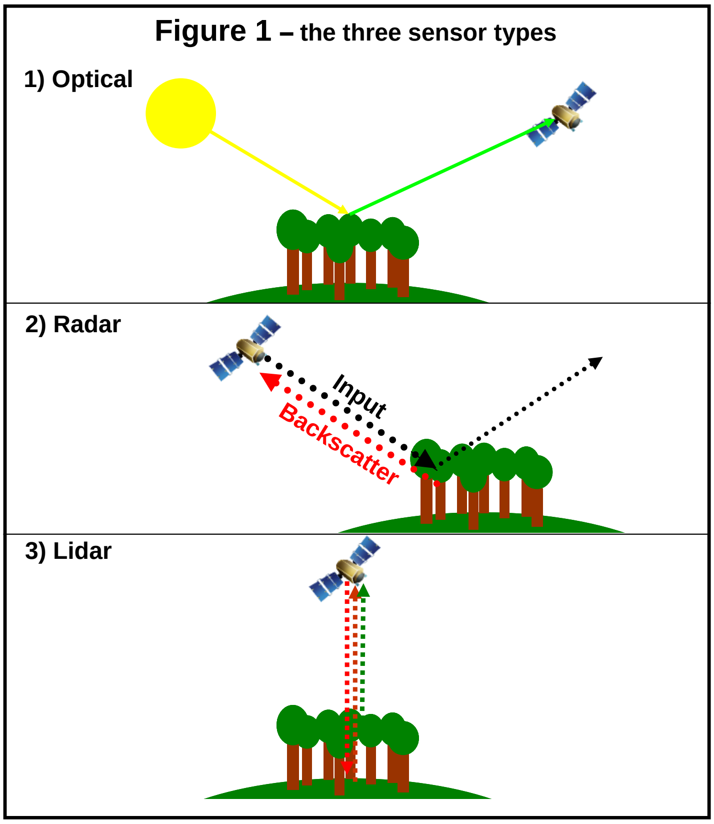
Therefore, while field plots are used to calibrate and validate EO based maps for a single time point, it is typically remote sensing data alone that is used to map changes in forest parameters. This introduces significant challenges, as the change in the signal detected by the EO instrument(s) over time is not necessarily related to changes in the forest characteristics, but may be due to changing atmospheric conditions, the vegetation looking different due to the season or recent rainfall, or calibration of the sensor itself. It is therefore important to test the accuracy of the change maps themselves using further ground data or independent EO products, and to choose EO data and methods that are least likely to lead to errors and biases in the resulting change products.

1.2 Earth observation data types

There are three main types of EO data: optical, radar and LiDAR (Figure 1). Each has different characteristics, strengths and weaknesses, and all three will be discussed throughout the report.

Optical: Optical remote sensing data is the most widely available of the three, with over a hundred satellites collecting data regularly. There are a number of free options for optical satellite data, with the most widely used traditionally being Landsat, a series of satellites that started collecting data in 1972, with the data freely distributed for any use by the United States Geological Survey (USGS). There are currently two Landsat satellites in orbit (7 and 8), collecting data at a 30 m resolution. There are other satellites now collecting data at a far higher resolution, up to 31 cm pixels for Worldview-3, but these have a high cost. Optical data can also be collected from UAVs or manned aircraft, allowing cm-scale resolution from which it is possible to map individual trees, and if stereo data is collected (easy with such platforms through the use of overlapping flight lines) their relative heights. UAVs and manned aircraft also allow the collection of data using sensors with thousands of narrow bands (hyperspectral), from which characteristics such as drought stress or species type can be ascertained from the spectral signature.

Optical data views the top of the canopy, and thus can be used to assess canopy cover and potentially estimates of the density and health of leaves. It has traditionally been the main tool used to map deforestation, and has been used with success to detect forest degradation, especially using data with high temporal and/or spatial resolution. However, it has two major problems: it cannot see through clouds, which cover much of the tropics most of the time, limiting observations; and it cannot see through the top of the forest canopy, meaning low-level degradation, not involving canopy trees, will be invisible.



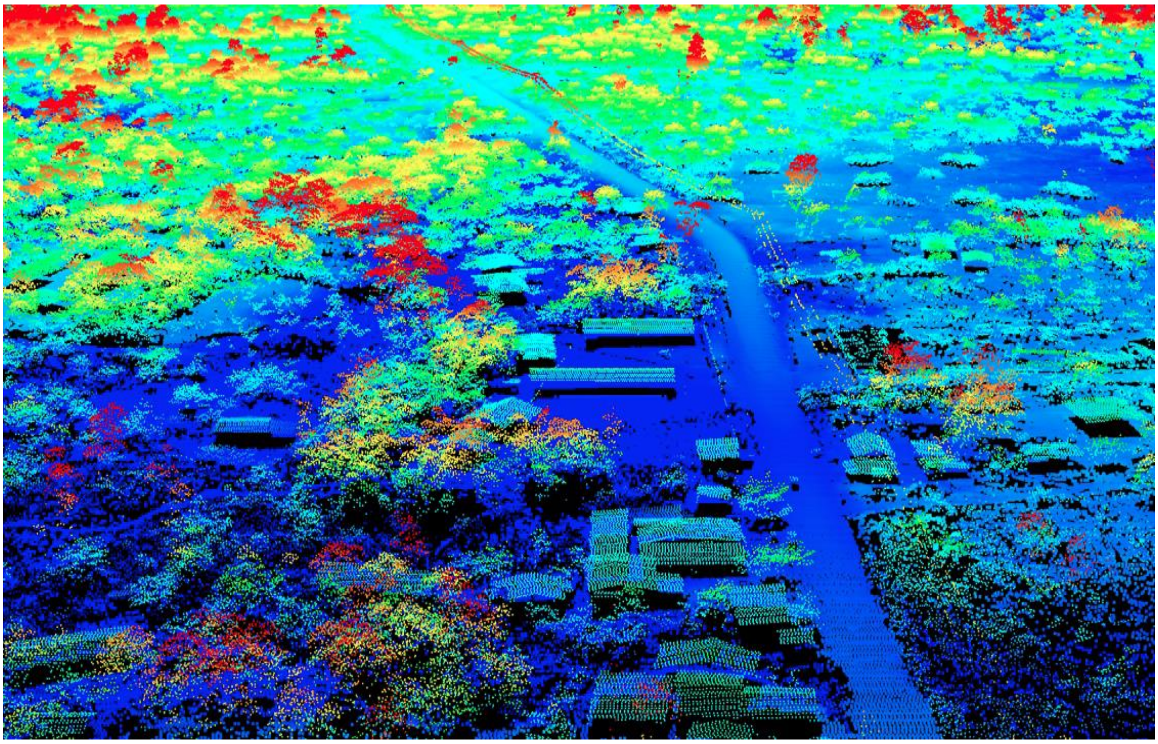
Radar: Radar satellites look obliquely at the Earth's surface using microwave data (in the mm – cm wavelength range). This microwave data can penetrate through the forest canopy to obtain information on forest structure, with the amount of radiation scattered back to the instrument ('backscatter') increasing as the number and/or size of trees present in an area increases. Therefore radar satellites have been used to map aboveground biomass, and to map degradation. However, they are limited by a saturation point, typically around 150 tonnes ha^{-1} aboveground biomass for L-band (the longest, and therefore most sensitive, wavelength currently available), and 50-75 for C-band (which is more widely available). For comparison, dense tropical forest can have biomass values of over 400 tonnes ha^{-1}, though values in the 250 – 350 range are more typical. Therefore available radar data is most useful for mapping biomass in savannas and woodlands.

The letter names associated with different wavelengths are derived from military use, and have no particular significance. In order of increasing wavelength, those of relevance for forest mapping progress through X-, C-, S-, L-, and P-band. There has never been a P-band satellite, but one is planned for launch in 2021 (called BIOMASS), and this will have a saturation point for biomass sensitivity well above the 150 tonnes ha^{-1} mentioned for L-band above.

Radar can also be used to accurately estimate surface/canopy height through a process called interferometry, which involves looking at the same area twice but from a slightly different angle and studying the phase difference between the waves. This has great potential for mapping degradation through studying changes in these canopy height models through time, but it does not on its own allow for the direct estimation of tree height unless an accurate model of the ground elevation is available (currently not available in most developing countries). It is theoretically possible to obtain ground as well as canopy height models from radar data, but not using any of the sensors currently in orbit. Interferometry can be used to map millimetre scale changes in ground elevation following earthquakes, but cannot achieve that same precision over forests due to temporal decorrelation: when returning to view a forest after a few days it will often have an entirely different response (as the leaves will be at a different angle, the wind may be blowing in a different direction, the water content might be different, let alone if trees have actually been removed), preventing accurate change mapping. One mission, TanDEM-X, solves this problem by using two satellites orbiting very close to each other, meaning data is collected from two angles simultaneously. Such data has been used successfully to map changes over forest, but its high cost limits its use over wide areas. In general, and even with TanDEM-X, interferometry is a difficult technique involving specialist software and expertise, and significant processing time. This method therefore remains more an area of research than an actively used technique, and most forest characterisation and change mapping is performed using backscatter information alone. Another active area of research is stereo radargrammetry, which again compares two radar images to build a canopy surface height model, but is able to use images with a wider difference in incidence angles and is potentially less sensitive to temporal decorrelation.

LiDAR: LiDAR data uses laser light looking directly down to give tree height and structure. This enables a representation of a forest to be built up with structural parameters such as height, stem density and canopy cover estimated directly. Repeat surveys can therefore see the removal of individual trees, and thus it is the only remote sensing method that can guarantee to map degradation with high accuracy even if the magnitude or size of disturbance is low.

Figure 2. LiDAR data captured from a helicopter over Gabon, showing houses and surrounding small and tall trees.



Most aircraft LiDAR data collected is discrete, small-footprint LiDAR, where a number of individual narrow pulses is sent into each m^2 (1-5 pulses would be typical), and 3-5 returns detected for each pulse, so that the height difference between the ground and a point near the top of a tree can be calculated. This gives high resolution maps of canopy cover and height, from which biomass can be calculated. More sophisticated products can be produced through full waveform LiDAR, in which the full return profile from each beam is stored, allowing more detailed characterisation of sub-canopy layers. In both cases the stems of individual trees can often be mapped, but the resolution and views are too low to allow for the direct mapping of tree stem diameter – instead tree height is the main characteristics that can be used to estimate tree biomass. Full waveform LiDAR can also be collected using wider beams from a higher altitude plane: such data can cover a much larger area during one flight, but the forest characteristics are normally averaged within 10 or 20 m pixels, and individual trees cannot be identified.

No LiDAR satellite is currently collecting data, so LiDAR can only be obtained through aircraft or UAVs, at high cost. However, two spaceborne missions, GEDI and ICESAT-2, are soon to be launched, while the data from a satellite in the mid-2000's (ICESAT GLAS) has been used to assist in the development of pantropical tree height and biomass maps.

1.3 Earth observation platforms and trade-offs

There are certain trade-offs in EO data that apply regardless of the type of data collected. These include:

- the higher the spatial resolution of a satellite sensor, all else being equal, the longer the gaps between repeat images of the same location as the sensor will normally have a narrower field of view, capturing a smaller portion of the Earth during each orbit
- the type of platform used, comparing the low-cost and ease of use of a satellite with the high resolution and flexibility of a UAV or aircraft
- the more cutting edge the sensor, the less likely there will be comparable historic data available
- the higher the spatial resolution, or the more esoteric/advanced the data type, the higher the cost for the data and the greater the complexity in retrieving parameters of interest.

Each of these is discussed in turn below, and will return as constraints throughout this report.

Spatial/temporal resolution trade-off. This is best illustrated by an example using satellite sensors. MODIS is a widely used sensor that has operated from 2000, collecting data at a maximum resolution of 250 m (when resolution is discussed like this for an EO sensor, we mean that the smallest pixel size of its outputs are squares with a side of 250 m, and thus a total pixel area of 6.25 ha). It is carried by two satellites, and due to its relatively coarse resolution each can view a wide strip of the earth on every orbit: thus most of the planet is viewed 4 times per day, and at least one cloud-free view of everywhere on the earth is pretty much guaranteed in a 16-day period. MODIS is therefore ideal for monitoring changes with a small temporal lag, and for recording exactly when a change occurred. However, the pixel size is far larger than most deforestation events, so much deforestation could occur and remain invisible to MODIS. Landsat 8, another widely used satellite, captures images in similar wavelengths but with a resolution of 30 m (for most bands). This means it has almost 100 pixels for each MODIS pixel. However, this higher resolution means it can only image the world once every 16 days, and it may therefore only obtain a cloud-free image 1-2 times per year in much of the tropics, and in some very cloudy areas the ground has never yet been seen by Landsat 8, even though it has been operating since 2013.

This general trade-off applies to radar and LiDAR sensors as well: in general high spatial coverage (and consequent frequent revisits) is not compatible with high resolution. There are three exceptions to this general rule. Firstly, hyperspatial (exceptionally high resolution) sensors, such as Worldview-3 with a 31cm pixel size, do not attempt to systematically image the whole planet. Instead their acquisitions are targeted based on the requests of paying customers. While individual image footprints are small, the sensor can be pointed so that revisit times as low as 1 day can be achieved. Thus given sufficient funds, frequent high-resolution images are possible. Secondly, a new generation of satellite sensors are being launched that manage to capture comparatively high resolution data at a frequent temporal resolution: for example the two Sentinel 2 satellites capture 10 m resolution optical data with a 5-day repeat cycle through the use of a sensor with a wide swath and very high pixel density. Looking further ahead, similar or better data may be available through 'swarms' of tens or hundreds of smaller satellites launched by private companies (for example Planet Labs is hoping to launch a sufficient number of its Dove cubesats to image the whole Earth every day at 3-5 m resolution). Finally, the rise of cheap UAVs has allowed the easy capture of high resolution data over an area of interest as frequently as desired, though logistical issues related to sensor maintenance, site access, and data processing, may make this less effective for monitoring in practice than theory suggests.

Platform type. There are three types of regularly used EO platform: satellites, aircraft and UAV. Optical, radar and LiDAR sensors can operate from all three. Satellites are the most widely used of the three, for a number of reasons:

- They are the only option that captures data that is consistently provided free to the user, with much satellite data now given away under open licences.
- They represent the most stable and consistent platform for EO data capture, which is very useful for change detection. Most EO satellites are set up to consistently capture data from the same point in the sky at the same time of day, and can continue doing this for many years. This increases the confidence that changes observed are due to changes on the ground, rather than to sensor characteristics or look angle.
- From space it is possible to view a very wide swath of the earth, so they are the best option for imaging large areas.
- Viewing the world from a very long way away means that the extreme left and right of an image scene are viewed with quite a similar angle. By contrast, viewing from a hundred meter altitude by a UAV, a wide-angle lens results in a very different look angle to the left and right of the scene. Mosaicing images and producing consistent change products is much easier if look-angle variation is smaller: many satellite data products effectively assume every pixel is looked at from directly above, which can be a reasonable approximation in many cases; this is not possible from UAV data.

However, airborne and UAV platforms do offer advantages to a potential user in that a user can have far more control about what instruments are flown and when. For some sensor types, for example complete coverage LiDAR, there may be no choice but to use airborne or UAV platforms. These advantages do come at an often considerable cost, both in terms of the data capture itself, but also in terms of post processing, which is often far more time consuming and difficult from such platforms due to the need to stitch together many narrow passes, with differing angles and from different elevations.

Advanced technology vs historical data. There is often a desire to use the latest possible technology and most advanced techniques to map forest characteristics. However, the range of sensors available in the past was much more limited than the present day, with the variety and resolution of satellite sensors we are used to now only really available from the late 2000's onwards. When setting up Reference (Emissions) Levels for REDD+, as an example case where historical data is necessary, it is often necessary to go back in time to a date near 2000 where long-wavelength radar and hyperspatial optical data is not available. Landsat may represent the only reasonable option, despite its limitations. The problem obviously also applies to UAV and LiDAR data, where it is very unlikely that sites will have been flown in the past.

This means that projects that do use the most advanced technologies, but also need historical data, often end up needing to cross-calibrate their modern layers with lower resolution or different satellite products, in order to have comparable datasets to those available from the past. This necessarily results in a loss of some of the advantage of having the advanced data for the current time period. It is for this reason that there is often a lag in taking up the most recent technologies for change monitoring, and why Landsat (the satellite series with the longest continuous record, with data comparable to that still captured available from 1984 onwards) will continue to be used far into the future.

Cost vs resolution/sophistication. Much satellite EO data is now available free of charge. This typically includes all coarse resolution satellites (>250 m resolution), and increasingly most medium resolution satellites (~>15m). The highest resolution free data comes from the EU's Sentinel satellites, with Sentinel-1 and Sentinel-2 both offering open data at 10 m resolution, at C-band radar and multi-band optical data respectively. However, all satellite data with a resolution <10m, most satellite radar data, and obviously all data specially captured for a project using an aircraft or UAV, will have a cost. In general costs increase directly with resolution, with Worldview-3 data (31 cm resolution) about 10x more expensive per hectare than RapidEye data (5m resolution). Cost is therefore a significant factor in the choice a user makes as to whether to use a more sophisticated or higher resolution product, which might increase the accuracy or precision of the resulting maps but at a higher cost.

1.4 Definitions and the difficulty of categorising continuous data

Another major issue in the mapping of forest characteristics and their changes is in defining the relevant processes. Terms such as 'forest' and 'deforestation' can be defined very differently by different actors and in different contexts, meaning that the same remote sensing signal can result in an entirely different output under certain conditions.

Ultimately there is a contrast between continuous parameters, such as aboveground biomass or canopy cover, and human constructs such as 'secondary forest'. In most cases such terms are defined in terms of a continuous variable, for example secondary forests might be defined in a particular landscape as having a canopy cover between 30 % and 60 %. Where it is possible for results to be reported in terms of continuous maps of change they should be, as there is then less room for inconsistencies between products due to definitions, but often for practical reasons or to meet user requirements it is necessary for reporting to take place in terms of the movement of pixels between binary categories.

Forest is typically defined in terms of an area of woody vegetation that meets or exceeds specific thresholds of canopy cover, height and area (see Section 2). Deforestation is thus defined as areas that once met this forest definition, but no longer meet it. Given forest definitions change from user to user, it is possible for the same removal of trees to be counted as deforestation in only one of two products, with both being technically correct. Similarly, most definitions of forest degradation, a harder concept to define than deforestation, include a statement that the removal of biomass or other damage to the forest must have been caused by humans. This means that exactly the same loss of aboveground biomass, causing the same signal in the remote sensing data, could be caused by either humans or by a hurricane, but only in the former case would it count as degradation. In these cases it is clear that detection of changes is a harder task than simply knowing what has happened to the trees within an area: ancillary information and rules are necessary. This adds a further challenge, meaning that generally-applicable algorithms and products will often need adapting to local circumstances, to produce results that are consistent with ecological definitions as well as policy and legal interpretations.

2 Diversity of forests and forest change processes in the tropics

There is an enormous diversity of types of woody vegetation in the tropics, made up of tens of thousands of tree species arranged in different ways under very different physical and climatic situations. Similarly, there is a great diversity of ways in which these forests are changing, some related to human activity, and others related to natural processes of succession and responses to our changing climate.

Every forest is unique and much variation in space and time is continuous, defying easy classification into hard categories. Nonetheless, such classification essential if we are to develop maps and change products. This section reviews first the definition of forest and forest types, and then the definitions of change, in order to allow an understanding of what it is we are trying to map with EO data.

2.1 Definitions of forest

We traditionally understand the term forest to mean an aggregation of trees, and normally picture a large expanse of mature or reasonably mature trees. One comes into difficulties when attempting to use this definition as the individual terms must be defined: what exactly is a tree? How many trees need to be together for it to be an aggregation? How close do these trees need to be to each other? How large should they be?

Scientists have often been able to sidestep this question, choosing definitions that suit the question at hand. However, once a forest area became part of Land Use, Land Use Change & Forest (LULUCF) reporting requirements under the treaties of the United Nations Framework Convention on Climate Change (UNFCCC), it became necessary to have a legal definition of forest. However, in negotiations it became clear that countries did not wish to have a single definition enforced on them, as differing environmental conditions and political requirements meant they had different desires. There was therefore an agreement to allow countries to choose their own forest definition, but only within a specified range of three axes:

- **Canopy cover:** between 10 and 30 %
- **Minimum Tree height:** of between 2 and 5 metres
- **Minimum area:** of between 0.05 ha and 1 ha

Almost all countries have now chosen definitions using these axes, with those for a few example countries given in Table 1 to show the variety chosen:

Table 1. Forest definitions for UNFCCC purposes for various countries

Country	Canopy cover	Tree height	Minimum area
Brazil	10 %	5 m	0.5 ha
Democratic Republic of Congo	30 %	3 m	0.5 ha
Ghana	15 %	5 m	1 ha
Guyana	30 %	5 m	1 ha
Kenya	15 %	2 m	0.5 ha
Vietnam	10 %	◦ 5 m (natural forest) ◦ 1.5 m (slow-growing plantations) ◦ 3 m (fast-growing plantations)	0.5 ha

It can be seen from the example above that countries have not coalesced on a single value of any of these parameters. The only one with some consensus is the minimum area, which once saw a wide spread of values from 0.05 ha up to 1 ha. The message from remote sensing specialists that the smallest area of forest that could reasonably be mapped using free data (or even, in all likelihood, with commercial data, if considering a country scale) is half a hectare, and that 1 hectare was preferable. The use of such a number also greatly simplified reporting and monitoring by greatly reducing the number of individual forest patches, without normally reducing actual forest area much, compared with using a smaller minimum value. However, the variety of tree height and canopy cover characteristics represent a continued challenge for remote sensing methods, meaning that solutions cannot be easily transferred across borders.

It should be noted that these parameters do not directly correspond to the carbon storage of the ecosystem. It is possible to estimate the aboveground biomass (AGB) of an area by multiplying these three factors, as an increase in canopy cover, tree height, or area all approximately correspond linearly to an increase in AGB. However, more normally (and accurately) AGB is estimated by measuring the diameter of individual trees within a fixed area, and ideally also estimating their height (Chave *et al* 2014). It is therefore quite possible for an area of trees in one location in a country to not be classified as forest, and yet have a higher carbon storage than another that is classified as forest. Further, significant carbon may be stored in other ecosystem carbon pools, for example in soil (especially in peat areas). Such carbon pools are not easily mapped by remote sensing, but can be estimated using ground data, and then extrapolated through the mapping of different vegetation types with different yet known, below-ground, carbon stores (Draper *et al* 2014).

2.2 Definitions of deforestation and degradation

From the above, it is relatively easy to define deforestation. This is generally accepted to be the clearing of trees from an area that was classified as forest such that it no longer meets one or more of the three forest criteria in that jurisdiction. Also that the clearance can occur either directly through harvest, or by setting fires, but would not normally include natural processes such as the destruction of forest following a hurricane.

Degradation is however more difficult to define. The IPCC has defined it, somewhat confusingly, as ‘direct human-induced long-term loss (persisting for X years or more) of at least Y% of forest carbon stocks (and forest values) since time (T) and not qualifying as deforestation' however, this definition requires definitions of X, Y and T, something the IPCC does not attempt (IPCC, 2003). Others have suggested definitions need to include characteristics relating to biodiversity or ecosystem services, which can be very hard to map on the ground, let alone by satellite (Herold & Skutsch 2011).

For the purposes of this review we will use a definition based on parameters that can be easily monitored from EO data and that relate to carbon emissions: ‘*degradation is the loss of aboveground biomass due to anthropogenic disturbance from an area defined as forest, that remains defined as forest after the disturbance*.’ The loss could equally be defined in terms of canopy cover, which is the parameter most easily monitored by optical remote sensing data, but aboveground biomass is preferred because the removal of sub-canopy trees is definitely degradation, but will often not change observed canopy cover. In all cases though the removal of trees will cause a reduction in forest biomass.

3 Classifying forests

Mapping forests and forest change can be broken down into two related, but distinct, problems. One is the production of one-time maps for forests and forest types, the other is maps of change. One-time maps range from the very simple, mapping of forest vs non-forest, through to the more complicated maps dividing forested areas into different strata, or the whole landscape into land use as well as land cover categories. Such one-time maps may also have classes that relate to change, for example classes called ‘degraded forest’, which suggest that such forest was at one time ‘intact forest’ and has since been degraded. Similarly, a comparison of one-time maps produced at different points of time is often used to provide statistics and maps of the area of forest that has changed.

One-time forest classification and change detection are however distinct disciplines, and a naïve comparison of forest type maps produced at different points in time should not be considered as change detection and can lead to spurious results (GFOI 2014, GOFC-GOLD 2015). Change statistics between one-time maps must consider the errors and biases involved in each map, their comparability, and the resulting error characteristics of the change maps themselves, rather than simply propagating the thematic accuracy for the individual land cover classes. It is now widely recognised that change detection should be approached through direct comparison of remote sensing products from multiple time periods, rather than from comparing individual maps (GFOI 2014).

Here we therefore consider the two problems separately, in this section discussing and evaluating methods for mapping forest types and strata, and in Sections 4-6 discussing the more difficult problem of change detection.

3.1 Satellite datasets used for mapping forest type

Table 2 shows the main satellites that have been and are used for mapping forest from non-forest, and for mapping different forest types. Example studies are given that have used the satellite in question, along with a short description of methods used and, where available, information on accuracy of the results.

This table is a demonstration of what is possible with each satellite dataset. As with all reviews of the literature there is a significant publication bias: negative results are rarely published (Fanelli 2012). It is therefore necessary to infer from what is not published, in terms of types of stratification and study areas, in addition to considering the accuracy provided, when attempting to use these data to assess the strengths and weaknesses of each satellite sensor and methodology.

Table 2. Satellites used for one-time forest and forest type mapping

Satellite sensor	Period operational	Resolution	Study and site	Number of classes mapped & method	Accuracy assessment
Optical satellite data					
Corona (spy satellite)	1962-1972	2-3 m	Song *et al* (2015) Central Brazil (covering parts of Mato Grosso, Tocantins & Para).	Corona satellite data has only one band, i.e. it is black & white. Its high resolution texture was used to enable SVM classification of forest/non-forest at a 30 m resolution.	90% accuracy for forest/non-forest against independent (but visually derived) training points.
Landsat MSS	Landsat 1: 1972-78 Landsat 2: 1975-83 Landsat 3: 1978-83	57 x 79 m	Roy *et al* (1985): forest types in Arunachal Pradesh, India.	Uses Landsat 2 MSS data from 1979. Six different forest types are considered. Both automated (using a simple computer classifier) and manual classification tested.	Accuracy assessed using independent field data, best map varied between 54 and 95 % by class. Overall ~75%. Computer classifier outperformed manual classification.
			Huang *et al* (2009), Atlantic Forest of Paraguay	As part of a larger study, 3x3 windows of Landsat 1 MSS pixels were visually assessed as being 'forest', 'non-forest' or 'partially-forested'.	The resulting points were compared to Landsat TM classifications to estimate deforestation rates, but no accuracy assessment was attempted.
Landsat TM	Landsat 4: 1982-1993 Landsat 5: 1984-2012	30 m	Foody *et al* (1996), regenerating forest near Manaus, Brazil	Maximum likelihood classification of 5 regeneration classes.	User's accuracy for classes ranging from 97% (for <2 years and >14 years) to 39% (for 3-6 years). Overall accuracy 73%. Much misallocation between neighbouring classes.

Landsat ETM+	Landsat 7: 1999-present *(Scan-line corrector failed 2003)*	Pan: 15m MS: 30m	Salovaara *et al* (2005), intact primary forest in NE Amazonian Peru	3 forest types: Inundated forest, terrace forest and Pebas formation. All have distinct species assemblages. Classification using simple discriminant analysis using ETM+ and elevation variables.	Accuracy was low at 200m scale, but better at 500 m scale. Overall accuracy of 85%, but with user's accuracy of only 48% for the Terrace forest class which was confused with the Pebas formation.
			Hansen *et al* (2013), global maps of % tree cover	% tree cover mapped globally for 2000 (data available here[1]) and 2010 (here[2]) at 30 m resolution, based on ETM+ data from 2000-2012 and training data derived from hyperspatial (<2 m resolution) imagery and a bagged regression tree approach. Effectively an update of the Vegetation Continuous Field product, an annual tree cover product produced using MODIS data at 250 m resolution.	No formal accuracy assessment was performed for these tree cover products. Various studies since have found them to have significant regional biases, but overall to show the correct patterns. Clearly these tree cover percentage products are not true classifications, but the continuous %tree cover layers can be easily divided into classes within a country or region, with differing ecological characteristics and/or disturbance histories.

[1] University of Maryland (2016). 'Global Forest Change 2000–2014 Data Download' URL: http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html
[2] USGS (2016). 'Global Tree Canopy Cover circa 2010' URL: http://landcover.usgs.gov/glc/TreeCoverDescriptionAndDownloads.php

			Hansen *et al* (2016b), vertical transect through the entire African tropics, covering grassland, savanna, woodland and tropical forest.	Uses ICESat GLAS LiDAR data to provide training data on tree height, then maps this at 30 m using Landsat 7 & 8. Discovers the data naturally fall into 3 classes of forest height: 5-10m, 11-17m, and >18m. Training using a bagged regression tree algorithm, choosing the median results of 7 bagged models each based on 10% of the training dataset.	Found no ability to distinguish heights of trees >20m using Landsat data; showed that accuracy of height modelling increased greatly with multiple observations. Mean Absolute Error is ~4m with 10 good observations, but falls to <2 with >40 observations. Interquartile red reflectance (i.e. mean of the middle 25%-75% of observations for each pixel) was the most important variable.
Landsat OLI	Landsat 8: 2013 - present	Pan: 15m MS: 30m	Fan *et al* (2015), Xishuangbanna region of southwest China	Examined 3 classes: natural forest, rubber plantations and agriculture. Multi-temporal OLI data from March 2014 was differenced from February 2014: over this period rubber loses its leaves so has a big difference, but natural forest stays green.	96% accuracy in distinguishing the classes, against independent test data derived from visual interpretation of high resolution (<5m) optical data and field plots.

SPOT-4 VGT	SPOT-4: 1998 - 2013	1000 m	Mayaux *et al* (2006) – Global Land Cover 2000 (GLC2000) map	A global land cover map was produced for the Millennium Ecosystem Assessment by the EU's Joint Research Centre, involving hundreds of global collaborators. It had a common 16-class legend involving 8 forest classes (though some regional maps divided these into further classes).	Validation against Landsat data suggested an overall accuracy of around 45%. However this is mostly due to the effect of mixed pixels in this coarse resolution dataset. For 1000m pixels that were entirely homogeneous accuracy was 91% - but this was only 9% of the total validation data. When classes were collapsed to just forest/non-forest accuracy increases to 80%.
			Carreiras *et al* (2006) Brazilian Legal Amazon	4 forest classes: Cerrado savanna, agriculture/pasture, secondary forest, primary forest. Trained using visual analysis of Landsat. Used various machine learning algorithms; tested Probability-bagging Classification Tree (PBCT) had highest accuracy.	Overall accuracy reported at 92% using PBCT. However, this overstates accuracy as this was poor for some classes, especially Secondary Succession Forest which had commission errors of >40% and omission errors of >60%. Cerrado savanna also had errors >80%. Waterbodies, pasture and primary forest were very well mapped, inflating the overall reported accuracy.

MERIS	ENVISAT: 2000 - 2012	300m	Arino *et al* (2007), GLOBCOVER: Global land cover maps for 2005 and 2009	Global landcover map for the years 2005 and 2009 was produced by a consortia of ESA & EU organisations, essentially updating the GLC2000 map described above but at 300m resolution and using 22 classes.	The thematic accuracy of GLOBCOVER is estimated at 73% weighted across all classes (Defourny *et al* 2012), considerably exceeding that of GLC2000. Considerable confusion still existed between forest classes.
MODIS	Terra: 2000-present Aqua: 2002-present	250m – 1000m depending on band	Friedl *et al* (2010), global landcover, produced annually at 500 m resolution from 2000 – present.	Defined 17 classes, divided into various different higher-level schemes. Classification confidence layer also produced. Ten boosted decision trees used to produce the product, based on training data from 1860 sites distributed globally.	Overall accuracy estimated at ~75%, though errors for some classes and in some areas can be far higher. Considerable confusion exists between forest classes, especially when pixels may be mixed at 500 m scale.

			Baccini *et al* (2012), pantropical map of Aboveground Biomass (AGB)	Mapped Aboveground Biomass (AGB) throughout the tropics for 2007 using 500 m MODIS data, trained using ICESat GLAS laser footprints. RandomForest was used to extrapolate the GLAS footprints using the MODIS data.	Root Mean Squared Error (RMSE) of ~25 Mg C ha^{-1} against independent test data (though this itself has errors and biases, (Mitchard *et al* 2014)). Approximately equivalent to an accuracy of about 70% if attempting to place 500 m pixels in the correct 50 Mg C ha^{-1} biomass class (this would divide most tropical woodland/forest areas into 4-5 classes).
Rapid Eye	2009 – present	5m	Adelabu *et al* (2013), mapping types of mopane woodland dominated by different species in Botswana	Training data were collected for 5 different classes of Mopane woodland in the field, and then pixel-based RandomForest or Support Vector Machine classifiers used on the 5-band RapidEye data.	Overall accuracy against test data of 89% for SVM, 85% for RF. Some classes only achieved user accuracies of 82-84%, others ~94%. Pixels were averaged within polygons collected on the ground for training data, so the training was object-based.
Sentinel-2	2016 – present	10m	*No studies are published as yet. However Sentinel-2 will become very widely used for forest mapping in time due to its high revisit time (<5 days, compared to 16 days for Landsat) and high resolution. It is thus included in this table for completeness purposes.*		
IKONOS	2000 – 2015	Pan: 1m MS: 4m	Wang *et al* (2004), mangroves on the Caribbean coast of	Here 3 types of mangrove plus rainforest were distinguished using object-based and	A combined object-based and pixel-based method achieved an overall accuracy of 92%,

	A number of satellites with a similar capacity but higher resolution still now fly, named GeoEye-1 and WorldView-1/2/3/4		Panama	pixel-based methods, using standard spectral-based classifiers obtaining data from either the clusters or the pixels.	with individual user's accuracies ranging from 74% for 'red canopy mangrove' to 98% for 'white canopy mangrove'.
Synthetic Aperture Radar (SAR)					
JERS-1 *(L-band)*	1992-1998. HH only.	20 m (normally used at 100m)	Podest and Saatchi (2002), Amazon rainforest	Tested in two sites: a forest/savanna area (4 classes) and a flooded forest area (6 classes), using a multi-scale texture classifier.	Accuracies >87% for all cases, except for permanently and seasonally flooded forest where there was confusion between the two classes giving ~76% accuracies.
ALOS PALSAR *(L-band)*	2006 – 2011	12.5 m Most widely used mode (FBD) is HH+HV	Hoekman *et al* (2010), complete vegetation map of Borneo	FBD (HH+HV) and FBS (HH only) mosaics for all of Borneo created for 2007. Semi-supervised mixture modelling followed by Markov Random Field classification. 9 forest classes, plus 11 other land cover classes.	86% accuracy, with further 8% of confusion a case of 'partial agreement', i.e. confusion with a very similar class. Given large number of classes this is an excellent performance.
			Thapa *et al* (2014), forest-non/forest map of Sumatra, Indonesia.	Attempted to use a single HV threshold to separate natural forest from non-forest across the island.	A threshold of -11.5 dB HV had the highest accuracy, with 79% of pixels correctly classified compared to a test dataset.

Radarsat 1/2 *(C-band)*	Radarsat-1: 1995-2013 Radarsat-2 2007-present	8 m (HH) 8 m (HH + HV, or full pol, i.e. also VV + VH).	Li *et al* (2012) Pará state, Brazil, along Transamazon Highway	ALOS PALSAR (HH+HV) and Radarsat-2 (HH+HV) used alone and in combination to map 6 forest classes, including 3 intact and 3 recovering classes. Various algorithms tested, from simple maximum likelihood through to neural networks (Fuzzy ARTMAP)	Neither performs well individually. When forest split into just two classes (along with 4 other non-forest classes), ALOS PALSAR metrics (including texture) achieves 74% accuracy, and Radarsat-2 55 %. The neural network (Fuzzy ARTMAP) and regression tree classifiers performed similarly and best, outperforming the simpler maximum likelihood classification.
ASAR *(C-band)*	ENVISAT: 2000-2012	30 m (HH + HV)	Dong *et al* (2015), Riau Province, Sumatra, Indonesia	Multi-temporal ALOS PALSAR (HH+HV) and ENVISAT ASAR (HH+HV) data were compared with Landsat 7. A 4-class classification was attempted, differentiating Oil Palm, Acacia, Natural forest and non-forest classes, using maximum likelihood classifications both alone and in combination.	Dual-band ASAR data could distinguish classes with an accuracy of 86% (compared to an unvalidated optical map). Adding L-band data did not improve the accuracy, suggesting C-band data can classify these forest types well.

Sentinel-1	Sentinel-1a: 2014-present Sentinel 1b: 2016-present	Normal IWS mode (HH + HV, or single HH or VV) 20 m	Balzter *et al* (2015), Thuringia, Germany *(no tropical studies have been published as yet)*	Sentinel 1A HH/HV and VV/VH scenes tested for classifying 27 CORINE classes, including 3 forest classes (broad-leaved, coniferous and mixed forests), with elevation data also used to assist the classification.	Best overall accuracy of 68%, including the elevation data. Radar alone had a best accuracy of 48%. User accuracy for the forest classes in this best classification were 71%, 79% and 42% respectively, with almost all confused pixels classified as an alternative forest class. 92% accuracy for identifying forest when considered together.
TanDEM-X *(X-band)*	TerraSAR-X 2007-present TanDEM-X 2010-present	From 1 m	De Grandi *et al* (2016), Sungai Wain Protection Forest, Kalimantan, Borneo, Indonesia.	Operating together, these two satellites allow the production of very accuracy Digital Surface Models (DSM). This study uses the texture of a DSM at 5m resolution (the satellite did not collect the data used here at the maximum possible resolution) to differentiate primary and secondary forest, as well as scrub and grassland.	The accuracy of separation of primary and secondary forest is estimated as lying between 85 and 98 %. This compares poorly to airborne LiDAR compared in this study (94-99%), but is still an encouraging result. Forest/non-forest were separated with an accuracy >95% by both radar and LiDAR.
Radar/Optical Fusion					

Landsat 5 TM, JERS-1 *(L-band)* SIR-C *(C-band)* X-SAR *(X-band)*	Landsat 5: 1984-2012 JERS-1: 1992-1998 SIR-C: 1994 X-SAR: 1994	Analysis performed at 25 m.	Kuplich (2006) regenerating forest north of Manaus, Brazil	Six forest classes at various stages of regeneration. Neural network classifier trained using ground data with 2 hidden layers.	Both SAR and TM bands alone could distinguish pasture, regenerating forest and mature forest 'accurately'. For all six classes accuracy low for radar bands alone, but rises to 70% with radar & TM together. 87% accuracy if regenerating classes lumped into two – 0-5 years and 6-18 years.
MODIS, Quic-SCAT *(Ku-band)*, ICESat	Mid-2000s only, limited by operation of ICESat GLAS LiDAR.	Analysis performed at 1 km	Saatchi *et al* (2011), pantropical map of aboveground biomass (AGB).	Divided global forests into 11 classes of differing biomass values. Put pixels into one of these classes using tens of thousands of GLAS LiDAR footprints, then extrapolated those using MODIS optical and QuickSCAT radar data, using a Maxent model.	Error was determined on a pixel level, and varied between 6 and 53% of the class value. Average relative error of 31% per pixel across the dataset, suggesting about a ~50% chance of putting a pixel in the correct of the 11 classes, but a ~80% chance of putting a pixel in the correct or neighbouring class. However, biases in the input dataset suggests these may be overstatements of accuracy (Mitchard *et al* 2014).
Optical/LiDAR Fusion					

Landsat TM/ETM+, SRTM DEM, airborne LiDAR	2000 for SRTM elevation 1984-present for Landsat TM/ETM+ Airborne LiDAR available on demand.	Maps produced at 30 m, airborne LiDAR had a far higher resolution.	Asner *et al* (2012), study site covers 40% of Amazonian Peru.	While not strictly comparable to other studies in this table as it uses aircraft LiDAR in addition to satellite optical data, it was thought useful to include an example of what can be achieved using LiDAR data fused with Landsat. AGB maps were made for small sections of the landscape based on aircraft LiDAR data, then scaled to the landscape using Landsat and elevation data and either a stratification or a regression based method. Landsat was converted to estimates of Vegetation Cover using CLASlite software.	The stratification approach produced the highest accuracy when tested against independent (withheld) LiDAR data. It achieved an error of 33% of the mean carbon stock at a 30m resolution, falling to 24 % at the 1 ha resolution (assuming the field plot data is 'true', i.e. ignoring errors from allometric equations). This suggests about a 50% chance of putting a pixel in the correct 50 Mg ha^{-1} AGB class, lower at low biomass values and higher at high biomass values. LiDAR data alone (in areas where it was available) could map AGB with about 80% accuracy for a 0.28 ha field plot.

From Table 2 it is clear that a wide range of satellite data are available that can map forest cover and forest types. In general more recent studies have higher accuracies, due to a combination of higher resolution satellite data and more advanced methods. Table 3 synthesises the data collected in Table 2, along with the opinion of the author based on experience working with these datasets, in order to assess the suitability of different satellite datasets and analysis methods for three tasks:

- **Forest/non-forest mapping (*F/NF*):** the simple binary classification of a landscape into these two classes, according to the local forest definition
- **Simple within-forest stratification (*SimpStrat*)**, e.g. dividing forested areas into two classes, e.g. 'intact' and 'degraded', or 'forest' and 'woodland'
- **Complex within-forest stratification (*CompStrat*)**, involving more than two classes. Included here are consideration of studied that have mapped tree cover, tree height or aboveground biomass continuously: such maps effectively provide the ability to separate out many different forest classes, or indeed to use the full continuous distribution.

The ability of the data to perform these three tasks are given using these categories:

- **Not attempted:** no peer reviewed publications were found that attempted this
- **Unsuccessful:** classification accuracy lower than 70% in studies found, making this data/method unlikely to be useful for any users
- ***:** User's accuracy of 70-80% found in studies – unlikely to be useful for most purposes, but some potential
- ****:** User's accuracy of 80-90 % found – likely to be useful in some circumstances, though unsuitable for change detection between layers as is
- *****:** User's accuracy of >90% found in some studies – useful in many circumstances, and potentially usable for direct change detection, with caveats.

The data layers in the table are ordered in ascending order of resolution. As discussed in 1.3, it should be noted that while accuracy is normally higher with higher resolution data, higher resolution data is in general more expensive to both collect and process, and is available at a lower frequency, than lower resolution data.

Table 3. Accuracy of satellite platforms for one-off forest and forest type mapping

Satellite sensor	Period operational	Resolution	Frequency and cost	F/NF accuracy	SimpStrat accuracy	CompStrat accuracy
Optical						
Hyperspatial e.g. IKONOS, WorldView, GeoEye	2000 – pres	Pan: 0.3–1m MS: 1.2–4m	On demand, up to daily. *High cost.*	***	***	**
Corona (spy satellite)	1962-1972	Pan: 2-3m	Only 1-2 observations ever over most of the tropics. *Free*	**	Not attempted, possible	Not attempted, unlikely to be successful
RapidEye	2009-pres	5m	5 days *Medium cost*.	***	***	**
Sentinel-2	2016 – pres	10 m	5 days. *Free*	**** (based on OLI results)*	**** (multi-temporal, based on OLI results)*	*** (multi-temporal, based on OLI results)*
Landsat 8 OLI Landsat 7 ETM+	2013 – pres 1999 – pres (scan-line corrector failed 2003)	Pan: 15m MS: 30m	16 days. *Free*	***	1 image: *** Multi-temporal: ***	1 image: * Multi-temporal: **
Landsat 4/5 TM	1984-2012	30 m	16 days, though often less frequent in practice. *Free*	***	*	*
Landsat 1/2/3 MSS	1972-1983	57 x 79 m	18 days. *Free*	**	*	*
MODIS	2000-pres	250m – 1000m	Daily, 16-day composites often used in practice. *Free*	**	*	Multi-temporal: *
MERIS *Sentinel-3*	2000-2012 *2016-*	300m	Daily. *Free*	**	*	Multi-temporal: *
SPOT 4/5 VGT	1998 – 2014	1000m	Daily. *Free*	**	Unsuccessful	Unsuccessful
Synthetic Aperture Radar (SAR)						
X-band TerraSAR-X TanDEM-X	TerraSAR-X 2007-pres TanDEM-X 2010-pres	From 1 m, normally 3m. Normally HH only.	Complete coverage of the planet completed once. Further data on demand. *High cost.*	***	**	Not tested
C-band	Radarsat-1:	8 m	24 days	**	*	Unsuccess-

Satellite sensor	Period operational	Resolution	Frequency and cost	F/NF accuracy	SimpStrat accuracy	CompStrat accuracy
Radarsat- 1/2	1995-2013 Radarsat-2 2007-pres	(HH) 8 m (normally HH + HV).	*Medium-high cost*		(dual-pol)	ful
C-band Sentinel-1	Sentinel-1a: 2014-pres Sentinel 1b: 2016-pres	20 m (normal IWS mode, either HH/VV only or dual pol)	8 days *Free*	*** (single test in Germany)	Unsuccessful using single images in German test site, no published tests elsewhere. May be possible especially with multi-temporal data	
C-band ASAR	2000 – 2012	30 m (HH + HV)	Infrequent, acquisitions	**	** (dual-pol)	Not tested
L-band ALOS-1/2 PALSAR-1/2	ALOS PALSAR: 2006-11 ALOS-2 PALSAR-2 2014-pres.	12.5 m (normal FBD mode HH+HV) 6.25 m (normal FBD mode HH+HV)	Every 2-3 months over most of the tropics. *Cost, though free annual mosaics produced at 25m.*	***	** Maybe *** in drier ecosystems with maximum AGB <150 tonnes ha^{-1}	**
L-band JERS-1	1992-1998	20 m (normally used at 100m)	Variable. At least 2 observations across tropics. *Free*	***	**	*
Data Fusion						
Radar/ Optical, e.g. Landsat L-band SAR	Possible from 1990's to present	25-30 m	Variable. Gaps in L-band record 1998-2007, 2011-14. *Free, except 2014-pres.*	***	**	**
Radar/ Optical/ satellite LiDAR, e.g. MODIS, QuikSCAT & ICESat	Mid-2000s, (limitation ICESat; similar data from GEDI will start 2018)	500 – 1000 m	One-off only as limited ICESat collections, *all datasets free*	***	**	*
Optical/ airborne LiDAR	Present-	30 m	Dependent on airborne Lidar. *High cost.*	***	***	** (*** possible where airborne LiDAR collected)

From Table 3 it is clear that there are many datasets which can distinguish forest from non-forest with high accuracy (>90%). These include free 10 and 30 m resolution optical data (Sentinel-2 and

Landsat), and free 20 m resolution radar data (Sentinel-1 and, only free for annual mosaics, ALOS PALSAR), as well as data at a higher resolution for a cost, and at a lower resolution for increased spatial coverage. Given the discussion of forest definitions in Chapter 2, it is apparent that the free datasets will be sufficient for monitoring the change in forest area in most situations. This does not mean that any of these datasets can automatically be used to track changing forest area through time: the error characteristics (errors of omission and commission) and any resulting biases still need to be considered when comparing maps produced using these methods at different points in time, as discussed in the next chapter. However, when analysed properly, any dataset given *** in the above table should be useable.

Stratifying forest into two types is clearly a more challenging problem. The only free dataset to achieve *** here is Landsat OLI when analysed in a multi-temporal fashion, with it being likely (though unproven) that Sentinel-2 could be used in a similar way at a 10 m resolution. Applying such analysis methods in practice can be difficult due to cloud cover and data volumes, and multiple observations per year are rarely available pre-2013 (when Landsat 8 was launched), though are ever-more likely to be available as both Sentinel 2 satellites become operational. Sentinel-1, a C-band radar satellite, also offers potential in this regard when analysed in a multi-temporal fashion, with an advantage over optical methods in that it is insensitive to cloud cover; however this has not been proven by any studies as yet. There are clearly a number of commercial datasets that can achieve this split, from high cost options such as the use of airborne LiDAR, through to the lower cost option of purchasing RapidEye data. It also appears that in lower biomass/drier ecosystems, L-band radar may be an option, for which free data is now free in the mid-90's and from 2007-11, and with one free annual mosaic produced for 2014/15, though with no more free data guaranteed it may not be a cost-free option.

Stratifying forest into more than two classes is clearly a very challenging task using current satellite technology. No satellite methods achieved >90% accuracy for this task in the literature review, with the single successful study (Asner *et al* 2012) only achieving this under the small areas where airborne LiDAR was collected. Recent developments in UAV LiDARs will reduce the cost of data collection (Esposito *et al* 2014, Gottfried *et al* 2016), but collecting data from airborne sensors and processing LiDAR data will always be expensive. If such stratification is necessary then it will likely be necessary to pay for satellite data, of either high resolution optical or radar data, potentially to undertake some data fusion, and accept that accuracy is unlikely to exceed 90%, making change detection difficult. It is also clear from the literature review that accuracy decreases the more classes are considered, and that the classes that are easiest to distinguish from remote sensing data, for example based around different levels of canopy cover, may not be those required by users, which may for example relate to different species groupings.

3.2 Complementary datasets

It should be clear from Table 3 that even separating forests into two classes ('SimpStrat') is challenging, and into more than two classes ('CompStrat') is more challenging still. In practice the difficult relates directly to the separability of the classes, with some likely to be easier to separate than others. Optical sensors see only the top of the forest canopy, limiting their ability to infer characteristics of forest structure (such as biomass, tree height, the presence of tree stumps indicative of disturbance). Although radar sensors may be more sensitive to such forest characteristics, the data is often expensive and there is more need for research in order to create optimal methods. Moreover, the accuracy of studies does not suggest radar can provide suitable stratification results as yet. In turn, LiDAR data, the optimal tool for forest stratification, is too patchy from satellite mounted sensors (only rare, isolated footprints from ICESat GLAS in the mid-2000s are available) and expensive from aircraft/UAVs.

There is therefore a role for using spatial datasets from other sources. Field data is one obvious option, but collecting sufficient field data to create good maps on its own is normally unfeasible, unless the study area is very small. Nevertheless, other ancillary datasets that may be useful exist, for example:

- Vector layers of the road network and settlements (ideally with additional data on the quality of each road and the population of settlements)
- Vector layers of rivers and elevation data (which provide access points, but proximity to rivers may also indicate different forest types)
- Expert vegetation maps, based on long field experience
- Historical land cover maps, which may indicate vegetation history
- Topographic maps and DEMS
- Climate maps
- Soil and geological maps

The vector layers of roads and settlements are especially useful in mapping forest degradation, as this is likely to occur only where human access is possible. The difficulty is that in introducing such data the resultant map becomes more of a theoretical model than a scientific data layer, but if combined with good ground data, useful maps can then be produced. We do not know of cases where road data have been used directly to assist with forest stratification, but there is evidence that such an approach could be effective based on a study showing significantly different vegetation around abandoned and active roads in the Congo basin (Kleinschroth *et al* 2015).

Rivers provide access to forests, being the predominant means of transport throughout much of the remaining large rainforest areas. Therefore, similarly to the argument above, we would expect differences in forests to associate with distances from rivers, and indeed that has been found (Imbernon & Branthomme 2001, Kumar *et al* 2014). Equally, forests near rivers may be very different from those in the surrounding area, as they may flood and have different soil and water availability characteristics (Hess *et al* 2015), aiding classification. A Digital Elevation Model (DEM) may be useful in conjunction with a river map to predict how far the river's influence may spread, and in general as vegetation does change with elevation (Frederick *et al* 2014).

The use of historical landcover maps to inform forest stratification may be considered close to a change detection application, and belong in Chapter 4. However, it is a different approach, as a one-time map of vegetation characteristics (often age of regeneration) is derived from images of multiple time periods in the past. For example, Kimes *et al* (1998) reviewed this method and presented its strengths in terms of greatly increasing accuracy compared to using remote sensing data from a single year, as well as weaknesses and biases due to the nefarious influence of missing data due to cloud cover, which can result in an over-estimate of forest age. It has been used successfully since, especially in temperate or boreal forests (e.g. in Oregon, Pflugmacher *et al* (2012)), but also in the Amazon where a strong dry season almost guarantees at least one cloud-free Landsat scene per year (Espírito-Santo *et al* 2005, Etter *et al* 2005). However, such a method does have a cost in terms of the necessity of analysing many scenes to produce a one-time map, and also a limitation in that the maximum age of regenerated forest that can be established using this method is the same as the length of time between the oldest image and the more recent image. Theoretically this could be over 40 years if Landsat 1-3 scenes from the 70s are compared to present, but cloud free Landsat 1-3 scenes are rare, so typically the earliest good Landsat data is from the mid-1980s with Landsat 4 or 5, meaning a maximal chronosequence class of '>30 years'. There may be a very large ecological and carbon storage difference between forest of 30 years age and primary forest, so in many cases this will not be sufficient to produce a useful stratification.

4 Change Detection Approaches

The perfect detection method would provide frequent, accurate, high resolution, wall to wall coverage of the timing of forest disturbance events with high (and known) accuracy, along with information about the degree and type of disturbance, with guaranteed continuity and all at low cost. Even better, such a system would also detect and be able to map the presence and magnitude of forest growth. Unfortunately, this perfect solution does not exist.

In this chapter we will first cover existing services, which provide some aspects of this system for deforestation monitoring. We will then consider what has been proven possible for change detection, considering both deforestation and degradation/regrowth monitoring, and assess the utility of different sensors and analysis systems for producing such results. Finally, we will look to the future and what could become possible with new sensors, either recently or soon to be launched, and using UAV/aerial data.

4.1 Current systematic deforestation products

There are some services that provide aspects of the ideal system discussed above. For example the University of Maryland (UMD) product (Hansen *et al* 2013) provides annual global maps of deforestation at a 30 m resolution, though with a time lag (at the time of writing, October 2016, the latest layer available is for 2014). Alternatively, the terra-i and FORMA systems give more frequent (every 16 day) alerts of deforestation at a coarser resolution (250m and 500m respectively). The features and capacities of these systematically produced, free-to-use products are given in Table 4 . Note that all these datasets are attempting to detect total tree cover loss, none aim to detect degradation, though some may in fact detect more severe forms of degradation and report it as forest loss.

Table 4. Existing systematic and open deforestation datasets

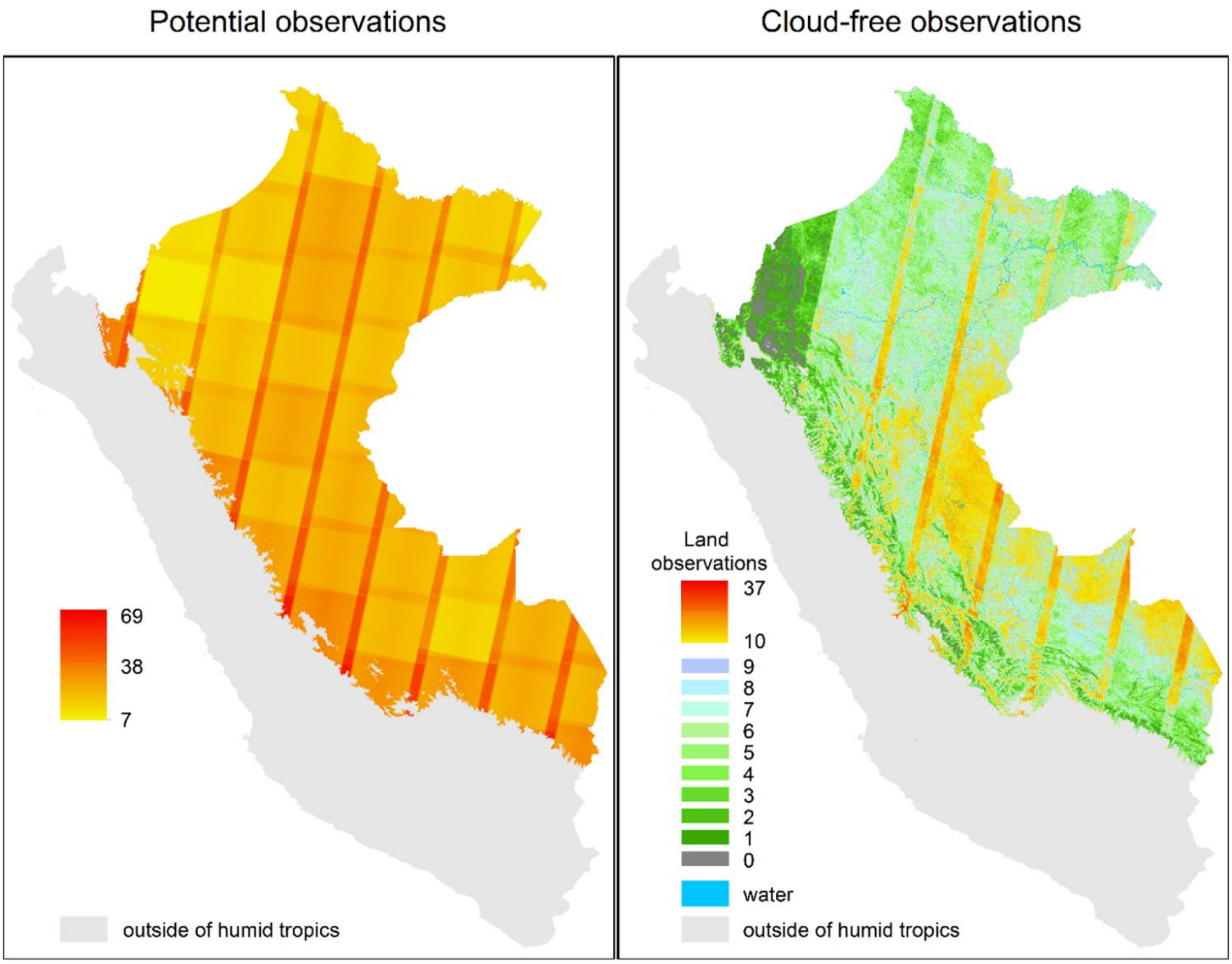
1 Dataset	2 Coverage	3 Spatial resolution	4 Data source	5 First year	6 Temporal resolution	7 Maximum lag*	8 Reference/ website
Hansen/University of Maryland/ Google/USGS/ NASA ("UMD")	Global	30 m	Landsat ETM+/ OLI	2000	Annual	2 years	(Hansen *et al* 2013) website[3]
Global Land Analysis and Discover (GLAD) alerts (from UMD)	Brazil, Peru, Republic of Congo & Kalimantan	30 m	Landsat ETM+/ OLI	2014	Dependent on cloud cover, from weeks to many months	~2 weeks after detection, but longer for cloud-covered areas	(Hansen *et al* 2016a) website[4]
PRODES (produced by INPE, Brazil's National Institute for Space Research)	Brazilian Amazon	60 m (minimum mapping unit 6.25 ha)	Landsat TM/OLI; CBERS; LISS-3; DMC-2	1975, data available online from 2000	Annual	~3 months	(Camara *et al* 2013, PRODES 2016) website.[5]
Terra-i	Latin America	250 m	MODIS + TRMM (rainfall)	2004	16 days	~2 months	(Leisher *et al* 2013) website[6]
DETER (produced by INPE)	Brazil	250 m	MODIS	2004	Monthly	~4 months	(Shimabukuro *et al* 2012) website[7]
FORest Monitoring for Action (FORMA)	Humid tropics	500 m	MODIS	2006 - 2015	16 days	~1 month, no data released since mid-2015.	(Hammer *et al* 2014) website.[8] *New 250m product to start soon.*

[3] http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html
[4] http://glad.geog.umd.edu/alarm/openlayers.html
[5] http://www.obt.inpe.br/prodesdigital/cadastro.php
[6] http://www.terra-i.org/terra-i/data.htm
[7] http://www.obt.inpe.br/deter/dados/
8 http://data.globalforestwatch.org/datasets/550bd7fc2c5d45418e5e515ce170da22_3

*Defined here as the maximum wait from the end of the period considered to the data being made available. For example if data for deforestation in 2014 was provided in June 2016 that would be a 6 month lag, as the deforestation data period under consideration finishes 31st December 2014.

Looking at Table 4 it is obvious that all entries use optical satellite data, and mostly from either the Landsat or MODIS satellites. The reason for this is largely that of data availability: to make change detection products one needs consistent data, ideally several times per year, and only optical satellites have provided that over the past decade. Traditionally the only products that can produce estimates with an update frequency smaller than a year have relied on medium resolution optical data, mostly MODIS: as this records everywhere on the planet 2-4 times per day, cloud-free images are pretty much guaranteed within the 16-day composites they produce. This results in a resolution trade-off, with the maximal 250 m resolution meaning that many deforestation events will never be detected as they are too small. The GLAD group have recently attempted to produce alerts using Landsat data at 30 m, and will soon role this out across the tropics, but the observation frequency suffers from cloud cover, as displayed in Figure 2 below:

Figure 2. Potential and Cloud-free observations over Amazon Peru from Landsat 7 and 8 combined over an 18 month period 2014-15 (Hansen *et al* 2016a)



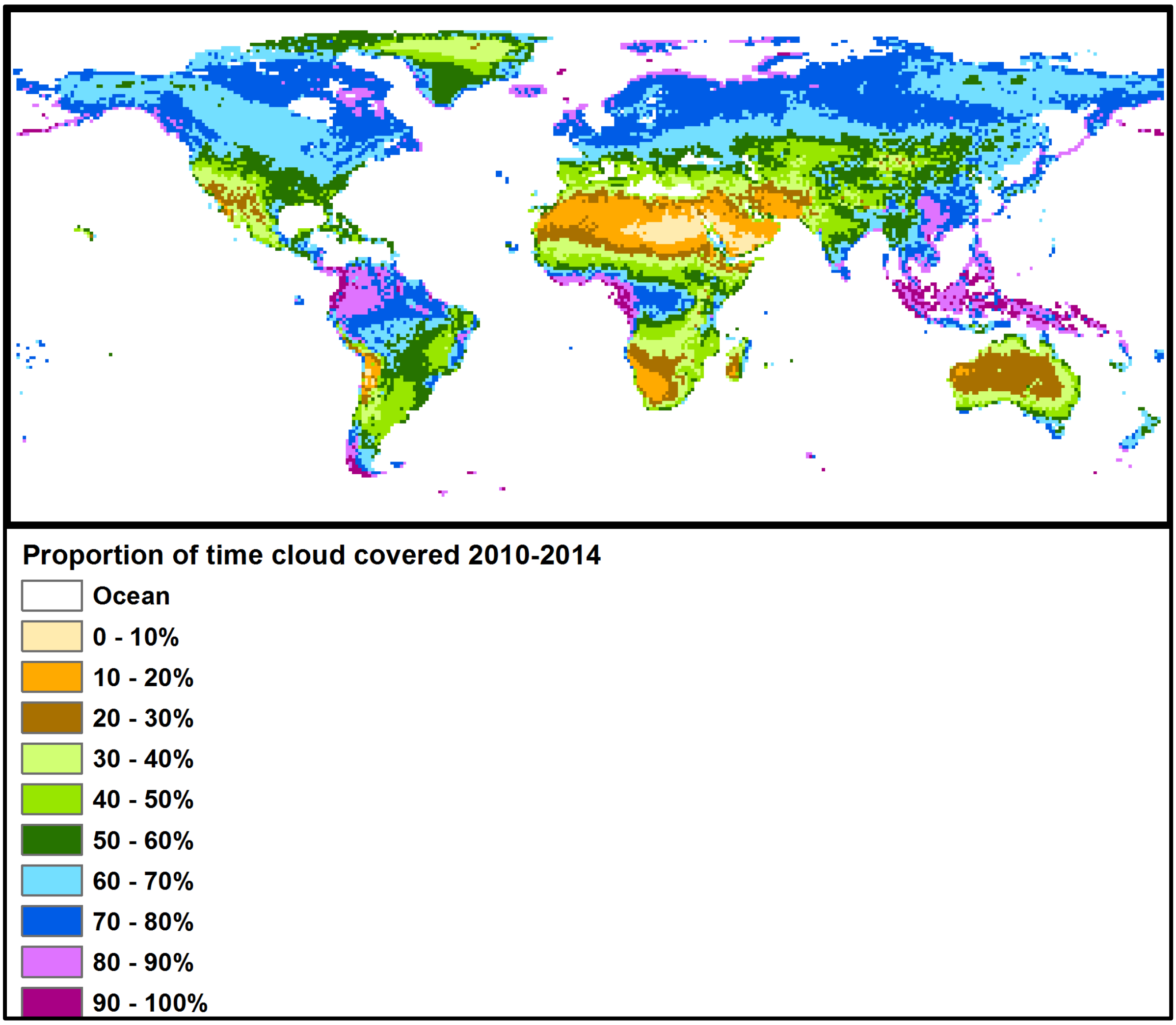
The narrow stripes of increased scene availability in Figure 2 are from pixels that are on the overlaps between scenes. Both Landsat satellites are on the same orbit, repeating an identical sequence at an offset of 8 days.

This cloud-cover limitation is severe in many areas of the tropics, and has led some to call for optical data to be dropped as the main way of monitoring deforestation and degradation in favour of radar data, which is insensitive to cloud cover (Asner 2001). A lack of data availability has held back the use of radar data in such services, but this may be changing, as discussed later in this section.

In some areas, it is clear that cloud cover will make it impossible to produce sub-annual or rapid response alerts. This is regardless of the increasing frequency of observations that has been triggered with, for example, the launch of the Sentinel-2 service, which should allow observations every 5 days (as opposed to every 16 for Landsat): that will improve matters, but some areas will remain cloudy continuously for months and no level of additional observations will help. Cloud cover will have less effect on annual products, though it may still cause changes to be detected 1-3 years late, potentially giving a false picture of success of forest protection efforts after a cloudy year for example, and to be misattributed between years, making the mapping of trends and drivers more difficult (Hansen *et al* 2013).

For the purposes of this review we have mapped the proportion of daily observations for which different areas of the tropics are cloud covered, based on averaging five years of data from 2010-2014 from the MODIS cloud fraction data (NEO 2016) (Figure 3). This clearly shows that some areas may be highly suitable for regularly monitoring with Landsat data, with a high proportion of the ~44 Landsat observations per year being cloud-free. Whereas for some areas, achieving even one cloud-free image may be difficult (experience shows that in areas with >90% cloud cover every image in Landsat will typically contain at least some cloud cover, with cloud-free images only occurring every 2-3 years).

Figure 3. Proportion of cloud cover for the global land surface at a 1 degree resolution, data from NEO (2016) for 2010-2014, processed by Mitchard



We hope this figure may be useful in deciding whether using the optical based products listed in Table 4 could be best used, and where other products may be more suitable. For ease of access, this data layer is available to view at the accompanying website.[9]

In particular the NW Amazon, west-central Africa, and Malaysia/Indonesia, appear to have >80% cloud cover and thus we would expect low availability of optical data. In these areas there is likely to be a significant delay in deforestation being detected by optical data due to a lack of availability, and the accuracy of detections are also likely to decrease as many areas will regrow in part before detection is possible. Custom products based on radar data or the specific targeting and purchase of optical data, maybe targeted to hotspots using systematic products based on coarser resolution optical data with daily revisits (e.g. FORMA), may be preferable to reliance systematic systems based on high resolution optical data (e.g. UMD, GLAD).

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[9] http://cloudcover.ourecosystem.com.

4.2 Accuracy of systematic products

A few studies that have attempted to assess the accuracy of systematic products, and some have published reports giving their own accuracy proportions. Table 5 gives the references and results of these studies. Errors for change data should, where possible, be reported as separate rates of omission and commission, and if not given, I have attempted to convert the numbers to these here. These rates are defined as:

- **Rate of omission:** the proportion of total area of change in the reference data that is reported as unchanged
- **Rate of commission:** the proportion of total area of change reported in the dataset that is in fact unchanged according to the reference data

These terms are related to the user's and producer's accuracies discussed in Section 3, with a dataset having high Producer's Accuracy for a change layer if the rate of omission is low (with either high or low errors of commission), and having high User's Accuracy if rates of commission are low, even if there are high rates of omission. In fact, User's Accuracy of the forest change class is the complement of the Rate of Commission (i.e. if the commission rate is 10%, the user's accuracy will be 90%), and similarly the producer's accuracy is the complement of the error of omission, but in this context the commission/omission rates are normally used as they are easier to interpret.

Normally methods try to balance omission and commission errors, but there are some applications where one is more important than the other. For example, a rapid response product may prioritise reducing errors of omission, accepting that there will be false detections (errors of commission) but that these are better than missing disturbances as they happen. Conversely, a scientist wishing to take soil samples at sites cleared at different points in the past (in order to assess whether carbon is lost from the soil following deforestation), will prefer a dataset with a very low commission rate, as they wish to be sure the areas they visit have genuinely been cleared. As they are sampling the landscape, rather than estimating areas of change, they will not mind a high omission rate. But to obtain unbiased estimates of the area of change it is ideal to keep these errors as small as possible and as equal as possible.

It is possible to use area-corrected estimates of these rates to produce confidence intervals on the changes detected within a specific area, and bias-corrected areas accounting for the balance of commission and omission errors (Olofsson *et al* 2013). Following this method is recommended by the GFOI's Methods and Guidance Document when using these or other change datasets (GFOI 2014). These are however area-specific, depending on the relative proportion of change and unchanged pixels in the area of interest, so cannot easily be given for the overall dataset.

Table 5. Accuracy estimates of deforestation detections in systematic datasets

Dataset	Rate of commission (complement of User's Accuracy)	Rate of omission (complement of Producer's Accuracy)	Test area and method	Reference
Hansen/ University of Maryland/ Google/USGS/ NASA ("UMD")	*13 %*	*17 %*	Based on expert analysis of 628 120m x 120m blocks across tropics against Landsat or Google Earth imagery. Only gain/loss assessed, not year of change.	(Hansen et al 2013)
	25 %	*35 %*	*Independent test against RapidEye Data for two sites of high forest change in Acre and Rondonia 2010-14.*	*Milodowski et al (2016) unpublished results from UK Space Agency study*
Global Land Analysis and Discover (GLAD) alerts (from UMD)	13 %	33 %	Tested in Amazonian Peru using Google Earth data. NB most of the commission errors were on the boundaries of events. Ignoring these commission errors reduce to 4%, though omission errors remain at 30 %.	(Hansen *et al* 2016a)
PRODES (produced by INPE, Brazil's National Institute for Space Research)				
	36 %	*49 %*	*Independent test against RapidEye Data for two sites of high forest change in Acre and Rondonia. Test may be unfair as forest and deforestation definitions not equivalent*	*Milodowski et al (2016) unpublished results from UK Space Agency study*
	0 %	*9 %*	*Independent test against RapidEye data conducted by Celestral Green Ventures for the Trocano Aratama Conservation Project, Brazilian Amazon*	*Viergever and Morel (2014)*
Terra-i			*No validation figures available*	
DETER (produced by INPE)			*No validation figures available*	
FORest Monitoring for Action (FORMA)	21 % (30 % threshold); 13 % (50 % threshold) 7 % (80 % threshold)	87 % (30 % threshold); 90 % (50 % threshold) 92 % (80 % threshold)	Figures for 2007-2010 period, using PRODES as 'truth' (reasonable given coarser resolution). The very high omission errors are not a mistake: the algorithm is purposefully biased to avoid false positives, but this means it misses most events in the training data. Thresholds correspond to confidence of output – 30% is normally used.	(Hammer *et al* 2014)

Based on Table 5 it is clear that more validation data are needed. The GFOI MGD Module 2 (GFOI 2015), which will be fully incorporated into Version 2.0 of the MGD which will be published later in 2016, recommends that if these systematically-produced datasets are used as part of a country's MRV framework they are validated using either field data or the analysis of time series of very high resolution remote sensing data. Such local validation data can provide estimates with confidence intervals and corrected for bias (Olofsson *et al* 2013).

Using the generic validation data that is there it is clear that the UMD data features fairly well balanced errors of omission and commission, maybe with slight preference for keeping errors of commission low (i.e. reducing the rate of false positives), at the cost of slightly greater errors of omission. As would be expected, the GLAD data, which provides recent alerts of deforestation, has much higher omission errors than the UMD data, though manages to keep commission errors low. PRODES appears to have similar characteristics to UMD (a slight tendency for higher omission errors than commission errors), but with higher absolute errors – however our only test may not be fair as it uses a high resolution dataset and a different deforestation definition (counting all forest loss a deforestation, even if it occurred in areas that have previously been deforested, whereas PRODES will only detect areas as deforested if they start as forest that has never been cleared, with a minimum clearing size of 6.25 hectares).

The MODIS-based datasets are poorly assessed, but the only one tested, FORMA, has similar (if more extreme) error characteristics as GLAD, the Landsat-based rapid response dataset. It has a strong bias towards minimising errors of commission, with the result that it has very high errors of omission, missing over 87% of clearances in a test dataset. This incredibly high omission error, which is due to a combination of its coarse resolution as well as a bias in the algorithm to prevent false positives, may make the data useless for many monitoring purposes, but the low commission errors mean that the alerts it triggers can be trusted potentially making it a useful enforcement tool. As indicated in the discussion on cloud cover in the Section 4.1, MODIS-based detection tools could also be used to highlight hotspots of rapid change within a country, for investigation using commercial optical satellite data, UAV data, radar, or simply a ground visit.

4.3 Change detection methods

The systematic deforestation products above use three different methodologies. Firstly, PRODES uses a semi-automated classification method, involving a method of classification close to the one-time methods described in Section 3, with operators helping to decide if objects have changed based on a single best observation for each year. Secondly, FORMA, DETER and Terra-I use a statistical time series approach based on many observations per year, looking for pixels that deviate from a long term trend in a single vegetation index band. Finally, the UMD and GLAD datasets use bagged decision trees trained by an input dataset of thousands of pixels that have and have not undergone change, but not specifically hard-coding how the algorithm should consider the different available wavelengths. Note that these products use 4 Landsat bands in addition to vegetation indices derived from them, and correct them for atmospheric and angle effects in advance of considering them). All forest change products, including more experimental products described in 4.4, are based on these three basic methods: comparing one-time maps; analysing time series looking for statistically-significant differences; and machine learning approaches where the actual trigger for a detection is left to the computer. However, there is significant variation within these methodologies when using the same sensor, and of course significant variations in what is achievable comparing on the precise sensor used. These methods are described in more detail below.

1. **Comparing one-time layers:** in this method, processed layers, normally classifications (e.g. with classes such as forest/non-forest; primary forest/secondary forest/agriculture; etc) or more rarely continuous layers (e.g. canopy cover, AGB), are compared for multiple points through time. As discussed in Section 3, there are significant difficulties with this method related to the accuracy of the input layers. This is because classifications rarely have accuracies much above 90%, which means that achieving significantly low errors of omission and commission to accurately estimate trends in deforestation (which normally has annual rates on the range of 0.5 – 2 %) is difficult, as described below (Lu 2004). Nonetheless, this is the method used in practice by most voluntary-sector deforestation projects (e.g. under the Verified Carbon Standard, VCS (Conservation International 2013)), and is the basis of most Activity Data submitted by national REDD+ programs (Johnson *et al* 2016).

   In order for this method to be successful, it is important to assess the accuracy of the *change* results, rather than report the accuracy of the individual annual products. This is stated as essential by the GFOI MGD (GFOI 2014), the main advisory document produced for the use of national statistical processes aimed at the wider UNFCCC process, including REDD+, and is the view of many researchers. The relationship between the accuracy of individual layers and the change products that result from comparing these layers is not simple, and the accuracy of the change product cannot be determined without separate, specific change validation data. The change product can be both more and less accurate than would be expected from the accuracy of the individual layers. For example, if a set of sequential forest/non-forest maps each have an accuracy of 90%, but with errors randomly distributed in space, then differencing each will likely produce estimates of deforestation and reforestation of about 10%, in each direction, between each map, even if no forest change has actually happened. In this case, it is clear that the errors of commission and omission in the change product will be high. If, on the other hand, the maps had very similar error characteristics (for example reporting a particular swampy area of the landscape as forest, when it was in fact non-forest), then they might be very sensitive to deforestation elsewhere in the image, with very low commission and omission errors.

   The above thought experiment contains two lessons, which are borne out in the literature. Firstly, it is imperative to collect *change* validation data, that is to say validation data where the classes are ‘unchanged’ and ‘changed from land cover A to B (or vegetation characteristic A to B)’, rather than validation data that is ‘land cover A’ or ‘vegetation characteristic A’ from a particular point in time. Often it is impossible for these validation data to come from field studies. This is because it is impossible to go back in time, deforestation rates can be slow so plots set up at the first time point (if it has been possible) will mostly be unchanged, and if deforested areas are visited at time 2 it can be very difficult to say when the area was disturbed. Instead, it is often necessary to use higher resolution remote sensing datasets to perform the validation, and although this should be sufficient (GFOI 2014), it introduces further uncertainty as this ‘remote sensing based validation change dataset’ will be itself unvalidated. Secondly, it is best if the products to be compared are produced using the same sensor and method (or as similar a sensor as possible), with the data collected in as similar conditions as possible (i.e. same time of year, same look angle, after a similar amount of precipitation, etc). This will not necessarily increase the accuracy of the individual products, but should mean they are most likely to suffer from the same errors and biases, thereby increasing the accuracy of the resulting change products.

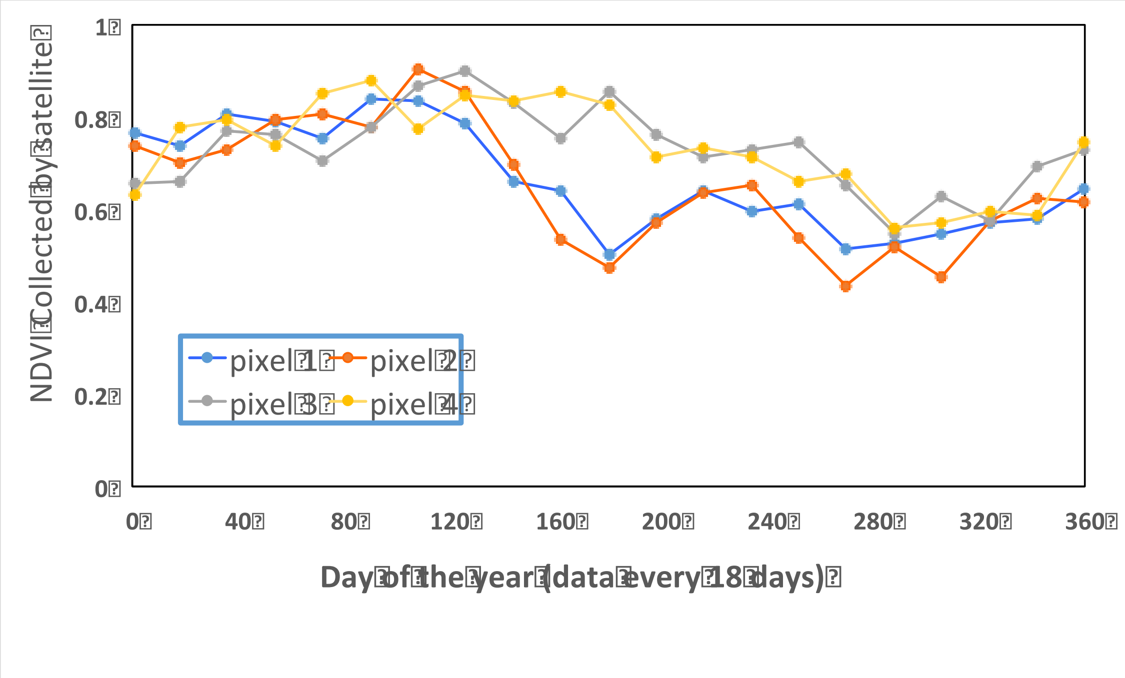
2. **Time series analyses**: in this method a series of observations of the same parameter (normally a vegetation index) are compared, with an algorithm attempting to distinguish departures from the normal that indicate deforestation or degradation. Normally, and ideally, such time series include many observations per year, but the analysis can be performed with only a few observations overall. In the latter case, the ratio or difference of vegetation index values can be subjected to a threshold in order to mark pixels as either changed or unchanged (e.g. Coppin & Bauer 1994), whereas if a long time series is available the algorithms focus on finding break-points in a time series (Schultz *et al* 2016).

   Such time series for a single pixel naturally vary due to seasonal effects, differences in the satellite sensor calibration, atmospheric conditions, and random error (see Figure 4 for a simulated example). Algorithms are therefore developed that try to distinguish a either a sudden break-point (for example due to a deforestation/degradation event) or a long-term trend (indicative say of forest regrowth), from the natural variation not indicative of a change in the forest's characteristics. There is a large branch of applied mathematics dedicated to finding signals in noisy time series data which are used in many other applications than just forest monitoring, and therefore a wide range of algorithms are available. However, their testing in tropical forest situations is not that extensive, probably held back by the only recent development of dense time series of freely available remote sensing data, the enhanced availability of high performance computing, and a lack of ground data. This is an active area of research and both algorithms and results are improving all the time.

   One widely used time series detection algorithms is BFAST (Breaks for Additive Season and Trend), which was developed at the University of Wageningen and has led to an open source R package[10]. This concentrates on trying to distinguish between the seasonal component of a time series and any trends or break points, which might correspond to deforestation or degradation. A more complex approach is used by Terra-I, which uses a neural network trained using both greenness and rainfall trends to attempt to find pixels that go outside expected ranges, and therefore likely to be deforestation (Leisher *et al* 2013).

[10] http://bfast.r-forge.r-project.org/

Figure 4: Simulated time series data. Degradation occurs to pixels 1 & 2 only on day 216.



In the simulated data shown in Figure 4 above, observations of the Normalised Difference Vegetation Index (NDVI, a standard measure of greenness with higher values corresponding to denser, healthier vegetation) are shown every 16 days. Cloud cover is ignored; it is assumed that an observation is achieved in each satellite pass, and that the data are corrected as far as possible for atmospheric effects. Four pixels are considered, of which two undergo degradation around day 140 (pixels 1 & 2), and the remaining two have no change. A seasonal cycle can be observed, giving highest values around day 100, and lowest around day 280, and there is also significant random scatter on all observations. A good algorithm would pick up the persistent lower values around the 140-180 day mark in pixels 1 and 2, either by comparing their values to the majority of the dataset up to that point (searching for outliers), or by comparing the pixels to their trajectories over previous years. It is clear, however, that a relatively naïve algorithm could easily either report all pixels as changing since all values fall to similar levels during the height of the dry season towards the end of the year, or otherwise miss all changes by requiring too harsh a threshold. In this example, which is not unrealistic, it is also obvious that a high frequency of observations is necessary to make a detection. Observe that there are only four detections where the difference in pixel values is significantly larger than the normal noise, and probably at least two of these low values detected in a row would be required for an algorithm to trigger a detection. An observation frequency less than monthly would be unlikely to result in a detection in this example, even if there was no cloud cover.

3. **Machine learning:** time series analyses can theoretically involve multiple bands, but most often only a single parameter thought to relate most strongly to the characteristic of interest (often canopy cover) is considered. When multiple observation bands or metrics are used it is common to move beyond deterministic algorithms, that is to say algorithms conceptualised and hard coded by scientists, to machine learning (or 'black box') algorithms. These are normally variations on neural network or regression tree

approaches, in which a set of input data is used to train a neural network consisting of many virtual neurons, linked in several layers to loosely mimic the way the brain learns and processes information. The 'strength' of each neuron, or the probability of it being used, is changed during training in order to achieve the best output results. This approach has been used in remote sensing mapping for a long time (Foody *et al* 2001), and is the basis for many computer services in the modern world, from powering Google searches and self-driving cars, through to beating the world champion at Go (Silver *et al* 2016).

Training a neural network can be computationally very expensive, as a vast parameter-space needs to be explored. While a neural network classifier can easily be implemented on a standard desktop for a classification involving a few scenes and training data of a few thousand pixels, as soon as large training datasets or many scenes are included, a server or set of servers become necessary. However, once developed, neural networks are computationally easy to run, and can be implemented by more portable hardware. For example, the Hansen et al. (2013) product used a bagged neural network classifier approach, whereby a number of neural networks are developed and the consensus view of the outputs of the neural networks for each pixel is the output. These neural networks were developed with an unspecified but large number of training pixels (hundreds of thousands of pixels) involving ~500,000 CPU-core hours for training. The resulting neural networks were implemented across 650,000 Landsat 7 scenes (a total of 20 terapixels of data) using about the same number of CPU-core hours.

The strengths and weaknesses of machine learning are closely connected. By not being constrained by a human being's preconceptions of how the data layers should relate, better accuracies are normally achieved by machine learning. Patterns in multi-dimensional space are difficult for humans to notice or conceptualise, but are easily detected in the training dataset by such methods. However, this feature also leads networks to *overfitting*, where patterns in the training data are picked up by the algorithm that are in fact specific features of the dataset itself, and not generalizable to the real world.

As an example, a classic thought experiment of overfitting comes from a neural network being used to attempt to determine from pictures whether or not patients were suffering from the common cold. The computer was fed a 100 images, 50 of those with colds, and 50 of those without. It so happened that in the small sample size those with colds were more likely to be wearing glasses than those that were not, and as a result the classifier when tested started stating that every image it was given where someone was wearing glasses had a cold. In this case, the problem was easy to spot, the test data could be adjusted, and a better model produced, but with a satellite dataset of many bands across hundreds of observations, it can be far more difficult to detect overfitting. Overfitting is most often guarded against by keeping a large proportion of the training dataset back for testing, and checking for any significant deviance in training and testing accuracy rates, and fixed through better optimisation (Deng *et al* 2013), but remains a significant challenge in remote sensing where ground truth datasets may have significant spatial or methodological biases. For example, see Mitchard *et al's* (2011a) criticism of the first AGB map of Africa (Baccini *et al* 2008) which, while groundbreaking, was significantly overfitted, resulting in large errors away from the training dataset locations).

Finally, the interpretation of results and analysis of their error characteristics suffer through their being black boxes. Some methods, such as Random Forests, do provide an indication as to which input data layers are most important, but not the way in which these data are used; others, such as bagged neural networks, are so complex that it can be hard to unpick even which data layers are most important, let alone what they are being used for. In some ways, this does not matter: the results can be tested using independent data and errors and biases assessed. Yet, if the input data are spatially biased, or input layer characteristics change in the future (due to, for example, the replacement of a satellite, or an artefact appearing in a particular dataset), it can be impossible to predict the effect on the results. In contrast it is much easier to predict (and thus correct) the influence of changing input characteristics on one-time maps and time series approaches described above.

In order to compare and contrast the type of results that are possible from different combinations of satellite datasets and the above methods, Table 6 presents a review of various studies that have attempted to map deforestation, degradation, or the direct change in some vegetation parameter (for example above ground biomass, AGB).

Table 6. Satellites and studies used for mapping deforestation

Sensor, period, resolution	Aim of change detection	Approach	Study and site	Method	Accuracy assessment of change*
Optical					
Sensors: Landsat MSS/TM/ETM+/ OLI *Period available:* 1972-present *Resolution:* 15 – 60 m	Deforestation	Comparing one time maps	Huang *et al* (2009) forest cover change in Paraguay	Used MSS, TM & ETM+ to develop change data from 1973 to 2001. Mapping done using unsupervised pixel clustering and visual labelling of clusters.	Accuracy >92% for thematic classification in 2000s, tested using aerial photos and <5m resolution satellite data. No assessment of change accuracy performed.
	Deforestation	Comparing one time maps, semi-automated	Alves (2002) deforestation in the Brazilian Amazon 1972-1997	Used deforestation maps provided by INPE from manual interpretation of MSS & TM.	No accuracy assessment attempted, though comparison to census data showed most deforestation occurred in medium and large farms.
Sensors: Landsat MSS/TM/ETM+/ OLI *Period available:* 1972-present *Resolution:* 15 – 60 m	Deforestation	Comparing one time maps	Song *et al* (2015) Central Brazil (covering parts of Mato Grosso, Tocantins & Para).	Forest cover at each time period mapped directly using an SVM approach for TM and ETM+ data over 10-year separation periods.	Commission errors: 12% (TM-TM); 28% (TM–ETM+) Omission errors: 22% (TM-TM); 10% (TM–ETM+)
	Deforestation	Time series.	Coppin and Bauer (1994) Minnesota, USA	Direct-differencing of vegetation indices using TM data at 2-, 4- and 6-year separation.	100% success rate at detecting at least some change in 714 forest stands >1ha in size where change reported on the ground. Overall accuracy against

Sensor, period, resolution	Aim of change detection	Approach	Study and site	Method	Accuracy assessment of change*
Landsat					ground data of 93-97%, but that includes both unchanged and changed pixels.
	Deforestation and forest gain	Machine learning	Hansen *et al* (2013) – global map of forest change 2000-2013	Bagged regression tree using complete Landsat 7 (ETM+) archive, trained using visual interpretation of high resolution data.	Deforestation: Commission error: 13% Omission error: 18% Forest gain: Commission error: 18% Omission error: 52% (see Table 5 for independent accuracy assessment of deforestation)
	Deforestation and degradation	Comparing one time maps	Margono *et al* (2012), mapping deforestation and degradation for the whole island of Sumatra, Indonesia, from 1985 to 2011.	One-time maps of forest cover were produced for ~1990, 2000, 2005 and 2010, but data from past time periods was used to assist with the classification at each point.	Deforestation: Commission error: 29 % Omission error: 44 % Degradation: Commission error: 18 % Omission error: 10 %
	Degradation (selective logging)	Comparing one time maps	Matricardi *et al* (2005), mapping degradation in Mato Grosso state, Brazil.	Compared manual and semiautomated methods for detecting deforestation and degradation, looking for features in the data at highest resolution that correspond to canopy	Manual (deforestation & degradation combined): Commission error: 1.5 % Omission error: 26.5 % Semi-automated (deforestation & degradation combined): Commission error: 18.9 %

Sensor, period, resolution	Aim of change detection	Approach	Study and site	Method	Accuracy assessment of change*
				openings, especially using texture.	Omission error: 19.1 % (assessed using IKONOS imagery and a field study)
	Deforestation and degradation	Time series: trajectories	Kennedy *et al* (2007), discovering date of deforestation and degradation within dense stack of Landsat data, tested in Oregon, USA	18 Landsat TM data from 1985-2004 are subjected to a trajectory-based time series analysis, trying to match given trajectories (no change, disturbance, disturbance + regeneration etc) to observed pixel dynamics.	Deforestation: Commission error: 14 % Omission error: 23 % Degradation: Commission error: 21 % Omission error: 39 %
	Deforestation and degradation	One-time maps	Asner *et al* (2009) tests CLASlite software in 900 km^2 of the Peruvian Amazon and 3000 km^2 of the Brazilian Amazon in Pará state.	Using the Carnegie Landsat Analysis System (CLASlite) package to create continuous maps of photosynthetic vegetation, non-photosynthetic vegetation percentage and bare ground, and difference these to trigger the detection of deforestation or 'forest disturbance' (degradation) if certain pre-determined thresholds breach.	The method produces good looking maps, but no accuracy assessment was performed. A study using the same method over Peru found these errors for deforestation due to small gold mining operations (<5 ha) (Asner *et al* 2013) Commission error: 18 % Omission error: 15.7 &
Multiple	Deforestation and	Comparing one time	Ravindranath *et al* (2012), mapping	While not clear on the method, this study	No accuracy estimate is

Sensor, period, resolution	Aim of change detection	Approach	Study and site	Method	Accuracy assessment of change*
	degradation	maps	forest area and rates of deforestation and degradation in India for REDD+	presents deforestation and degradation figures for India based on a collation of state-level figures on the area of forest within three different canopy cover classes (>70%, 40-70%, 10-40%).	attempted, but total areas of deforestation and degradation are given with high precision.
MODIS 2000-present 250 m	Degradation (selective logging)	Time series	Koltunov *et al* (2009), 670,000 km^2 of Mato Grosso in Brazil	MODIS 16-day nadir-corrected composites. Cloud-free time series generated for pixels that have and have not undergone logging.	Not formally tested, but suggested even minor logging (reducing canopy cover by 5-10 %) can have a significant and long-term effect on phenology, that is the long-term pattern of greenness, allowing degradation to be inferred after a time-lag of 1-2 years.
Synthetic Aperture Radar (SAR)					
ALOS PALSAR 2006 – 2011 12.5 m	Deforestation and degradation	Time series	(Joshi *et al* 2015)	An algorithm was set up to detect change based on finding persistent reductions in radar backscatter, or short-lived changes if in pixels that neighboured others that had undergone	Omission error: 37% (estimated from expert analysis of high resolution data covering 2740 pixels over farms) 15% (estimated from ground data of permits to log within Brazil nut concessions), Commission error: untested.

Sensor, period, resolution	Aim of change detection	Approach	Study and site	Method	Accuracy assessment of change*
				change.	
	Deforestation	Time series	Collins and Mitchard (2015)	A biomass map is made for 2007, and then deforestation mapped through detecting large reductions in backscatter in subsequent annual images (2008-10).	No validation data available. Internal uncertainty estimates produced on change estimates of total carbon stocks, at approximately ±25% of the total change value.
	Deforestation, degradation and regrowth	Comparing one time maps	Ryan *et al* (2012) mapping deforestation and degradation in Miombo woodland from central Mozambique	Maps of biomass, with uncertainties, were produced and differenced for each of 10 radar scenes from 2007-10, allowing landscape-scale estimates of biomass change, and the location of deforestation, degradation and regrowth with confidence values.	Omission error: 35% (generally at the edge of ground-based polygons) Commission error not calculated, but false positive rate estimated at 0.005 %/yr from a large area known not to have changed.
JERS-1 1992-1998 20m ALOS PALSAR 2006 – 2011 12.5 m	Deforestation, degradation, woody encroachment	Comparing one time maps	Mitchard *et al* (2011b), 15,000 km^2 region including and surrounding Mbam Djerem National Park, Cameroon	Direct regression between field biomass plots and HV backscatter used to classify landscape into biomass classes: 0-50, 50-100, 100-150, >150	At 500m resolution, a simulation model suggested change data accurate to >95% when describing if or not a 500 m pixel had changed class. Results also appeared to qualitatively

Sensor, period, resolution	Aim of change detection	Approach	Study and site	Method	Accuracy assessment of change*
				tonnes ha^{-1}. Change between these classes were mapped between 1996 and 2007.	match high resolution optical findings and field observations. No formal assessment of change was possible due to a lack of mid-90's field data.
ALOS PALSAR 2007-10 *L-band, HH&HV* ENVISAT ASAR *C-band* 2000-2012	Degradation and deforestation	Comparing one time maps	De Grandi *et al* (2015), Deng Deng National Park and surrounding area in central/eastern Cameroon, along rainforest/savanna boundary.	One time maps of intact forest, degraded forest, savanna and agriculture were attempted using texture for C-band and L-band radar separately, and then compared through time.	The method was highly successful at C-band, but gave no discrimination abilities at L-band. No validation of maps was undertaken, but the method showed potential.
LiDAR					
Airborne LiDAR	Change in aboveground biomass, to detect regrowth, deforestation, degradation	Comparing one time maps	Meyer et al (2013), detection biomass dynamics im Barro Colorado Island, Panama	(i) biomass maps created from two different LiDAR datasets separated by 10 years and differenced. (ii) differences in height from the two LiDAR maps mapped directly	Both methods had large errors when attempting to measure biomass change. Errors decreased significantly at the 10 ha scale or greater, but only only 60 % of 50 x 1 ha plots were given the correct change direction (positive or negative).
Data type fusion					
Landsat and ALOS PALSAR	Deforestation and degradation	Time series	Reiche et al (2013) detect small-scale deforestation and degradation in Guyana	Time series features are extracted from SAR and optical data, then	The results are better than optical or SAR alone, with the optical data improving

Sensor, period, resolution	Aim of change detection	Approach	Study and site	Method	Accuracy assessment of change*
				combined using a decision tree approach.	resolution, whereas the SAR data fills in data gaps in space/time. For the combined product: **Deforestation:** Commission error: 10 % Omission error: 12 % **Degradation:** Commission error: 22 % Omission error: 2.5 %

* Errors of commission and omission are given where provided. Error estimates given are from the source paper cited unless otherwise stated.

It is clear from Table 6 that the mapping of forest change is less advanced than the mapping of forest characteristics (Table 3), with generally lower accuracies and fewer cases where the mapping has been tested against independent data. Therefore, no attempt is made here to summarise Table 6 at this stage. Instead, Section 5 will look to the future, considering emerging technologies and methods, and then the two will be combined in Section 6 to provide guidance on optimal methods for different change applications.

5 Emerging technologies for forest and forest change mapping

5.1 Next generation satellite sensors

It can be seen from the literature presented so far that the past decades of forest change mapping have been dominated by the Landsat satellite series (with data from 1972-present and the majority of studies), with some contributions from MODIS (a sensor with similar characteristics to Landsat, but a coarser spatial and higher temporal resolution) and L-band radar satellites (JERS-1/ALOS PALSAR/ALOS-2 PALSAR-2, the longest wavelength radar satellites ever orbited, collecting data between them with gaps from 1992 - present). However, this will fundamentally change in the coming decade. There are a set of new sensors collecting data in optical, radar and LiDAR domains with their missions targeted either specifically or partially with forest monitoring in mind, and they represent either incremental improvements on what is currently available, or whole new data types that are not currently available. Those expected to be most significant are shown in Table 7, but this is not an exhaustive list of the new sensors that will become available over the coming decades.

Table 7. Next generation satellite sensors for forest monitoring

Name	Years operational	Type	Spatial resolution	Repeat time	Data policy	Closest current equivalent
Sentinel 2	2016-2030s	Optical, 13 band	10 m	5 days	Open	Landsat
Sentinel 3	2016-2030s	Optical, 21 band	300 m	1 day	Open	MODIS/MERIS
Sentinel 1	2015-2030s	C-band radar	15 m	Up to 6 day		
NISAR	2020-22	S-band L-band radar	10 m	12 day	Open	ALOS PALSAR
BIOMASS	2021-2025	P-band radar	50 m (biomass product 200m)	6 months (but 3 images captured 3 days apart)	Open	*none*
GEDI	2018-?	Spaceborne LiDAR	25 m footprints	Annual	Open	ICESat GLAS (2002-9)

One of the most exciting things about this collection of satellites is that in all cases the data policy is open, even for commercial use. There has been a general trend for government funded data to be made open access across countries, and it is excellent that this trend has spread to include satellite data. The potential of each of these new satellites will be discussed in turn.

Optical:

Sentinel 2: this pair of satellites, like all the Sentinels, is funded by the European Union but built and operated by the European Space Agency, with a commitment to continue providing similar data into the 2020's. It is, effectively, an evolution of the Landsat concept, offering far higher revisit frequencies (5 days rather than 16 days[11]) and resolution (10 m rather than 30 m). This will enable better time series analysis of forest characteristics (using phenology) and change than is possible using Landsat, and make an especially big difference for areas of medium-high cloud cover where obtaining several 10 m resolution images per year will become likely, whereas obtaining one 30 m resolution image was not guaranteed under the previous regime.

Sentinel 3: Sentinel 3 is less revolutionary than Sentinel 1/2, providing systematic medium resolution optical data at a similar temporal and spatial frequency to MODIS, and follows a similar design and capabilities to ESA's MERIS sensor that operated from 2000-2012. Sentinel 3 is included here because it will be widely used for forest monitoring, and is likely to take over from MODIS as the medium resolution platform of choice. This is for two reasons: firstly its spatial resolution is higher than most MODIS bands (only the red and near infra-red bands of MODIS are 250 m, with the others being 500 m or 1000 m, whereas all 21 Sentinel 3 bands are 300 m resolution). Secondly, because no successor is funded to the two satellites that carry the MODIS instrument (Terra and Aqua), and both are operating far beyond their expected lifetimes (they were launched in 2000 and 2002 with nominal 7 year missions), and though both are behaving normally they will eventually fail.

Radar:

The missions discussed here are presented in order of increasing wavelength. C-band has a wavelength of about 6 cm, S-band about 12 cm, L-band around 24 cm, and P-band about 60 cm. With increasing wavelength the penetration of the canopy increases, meaning the backscatter relates more to aboveground biomass and less to the roughness of the canopy, increasing their utility for directly mapping biomass.

Sentinel 1: prior to Sentinel 1's launch in 2014, all radar satellites were essentially experimental. Some ESA missions (ENVISAT ASAR, ERS-1/2) had attempted to provide systematic ice monitoring using radar C-band, but there were observation gaps and no commitment to provide even a semblance of global coverage. At L-band the Japanese Space Exploration Agency (JAXA)'s JERS-1, ALOS PALSAR and ALOS-2 PALSAR-2 had global observation strategies, but there were significant gaps in coverage between satellites (from 1998-2007 and 2011-2014). In both cases, this made it difficult to imagine a country or company relying on data provision from a radar satellite.

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[11] There are two Landsat satellites currently orbiting, Landsat 7 and 8, giving a theoretical revisit time of 8 days, not dissimilar to Sentinel 2's 5 days. However, in fact Landsat 7 has since 2003 suffered from a significant fault, with the failure of its Scan-Line Corrector (SLC) meaning about 30 % of each image is missing, with missing horizontal wedges becoming wider towards the edge of the images. While these data can still be used, they mean that an individual Landsat 7 ETM+ scene is not sufficient to make a map – several must be composited. Therefore the true revisit time is longer than 8 days, and for complete scenes it is 16 days (the time between Landsat 8 OLI observations).

Sentinel 1 changes this, as it comes with a commitment to provide frequent data and to keeping two satellites operating continuously into the 2030's, providing data every 6 days over Europe, and with a 12 or 24 day frequency elsewhere, depending on data demand. This is a step change in radar data provision, and for the first time allows the design of monitoring systems relying only on radar data. Therefore, even if the wavelength is not ideal for forest monitoring (longer wavelengths would be preferred), it is likely to become a widely used satellite for forest monitoring in the coming years.

NISAR: NISAR is a twin L- and S- band mission joint between NASA and the Indian Space Agency (ISRO). It resulted from the failure to secure final funding of a bigger planned mission, DESDynI, which was to combine radar measurements with simultaneous LiDAR readings, but was viewed as too expensive. NISAR is primarily designed to map earth deformation, with a focus on earthquake and volcano monitoring, but the data will also be very useful for mapping vegetation and vegetation change. The different backscatter responses from the two wavelengths could give information on structure/biomass, with, for example, an open canopy giving quite a different L/S difference than a closed canopy. However, the data will also be widely used as interferometric pairs of scenes, captured a few days apart and from slightly different angles. This interferometry allows the calculation of a Digital Surface Model (DSM). Normally such DSM's are of only limited use, as without a terrain height model it is impossible to estimate tree height; though subtracting them through time has potential as a mechanism for mapping degradation and deforestation. Yet, looking at the difference between DSMs produced for L- and S- band could allow for an estimation directly of tree height, because L- will penetrate the canopy further than S-, but they will produce the same height estimation over bare ground.

BIOMASS: as the name suggests, BIOMASS is the only one of these sensors specifically designed to study forests. It is funded by ESA, and should be launched in 2021 and operate for 5 years. It is the longest wavelength SAR ever to be put in space, offering the ability to directly map biomass using backscatter up to a higher saturation point than is currently available – potentially about 300 tonnes ha^{-1} (Le Toan *et al* 2011). Tropical forests have biomass values above this point, so its orbit has been carefully designed to observe forests three times in quick succession (~3 days apart) every six months. It will make these observations with full polarimetry, i.e. collecting HH, HV, VH and VV polarisations. This combination of three observations from different angles and full polarimetry will allow the use of a technique called tomography to characterise the height of the vegetation over the ground and the density and characteristics of different canopy layers.

Both the tomography and the backscatter measurements will be averaged to a fairly coarse resolution (200 m) in order to produce estimates of biomass and structure with low noise. Higher resolution satellites will therefore still be required to map small-scale deforestation and degradation. It is also only a one-off satellite – there is no current plan for a successor. However, while it is operational, it will provide a fantastically rich dataset on forest characteristics and their changes.

It should be noted that BIOMASS will not observe the whole world, due to a conflict between its P-band and the USA's ballistic missile detection system. This means that north America and most polar regions will not be covered, but mostly does not affect the tropics (a little of northern Central America, and potentially some of SE Asia, will not be covered).

LiDAR:

GEDI: the Global Ecosystem Dynamics Investigation LiDAR (GEDI) will be placed on the International Space Station in 2018. It will collect billions of 25 m diameter footprints across temperate and tropical forests, which will then be scaled up to provide estimates of forest aboveground biomass, vertical structure, and changes. While there will be no guarantees that any particular field plot will fall under a footprint, the high density of footprints (at least 1000 times denser than ICESat) should ensure many will fall in any area of interest, and the frequent repeats should allow degradation to be directly mapped. It will be particularly useful for providing well distributed and plentiful 'ground truth' data for other methods of mapping forest characteristics and changes. While GEDI only has a nominal mission of a year, if its data are widely used there is hope it will be extended.

A further spaceborne LiDAR will be launched in 2018: IceSat-2. Which this is the successor to ICESat-1, which was successfully used for vegetation monitoring, the characteristics of the ICESat-2 LiDAR make it much less useful for vegetation mapping than its predecessor. We therefore expect GEDI to be far more widely used.

5.2 Non-traditional satellites

The satellites described in 5.1 are all designed by space agencies (NASA, ESA, JAXA) and represent the result of years (often decades) of planning. They are invariably very large undertakings, with typical design and operating budgets in the hundreds of millions of dollars. Almost all EO products have come from such systems.

However, there has been a recent trend towards the launch of satellites by companies or research outfits. Often these are very small satellites (cubesats or nanosatellites), with the small size and weight greatly reducing launch costs as such satellites can 'piggyback' on the launch of larger satellites. Such satellites do not have large instruments or solar panels, and thus are individually not as capable as the large satellites launched by the major space agencies or large corporations, but their low cost means that many can potentially be launched, so they can act as a constellation.

Probably the longest running such constellation is that run by the DMCii (Disaster Monitoring Constellation for International Imaging)[12], which launched four small satellites in 2002/3 providing global 32 m resolution data, a further set in 2009 giving a 22 m resolution, and new satellites recently with 2.5 m resolution. The satellites are built in the UK by Surrey Satellite Technologies Ltd. (SSTL). The data from the DMCii satellites are provided at a cost to the user, with the possibility of users directly receiving data with their own dish, effectively offering a subscription service to images over a region or country. These data have been used for systematic monitoring, for example with Brazil purchasing data to fill in data gaps caused by clouds in its Landsat or CBERS data for its PRODES product. However, in general the medium resolution products are not that well used for forest monitoring due the availability of free Landsat (and now Sentinel-2) data at a similar or better resolution. However, the company has been successful through offering the technology for target countries to build and launch their own monitoring satellites, desired by many countries for data sovereignty and development reasons - for example, NigeriaSAT-1 and NigeriaSAT-2 were funded by Nigeria but built by SSTL under the DMCii program.

Since then other companies have started launching constellations of cubesats – satellites based around modules 10x10x10 cm in size. For example Planet Labs (a company based in California) have launched hundreds of their Dove satellites, which are triple cubesats (30x10x10 cm), launched in stages from various launch vehicles and directly from the International Space Station, capable of capturing 3-colour imagery with a 3-5 m ground resolution. They ultimately aim to be

[12] http://www.dmcii.com/

able to image the entire earth every day, for which they would need >150 operational satellites in an ideal range of orbits, plus spares orbiting in order to replace failures. Due to launch and orbit failures they are a long way from having 150 active satellites in orbit, but if they succeed in this goal they could revolutionise forest monitoring.

Companies such as ClydeSpace[13] have made it far easier for other companies and researchers to build their own cubesats by providing off the shelf platforms and sensor kits. While most cubesats that have been launched have simple optical sensors, the reduction in cost provided by these innovations may allow for very specific satellite sensors to be launched, targeting a particular application – for example targeting imaging in a particular wavelength or at an interesting angle, that might have relevance for only one particular forest system.

The problems with using cubesats for forest monitoring relate to their reduced imaging capacity and the ready provision of similar data from free satellites. It is not possible to hover a cubesat over a particular point on the earth as they are all launched into low earth orbits: geostationary orbits are too far out for low cost launches, typically requiring significant propulsion capacity on the satellite to hold the correct position, and due to distance, need powerful telescopes to image the earth. This is not a unique problem for Cubesats – very few EO satellites are in geostationary orbits, but it does prevent purchasing a custom satellite and instructing it to hover over the area of interest for the purchaser. Instead, it will only collect data overhead every few days at best (probably less frequently if a high resolution is required). To obtain a reasonable temporal frequency they would require a large constellation of many satellites, and at that point, they may as well purchase commercial data. However, if companies such as PlanetLabs manage to complete their constellations there could be great potential advances for forest monitoring. Until then, they will mainly be used for cheaply researching new methods and technologies.

5.3 Unmanned Aerial Vehicles

Since ~2011, the use of UAVs in forest monitoring and research has expanded very rapidly. This is as their costs have fallen simultaneously with their capabilities increasing. Much of this has been made possible due to developments in the mobile phone, resulting in the miniaturisation and mass production of processing chips, cameras and radios.

Much science can be performed with the low cost (<$1000) consumer UAVs that have proliferated, produced by Dji (Phantom series)[14] and 3DR (Solo)[15] but these typically have cameras optimised for video. These cameras have only 3-bands, in the visual wavelength (i.e. red, green, blue, not covering the infrared so useful for vegetation mapping), and often with a very wide angle lens, making stitching images together difficult. However, more capable out-of-the box systems including calibrated multi-spectral sensors are increasingly available (e.g. fixed wing systems from Delair Tech[16] and cameras that can be easily integrated into commercial multi-rotor platforms from MicaSense)[17]. With some engineering and electronics expertise, very capable systems can be built from widely available components, replicating much of the data that could previously only be collected using expensive, manned, aircraft. Active remote sensing is also catching up, with LiDAR

[13] https://www.clyde.space/
[14] http://www.dji.com/phantom
[15] https://3dr.com/solo-drone/
[16] http://www.delair-tech.com/
[17] https://www.micasense.com/

and even radar systems now available in addition to optical (Esposito *et al* 2014, Gromek *et al* 2016).

From reviewing the literature it is clear that small optical multi-rotor UAVs have great potential for performing two tasks:

a) Intensively monitoring small, high threat areas, for small-scale deforestation and degradation (Paneque-Gálvez *et al* 2014)
b) Calibrating and validating satellite-based mapping and monitoring systems, through the ability, for example, to map small canopy gaps or details of tree crown size distributions (Getzin *et al* 2014, Zhang *et al* 2016)

We expect them to be widely used in both cases, and increasingly used to supplement field forest inventories by forestry departments and researchers. Their ability to collect very high resolution on demand, and under cloud cover, will allow for remote sensing based enforcement where satellite data would be too expensive or unreliable, and will greatly complement coarser resolution satellite products through training and testing.

However, there are problems that may limit their use. These are described individually below:

a) The image footprint of a camera on a UAV is typically small, and logistical and legislative reasons prevent them flying very high (e.g. 400 feet in the UK). Therefore within a typical 20 minute flight (the limit of most battery systems for a quadcopter) only a few tens of hectares can be imaged, made up of hundreds of individual images. For many applications it would be preferable to image a much wider area.
b) While individual UAVs are low cost, with capable quadcopter systems available for under $1000, the actual costs in terms of training operators, visiting a site (particularly where a long-term presence is required in remote areas), and analysing data may be much higher. Data analysis costs are high because stitching together hundreds of individual scenes, in order to build up an image of an area, is difficult and time consuming. Ultimately the wide coverage images from a satellite, even with in the case of commercial images, may end up producing more useful data at lower overall costs.
c) UAVs often crash, whether due to component failure or human error. They therefore often do not represent a stable form of data provision, and again costs for maintenance, repair and replacement can be high.
d) Legislation around UAVs is evolving rapidly so no review is attempted, but restrictions on UAV use exists to some degree or other throughout the world. In some countries using UAVs with cameras is effectively banned (e.g. Sweden) for privacy or security reasons, and in most tropical countries it is necessary to obtain permits for their use. It is next to impossible to prevent a satellite image being captured of any area of the world, but governments can effectively prevent UAV image capture in all, or sensitive locations of, their territory.

Some of these problems can be solved by moving from small quadcopters to more capable fixed wing systems with a 1-3 m wingspan. Fixed wing UAVs need less energy to keep them flying as their wings generate lift, so flight times of 90-120 minutes are typical. However, such systems have higher costs to purchase and operate, need more space to take off and land, and are subject to more legislative control (at least for larger UAVs).

In conclusion, UAVs do have real potential for providing high spatial and temporal frequency EO data on demand. They can give control of the collection and analysis of remote sensing data to local communities or bodies, and in some circumstances have revolutionised what is possible with a given budget. Conversely, their application is limited by their small area coverage, data processing difficulties, unreliability, and legal restrictions.

6 Optimal EO strategies for detecting and measuring forest change

From Sections 1-5 of this report it should be clear that there are many different types of forest, types of forest change, and potential techniques for mapping these changes. There are also trade-offs in monitoring unconnected to monitoring accuracy, in particular between resolution and cost, and separately between resolution and repeat frequency. The review of systematic products and studies presented in Section 4, and the consideration of new techniques in Section 5, are here combined to produce guidance on the optimum method/dataset to use for a given budget, resolution, forest type and cloud cover regime (Table 9). Unlike for mapping forest characteristics, there is very little validation data available for these methods, and thus it was not possible to produce estimates of likely accuracy as for Table 4. Instead methods are listed that are expected to be able to produce errors of Omission and Commission below 20 %, with an understanding that higher cost methods within a particular resolution class will be able to achieve better accuracies and/or a higher temporal frequency. These are displayed in Table 9.

Table 9 features three different price ranges for each resolution. What is considered low, medium and high cost varies by the resolution considered, and thus these have been varied with resolution as per Table 8below.

Table 8: Budget ranges of monitoring costs per year per for Table 9 cost categories

	Very high resolution (<10 m)	High resolution (10-30 m)	Medium resolution (>100 m)
Low Cost (LC)	<$3/ha	<$1/ha	<$0.1/ha
Medium Cost (MC)	$3-10/ha	$1-5/ha	$0.1-2/ha
High Cost (HC)	>$10/ha	>$5/ha	>$2/ha

These costs are approximations, with the reality depending on the area and situation in question. In most cases, the majority of the cost relates to the data analysis, with a smaller proportion for purchase of image data where applicable. Where the proposed data is identical at multiple price points, it is because these data represent the optimal system at that resolution, and increases in accuracy can be achieved at higher cost through the use of more sophisticated algorithms and/or the processing of denser time series. Higher cost options may exceed the 20% omission/commission error requirement, and low cost options may offer imagery at a lower temporal frequency than high cost options.

Table 9: Optimal data for forest change mapping, to obtain errors of omission and commission both <20 %. HC=High Cost; MC=Medium Cost; LC=Low Cost; *ML*=Machine Learning; *TS*=Time Series; *OTC* = one time classification; Sen= Sentinel; PALSAR-2 = ALOS-2 PALSAR-2 L-band radar, with NISAR offering similar data from 2020; RapidEye = RapidEye or similar 5 m resolution low cost data (e.g. Planet Labs); Hyperspatial = <2.5 m resolution satellite, e.g. GeoEye, Pleides; UAV = optical UAV with <1m resolution; TDX = TanDEM-X, analysed through changing DEM height. Items with '?' at the start are not proven to achieve the accuracy stated.

	Medium/low cloud (<70 % time-averaged cloud cover, Fig. 3)			**High cloud** (>70 % time-averaged cloud cover, see Fig. 3)		
Resolution	<10m	10-30 m	> 100 m	<10m	10-30 m	> 100 m
	Tropical moist/wet forest (>1500-2000 mm rain, >200 tonnes ha^{-1})					
Mapping deforestation	**HC**: Hyperspatial, *OTC* **MC**: RapidEye, *TS* **LC**: RapidEye, *OTC*	**HC**: Sen-2, *ML* **MC**: Sen-2, *TS/OTC* **LC**: *UMD data* or Landsat/Sen-2 *OTC*	**HC:** Sen-3 & MODIS, *ML* **MC:** MODIS, *TS* **LC**: *FORMA* data*	**HC**: UAV or TDX, *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: Sen-1, *TS* **MC**: Sen-1, *TS* **LC**: *UMD data*	**HC:** Sen-3 & MODIS, *ML* **MC:** MODIS, *TS* **LC**: *FORMA* data*
Mapping forest degradation	**HC**: LiDAR, UAV or hyperspatial *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: full waveform LiDAR at high altitude **MC**: Sen-1/2, *TS* **LC**: *not possible*	**HC:** *?Sen-1/3 ML* **MC:** *fr. 2018* GEDI +Sen-3 **LC**: *fr. 2021* BIOMASS	**HC**: UAV or TDX, *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: full waveform LiDAR at high altitude **MC**: Sen-1, *TS* **LC**: *not possible*	**HC:** *?Sen-1/3 ML* **MC:** *fr. 2018* GEDI +Sen-3 **LC**: *fr. 2021* BIOMASS
Mapping changing biomass	**HC**: LiDAR, *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: full waveform LiDAR at high altitude **MC**: *not possible* **LC**: *not possible*	**HC**: *not possible now* **MC:** *fr. 2018* GEDI +Sen-3/MODIS **LC**: *fr. 2021* BIOMASS	**HC**: LiDAR, *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: full waveform LiDAR at high altitude **MC**: *not possible* **LC**: *not possible*	**HC**: *not possible now* **MC:** *fr.2021* BIOMASS **LC**: *fr. 2021* BIOMASS
	Tropical dry forest and savanna (<1500 mm rain, <200 tonnes ha^{-1}, grass may be present)					
Mapping deforestation	**HC**: Hyperspatial, *OTC* **MC**: RapidEye, *TS* **LC**: RapidEye, *OTC*	**HC**: PALSAR-2, *TS* **MC**: Sen-1, *TS/OTC* **LC**: Landsat/Sen2,*OTC*	*Grass, tree and regrowth confused for optical data and difficult to unmix at this resolution. No coarse resolution radar exists. Coarse resolution mapping*	**HC**: UAV or TDX, *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: PALSAR-2, *TS* **MC**: Sen-1, *TS/OTC* **LC**: *not possible*	*Grass, tree and regrowth confused for optical data and difficult to unmix at this resolution. No coarse resolution radar exists. Coarse resolution mapping*
Mapping forest degradation	**HC**: LiDAR, *UAV* or hyperspatial *OTC* **MC**:	**HC**: PALSAR-2, *TS* **MC**: Sen-1, *TS* **LC**: *?PALSAR-2 mosiac, OTC*		**HC**: LiDAR, UAV or TDX *OTC* **MC**: *not possible*	**HC**: PALSAR-2, *TS* **MC**: Sen-1, *TS* **LC**:	

	?RapidEye, TS **LC**: *not possible*		*therefore difficult, recommend using higher resolution products. Fr. 2021 BIOMASS will fix this.*	**LC**: *not possible*	*?PALSAR-2 mosiac, OTC*	*therefore difficult, recommend using higher resolution products. Fr. 2021 BIOMASS will fix this.*
Mapping changing biomass	**HC**: LiDAR, *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: full waveform LiDAR at high altitude **MC**: PALSAR-2, *OTC* **LC**: *?PALSAR-2 mosiac, OTC*		**HC**: LiDAR, *OTC* **MC**: *not possible* **LC**: *not possible*	**HC**: full waveform LiDAR at high altitude **MC**: PALSAR-2, *OTC* **LC**: *?PALSAR-2 mosiac, OTC*	

*FORMA is currently suspended, should recommence by 2017. Terra-I is also suitable, but only produced for Latin America.

When reviewing Table 9, the first thing to note is the 'not possible' classes:

Deforestation: in moist/wet tropical forests, there are suitable techniques at all costs and resolutions for deforestation monitoring in medium/low cloud regions. In cloudier regions only low cost monitoring at <10 m resolution is not possible.

Degradation: It is not currently possible to achieve reasonable accuracies for medium and low cost monitoring of degradation for moist/wet tropical forest at <10 m, and low cost monitoring of degradation in these forests <100 m, regardless of cloud cover. The situation is similar for tropical dry forests and savanna at <10 m resolution, though free PALSAR-2 mosaics released by JAXA make a low cost option at <100 m resolution possible.

Biomass change: it is clear that this is the most challenging to map using current technologies. LiDAR from aircraft is the only suitable technique given for <100 m resolution maps at tropical forest, and this is always a high cost option. At >100 m resolution no solution is available now, but the launch of GEDI and BIOMASS provide the possibility of suitable products. In dry forests/savanna LiDAR still represents the best options for <100m, and there are no current options for >100 m resolution, but at 10-30 m resolution ALOS-2 PALSAR-2 can provide biomass maps with reasonable accuracy.

Active research is continuing in these areas, and it is possible that high temporal frequency data from Landsat/Sentinel-1/Sentinel-2 over a whole year can map biomass changes with reasonable accuracy, but this is not yet proven.

In terms of what is possible, sadly the systematic products listed in in Table 5 do not fill many of the boxes. The UMD data provides a reasonable low cost deforestation option for tropical moist/wet forests at a 30 m resolution, though it should be tested using high resolution data to provide local estimates of the rates of error of omission/commission in order to discover if its use is reasonable and to calculate bias-corrected error estimates. Furthermore, FORMA has been suggested for deforestation mapping at a >100 m resolution (with Terra-I also being suitable for South America, which is the only area where it is currently produced). However, in drier forest systems where the forests are highly deciduous and grass may be present, it seems that these automated systems currently have too low accuracies to be recommended, though improvements are possible (Hansen & Loveland 2012).

In general, optical data is most useful for tropical moist/wet forests under low/medium cloud conditions, with radar data being preferred for dry forest systems and high cloud areas, as it is less easily confused by the grass layer and can see through clouds. The exceptions are for <10 m resolution data, where the pixel size is similar or smaller in size to a tree crown, and thus the confusion from grass is less of a problem, and at a >100m resolution in cloudy areas, where there may still be sufficient observations to allow optical data to be useful. Radar is especially useful for mapping biomass at a 10-30 m resolution in dry forests and savannas, and for mapping deforestation and degradation at <10 m and 10-30 m resolution under cloud cover in all forest types. Unfortunately no coarse resolution, wide-swath radar system exists (or at least no such data is captured over land), until the launch of BIOMASS in 2021. LiDAR from aircraft of UAV is the preferred option for biomass change in all situations at <100 m resolution, and also has a role for degradation mapping in higher biomass forests.

7 System design considerations

7.1 Customising methods to local conditions

When attempting to use Table 9 to choose the optimal method to meet user requirements, it is important to fully consider the temporal and spatial resolution and degree of precision required. There will always be a push on the one hand towards using lower cost methods, and on the other, to using higher resolution/cost methods. The most useful monitoring system will be at the coarsest resolution possible to meet the user requirements (as excess resolution adds cost and increases the size of all output files without necessarily increasing accuracy). It will also not overstretch a budget on data purchase/processing costs in order to ensure sufficient funds remain for ground truth and validation work (normally at least 20 % of the budget is required for such activities, and in difficult to access areas it may be far more).

It is not always necessary for validation to involve ground studies, though they are normally necessary as part of the validation effort. Often validation could be performed by using a method at the same price point but at a step up in resolution. So for example, a medium-cost deforestation map at a 10-30 m resolution (produced using a time series analysis of Sentinel-2 data in a low cloud area) could be validated using RapidEye time series data for subsets of the full study. Alternatively, a PALSAR-2 time series used for mapping degradation in a tropical dry forest could be validated with LiDAR, UAV or hyperspatial satellite data, again for a subset. Often such data is necessary for training, in addition to being useful for validation.

Validation should be performed across the range of forest types and disturbance regimes within the area being monitored. As the size considered increases from a small region (e.g. a national park) through to a whole country, the diversity of forest and change characteristics will increase dramatically, and it is imperative that the size of the ground truth effort increases as well. When the monitoring is being performed at a large (e.g. country) scale, it is quite possible that more than one method/technology will be necessary: for example Peru contains lowland Amazon forest, dry and cloud forests, all of which may need different systems.

The literature review of forest change methods found, unfortunately, few studies that had performed such accuracy assessments. This made it difficult to fully assess the expected accuracy of each method and data type in isolation, and impossible to split their accuracy into a finer range of forest types than the wet/moist vs dry shown in Table 9. However, it is inevitable that the optimum approach will vary by the local forest type, the dominant disturbance regime, and the frequency/accuracy requirements. These frequency/accuracy requirements are partially included in Table 9, as the user should assume that higher requirements will require the use of higher cost methods. However, modulation by disturbance type and forest conditions was not included.

Before setting up a monitoring system in an area, it would be ideal to find any published studies or reports that have monitored deforestation, degradation or biomass change in the area of interest, or even those that have made one-time maps of forest type or characteristics. This can give an idea of the local accuracy values that can be achieved, and any particularly issues with one method or another in that area. For example, it may be that in a steeply mountainous area, it was found that radar data performed worse than expected, or that a particular valley, an otherwise low-cloud area is always cloud/mist covered during the late-morning optical satellite passes. If such studies are not available, a pilot study or studies testing the methods to be used would be highly advisable, ideally involving the collection of ground truth data.

Ultimately, some or many user requirements may simply not be achievable for a given budget in a particular area. In this case it is possible to follow a sampling approach (GFOI, 2014), and collect monitoring data for only a subset of the full area of interest. Ideally, the full area would be still covered at a coarser resolution, in order to identify hotspots of change and target future higher resolution coverage, but sometimes this will not be possible. In such cases free datasets such as UMD, GLAD, FORMA and Terra-I are particularly useful: even if they do not monitor the parameter in question (e.g. degradation or biomass), including their data as a targeting system for a forest monitoring system involving sampling with custom produced data products can greatly increase the utility of a system without great cost.

7.2 Data management and dissemination

Most of the forest monitoring activities described in Table 9 involve significant data volumes and processing capacities. Many countries will have to purchase specialist hardware, invest in high-speed internet (or direct satellite downlink), or outsource the analysis to specialist companies (unlikely for most countries for reasons of sovereignty, but probably the main option for many companies policing their zero deforestation commitments or many subnational REDD+ projects managed by NGOs). These will be challenging, but international bodies such as UN-REDD, FAO and the Forest Carbon Partnership Facility (FCPF, funded by the World Bank), as well as many bilateral aid programs, will assist with training and setting up such systems. Costs will obviously be lowest if processed products (such as UMD or FORMA) are used, but investments in hardware and internet facilities may still be necessary to ingest and process these data to produce useful outputs.

Given the hardware challenges described above, it is vital that investment in data dissemination is not forgotten. Producing forest change products is only useful if the required stakeholders (government departments, NGOs, companies, citizens) can access and query the data. Data dissemination should be done through several routes aimed at different users, with the provision of appropriate metadata, manuals and training. This will be a significant cost; as a guide, most EO satellite missions allocate at least 10 % of their budget towards data dissemination, and often end up requesting significant further annual budgets if a mission exceeds its nominal lifetime or if data use exceeds expectations.

Ideally, all data would be made available as open data, free of charge and without restrictive licence terms. This will maximise the use of the product, benefitting the economy and citizens, and often leading to innovative users that could not have been envisaged in advance. Not insisting on complex registration and nominal payment architecture can also reduce administrative costs related to data provision, reducing overall costs, though data volumes will be higher than if restrictions are in place, increasing bandwidth costs. However, for data sovereignty or financial reasons, often it will not be possible for open data provision; in this case the most open terms possible should be used, and ideally, data should be provided to researchers for testing, validation, and research purposes without charge.

Regardless of the licensing discussed above, the data should be offered in a variety of ways to meet different user requirements and users with different levels of skill. For example, raw data could be released so that skilled users, such as researchers and companies, could validate it and use it to produce their own added value services. Also, processed data could be displayed on platforms allowing easy display and querying of the data without the need for it to be downloaded (requiring high bandwidth and specialist software and analysis skills). Lastly, for a lower level of capacity still, printed maps and reports could be made available, giving access to the data for areas without access to computers and the internet.

An example of good data provision is the UMD data. This is provided on:

- an easy to use interface allowing visualisation of the raw data along with other mapping layers for comparison: https://earthenginepartners.appspot.com/science-2013-global-forest
- a third-party site, allowing querying of the data and access to other related datasets http://www.globalforestwatch.org/
- a site offering the raw data at http://earthenginepartners.appspot.com/science -2013-global- forest/download_v1.2.html

Further services that could have been used to distribute these data could be alert services that send an email or text message if forest change is noticed in an area of interest, as exist for example derived from the MODIS fire product[18], and printed maps and documents available to target specific user groups.
Web services have also been developed that offer enhanced functionality for creating user-specific queries and reports without requiring any analysis software or downloads. An example of these is Ecometrica Ltd's EO Lab services: this website presents the output of a combination of forest monitoring and models over the Amazon Basin, derived from a project funded by the UK Space Agency and developed in partnership with Brazilian organisations and the University of Edinburgh.[19]

As REDD+ becomes fully operational in the 2020s, with individual active MRV systems in each tropical country and significant funds transferred related to success compared to reference levels, there may be significant advantages for all stakeholders in moving towards a common digital infrastructure for forest monitoring. Significant efficiencies of scale could be achieved by data processing occurring in the cloud, rather than within servers in each country, using common sophisticated tools to take in reference data and produce automatic accuracy/bias estimates, and disseminate data through common web platforms. As well as reducing cost and increasing accuracy, such a common platform would increase trust in the products produced and encourage the sharing of best practice. Satellite providers, both of free and charged data, could be interested in collaborating and thus providing data to a single platform rather than to many individual users distributed around the globe.

The GFOI, the Group on Earth Observations (GEO), UN-REDD, FAO, the World Bank, and others, could potentially facilitate such a platform; indeed in some ways Global Forest Watch could be considered a precursor of such a system, though without significant country buy-in. We consider it unlikely that such a platform will be created, at least any time soon: countries are protective of their sovereignty over monitoring and would prefer to create their own systems. Yet potentially, they could be prepared to give up some sovereignty on monitoring in order to reduce costs, increase trust (and therefore funding from REDD+), or access functionality that they are unable to replicate themselves. As such, any attempt to build a platform should be modular and flexible, so that countries could use parts of it even if not the end-to-end stream.

There are many areas in the forest monitoring chain where outside researchers and organisations can provide support; data dissemination may represent one that could easily be left out, with a rush towards supporting the use of advanced technologies, but support here could potentially result in very large gains from a relatively small investment.

[18] (https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms)
[19] https://cardamom.ed-ac.ourecosystem.com/interface/

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The UK has committed to support developing countries' efforts to mitigate and adapt to climate change as part of international agreements under the UNFCCC. The majority of this support is delivered through the UK's International Climate Fund (ICF). From 2011 to 2021 approximately £2 billion UK aid is likely to be directed, through the ICF, towards forestry programmes aimed at reducing deforestation, forest degradation or promoting forest restoration.

To ensure that UK aid is used effectively and to learn from its application ICF investments are required to report performance against relevant indicators. A key indicator for forestry programmes is the area of avoided forest loss and degradation, also known as the Hectares Indicator (KPI 8). There are several quantitative and qualitative challenges associated with producing credible, transparent estimates of this impact at reasonable cost.

The availability of accurate, consistent measures of forest area and forest change are critical to the assessment of the Hectares Indicator.
This document provides an assessment of current and emerging earth observation technologies based on satellites and other aerial data sources and an assessment of how these can be used to map forests and forest changes.

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