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Recent Advances in Forest Observation with Visual Interpretation of Very High-Resolution Imagery

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Abstract

The land area covered by freely available very high-resolution (VHR) imagery has grown dramatically over recent years, which has considerable relevance for forest observation and monitoring. For example, it is possible to recognize and extract a number of features related to forest type, forest management, degradation and disturbance using VHR imagery. Moreover, time series of medium-to-high-resolution imagery such as MODIS, Landsat or Sentinel has allowed for monitoring of parameters related to forest cover change. Although automatic classification is used regularly to monitor forests using medium-resolution imagery, VHR imagery and changes in web-based technology have opened up new possibilities for the role of visual interpretation in forest observation. Visual interpretation of VHR is typically employed to provide training and/or validation data for other remote sensing-based techniques or to derive statistics directly on forest cover/forest cover change over large regions. Hence, this paper reviews the state of the art in tools designed for visual interpretation of VHR, including Geo-Wiki, LACO-Wiki and Collect Earth as well as issues related to interpretation of VHR imagery and approaches to quality assurance. We have also listed a number of success stories where visual interpretation plays a crucial role, including a global forest mask harmonized with FAO FRA country statistics; estimation of dryland forest area; quantification of deforestation; national reporting to the UNFCCC; and drivers of forest change.

Keywords Forest cover · Biomass · Forest monitoring · Remote sensing · Satellite imagery · Visual interpretation

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1 Introduction

Remote sensing plays a critical role in the estimation of forest parameters, and in the monitoring of disturbances and changes in forest cover. Different types of satellite sensors (i.e., optical, hyperspectral, LiDAR and radar at varying spatial and temporal resolutions) play different and complementary roles in forest monitoring. Time series of moderate resolution imagery (MODIS, MERIS, etc.) have been used extensively to produce land cover, forest cover and forest-type maps (Defourny et al. 2006; Friedl et al. 2010), forest cover change, tree density (DiMiceli et al. 2011), vegetation indices, gross and net primary production (Running et al. 2004) and forest disturbances (Justice et al. 2002). Radar and LiDAR data have also been used successfully to estimate biomass and canopy height (Baccini et al. 2008; Saatchi et al. 2011; Simard et al. 2011; Thurner et al. 2014; Santoro et al. 2015). With the opening up of the Landsat archive in 2008 (Wulder et al. 2012) including a time series of more than 40 years, it has become possible to monitor long-term changes in forests at a higher resolution (Sexton et al. 2013; Hansen et al. 2013). The open data policy of the European Space Agency (ESA) with respect to the Sentinel satellites means more frequent coverage of the Earth at a higher resolution than Landsat, which is particularly relevant for forest areas dominated by clouds. Sentinel 1 can also complement the monitoring of forest structures using radar data at a higher spatial and temporal resolution than other radar products such as ENVISAT ASAR.

More recently, with changes in Web 2.0 technology (Hudson-Smith et al. 2009) and the development of applications such as Google Earth and Microsoft Bing Maps, very high-resolution (VHR) satellite imagery can be viewed over many parts of the world. Moreover, the land area now covered by VHR imagery has also grown dramatically over recent years (Lesiv et al. 2018b). This opens up the possibility to visually identify land cover and land use features, as well as the structure of forests. For the purpose of this paper, we define VHR imagery as having a spatial resolution of less than 2 m, while high-resolution (HR) imagery refers to the resolutions of Landsat (30 m) or Sentinel 2 (10 m). Forest parameters of interest that can be identified from VHR imagery include: the type of land cover/land use; identification of forest/non-forest areas; whether forest areas are homogeneous or heterogeneous; forest cover fragmentation; forest disturbances, degradation and change over time; identification of low, medium and high values of biomass; whether forests are young or old; differentiation between natural forests and plantation; forest and tree crops; forest phenology (evergreen or deciduous); and leaf types (broad leaf or needle leaf).

Although the automatic processing of remote sensing data for forest monitoring remains the standard procedure, visual interpretation of VHR imagery for reference data collection has a number of advantages over in situ data collection and can even be viewed as a bridge between remote sensing and in situ approaches. For example, it can be used to collect large amounts of training data for automatic classification algorithms. A probability-based sample design can be implemented so that the visually interpreted data can be used for the validation of maps produced using remote sensing. Areas with high uncertainty can then be identified, and additional reference data were collected to further improve automatic classification. Visual interpretation can also be used for deriving forest statistics directly from satellite imagery (Bastin et al. 2017a). Finally, visual interpretation can be used to identify drivers of change, e.g., automatically generated maps of forest loss can be further translated to areas of clearcutting, burnt areas, disease dieback, shifting cultivation, etc. (Ontikov et al. 2016; Curtis et al. 2018). Note that we do not explicitly discuss applications of biodiversity here because extracting meaningful biodiversity information from remotely sensed imagery in many forest contexts requires reliable and geographically representative information on the spectral and temporal signatures of species, and these traits must be combined with further assumptions about phylogenetic dissimilarity. Although there are candidate methods available, they are still highly experimental and therefore uncertain.

In this review paper, we focus on the state of the art in visual interpretation of satellite imagery, recognizing the continuing role of HR imagery but focusing on advances that are possible from VHR imagery, and highlight their unique and complementary role in remote sensing and in situ data collection for the observation and monitoring of forests. We first focus on the types of satellite imagery available and then provide an overview of the tools that have been developed for visual interpretation. The quality of visual interpretation is a key concern for users so we review recent work undertaken in this area. Finally, we highlight some successful case studies that have employed satellite imagery for forest observation.

2 Availability and Utilization of Imagery in Forest Observation

2.1 Availability and Distribution of Imagery

As a result of advancements in Earth Observation (EO), HR satellite data are being made openly available, e.g., free access to Landsat data by the United States Geological Survey (USGS) since 2008. Landsat data have played a significant role in monitoring of the Earth, particularly in forest observation studies, as more than 40 years of satellite data with consistent spectral bands are available. The data are distributed through various platforms such as the USGS Earth Explorer and NASA's Earth Data (USGS 2018; NASA 2018) as well as Google Earth Engine (Gorelick et al. 2017). Complementary to Landsat, ESA's Sentinel 2 mission was launched in 2015 (Drusch et al. 2012). Sentinel 2 data (10–60 m), along with other Sentinel mission data, are freely accessible to the public via the Copernicus Open Access Hub (Copernicus 2018).

In addition, VHR satellite data offer further possibilities for forest observation. Multitemporal and multispectral VHR data are acquired by passive sensors (e.g., QuickBird, WorldView-2, GeoEye, Pleiades) (Solano-Correa et al. 2018) and are distributed commercially via DigitalGlobe, Geo-Airbus and Planet (Airbus 2018; Harris 2018; Planet 2018). However, some of this imagery is openly available or available upon request via the USGS Earth Explorer and ESA's Earth Online portal (USGS 2018; ESA 2018). In addition to the data providers, there are multiple platforms that allow users to view VHR data, e.g., Microsoft Bing Maps and Google Earth. The latter was released in 2005 and allows seamless viewing and exploration of medium-resolution, HR and VHR satellite imagery globally (Sheppard and Cizek 2009; Bey et al. 2016). By 2011, Google Earth had been downloaded over one billion times (Google 2018). The appeal of these tools is evident, not only for private users but also for scientists, policy-makers and stakeholders in tackling environmental and planning issues (Butler 2006). Building upon these platforms, several free and open-source software applications have been developed to facilitate the collection and analysis of land and forest cover characteristics including: Geo-Wiki, the GLCF Labeling Tool, LACO-Wiki and TimeSync (Bey et al. 2016. In addition to using VHR imagery, these software applications use archives of Landsat and MODIS imagery to display automatically generated time series of vegetation index profiles (Bey et al. 2016). A recent assessment has been made of the spatial and temporal availability of VHR data in Google Earth and Microsoft Bing Maps (Lesiv et al. 2018b), including suitability for forest monitoring.

VHR and LiDAR imageries are also available from light-weight unmanned aerial vehicles (UAV), which opens up further possibilities for detailed land and forest monitoring (Zahawi et al. 2015; Paz 2017). UAVs are low cost, have high spatial and temporal resolution and provide flexibility in the types of sensors used (GOFC-GOLD 2011).

2.2 Utilization in Forest Monitoring

The use of remote sensing in forest resource assessment provides different types of information such as the spatial extent of forest cover and its change over time, forest types and biophysical and biochemical properties of forests (Boyd and Danson 2005). Assessments using remote sensing commonly involve visual interpretation, e.g., to generate training or validation data sets, particularly when analyzing the spatial extent of forests and their change over time. For example, a global forest cover change product at a 30 m resolution was calibrated and validated based on reference data created via visual interpretation of HR and VHR satellite data (Hansen et al. 2013). Similarly, an assessment of the suitability of this global forest change product for forest area estimation at the national level in Gabon was made using an independent validation data set, visually interpreted using available satellite imagery (Sannier et al. 2016).

A hybrid approach that combines automated processing of satellite data and visual interpretation is commonly used to monitor forest extent and its change over time. For example, Duveiller et al. (2008) assessed deforestation rates in Central Africa using sample-based estimation, which was created from automated image segmentation and visual interpretation of both HR and VHR satellite imagery. Sy et al. (2015) assessed the subsequent land use types after deforestation in South America using sample-based deforestation data from the UN-FAO Forest Resources Assessment (FRA), created from automated segmentation, and visual interpretation of VHR satellite imagery. In a study to create reference data for forest and tree cover fraction, Pengra et al. (2015) automatically classified 500 VHR images distributed globally and then manually edited them to obtain reference maps at a 2 m resolution. Bey et al. (2016) applied "augmented visual interpretation" by combining visual interpretation of VHR images with vegetation indices computed for all dates available back to the year 2000 from MODIS, Landsat and Sentinel.

Visual interpretation of VHR images is also used in other forest assessments such as forest structure and biomass estimation. Examples include studies on selective forest logging and its impacts (Read et al. 2003; Furusawa et al. 2004; Pithon et al. 2013), forest species classification (Clark et al. 2005; Valérie and Marie-Pierre 2006; Kim et al. 2009; Bilous et al. 2017), tree crown identification (Garzon-Lopez et al. 2013; Karlson et al. 2014) and biomass estimation (Hussin et al. 2014). In these studies, visual interpretation of VHR images was often used to create training data in the absence of in situ data.

Visual interpretation can also be used to produce statistics directly from sampling point approaches. In contrast to a map-based area estimation approach, this method has several advantages. First, when collecting information with photointerpretation, the land cover data collected are independent from other environmental layers. Secondly, there is no loss in information when upscaling to the map resolution (i.e., to Landsat, MODIS or any other product) because the raw information is still available. This is particularly relevant for regions with sparse tree cover. Moreover, this approach of directly obtaining statistics through visual interpretation is based on a transparent data assessment where the only uncertainty is potential photointerpretation errors, e.g., as debated in Schepaschenko et al. (2017) and the subsequent response by Bastin et al. (2017b). If such a sampling approach is applied at a larger scale, then independent statistical information can even be obtained globally, e.g., in the global dryland assessment by Bastin et al. (2017a), in which global statistics on forest cover from a visual interpreted sample were derived.

Visual interpretation of HR and VHR data has been recommended as one of the approaches for national forest monitoring and reporting by international committees such as the GOFC-GOLD (2011). As a result, several tools and software applications have emerged for collecting reliable reference data for map calibration and validation for forest and forest change monitoring purposes. Some of these tools are described in more detail in the next section.

3 Tools for Visual Interpretation

This section provides an overview of the main tools available for visual interpretation of satellite imagery. The final part of this section covers tools that exist but which are not openly available or they have been developed in the context of awareness raising and the monitoring of deforestation.

3.1 Geo-Wiki

Geo-Wiki was originally developed as an online tool to collect information on the accuracy of class descriptions from three global land cover maps (GLC-2000, MODIS and Glob-cover 2005) when viewed on top of VHR satellite imagery from Google Earth. Users could choose any location on Earth, and validation was on pixel-by-pixel basis (Fritz et al. 2009). Users could also view the main land cover products in a single application, along with layers highlighting the areas of disagreement in cropland and forest classes. Hence, Geo-Wiki served as an application for exploring the accuracy of existing land cover products using satellite imagery, which was not previously possible via an open application.

Since 2009, the Geo-Wiki tool has evolved in a number of ways. First, the Geo-Wiki interface was expanded into multiple branches, each related to a specific land cover or land use theme. For example, the biomass branch of Geo-Wiki (https://biomass.geo-wiki.org) was designed to allow users to visualize all the major data sets of above ground and forest woody biomass on VHR imagery in order to compare the layers with one another but also to provide feedback on the biomass estimates at any location on Earth (Schepaschenko et al. 2015a).

A second key adaptation to Geo-Wiki was the use of crowdsourcing campaigns to collect data related to a specific research question. The first six campaigns are documented in See et al. (2015a) and resulted in the visual interpretation of around 250 K locations around the world (Fritz et al. 2017). The campaigns were used to validate a map of the land availability for biofuels (Fritz et al. 2013), to develop maps of cropland and agricultural field size (Fritz et al. 2015; Lesiv et al. 2018a), wilderness (See et al. 2016) and global land cover (See et al. 2015b). The campaigns employed gamification and incentives such as Amazon vouchers and coauthorship.

New campaigns have since been run to collect a global validation data set for cropland (Laso Bayas et al. 2017a). At the same time, Geo-Wiki was also set up to run internal data

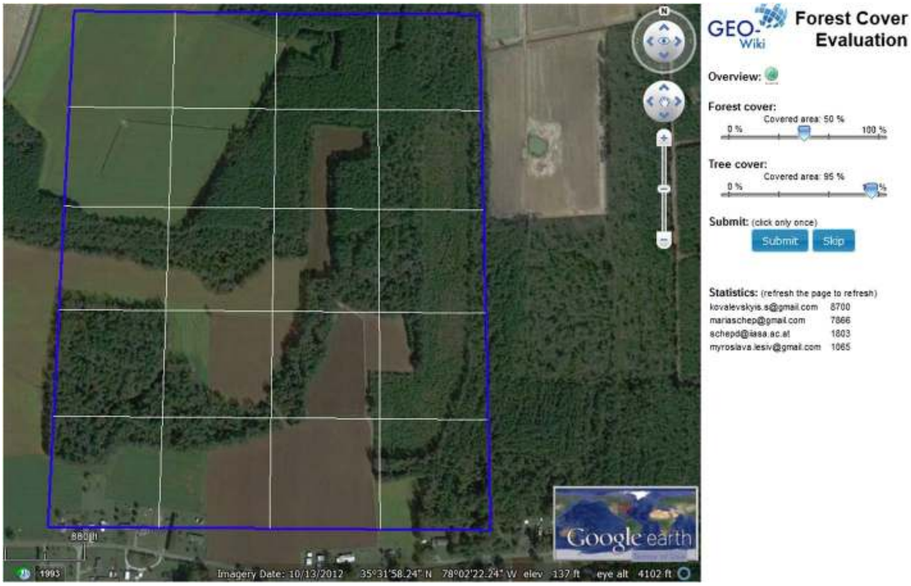

Fig. 1 An example of a Geo-Wiki interface used to collect data on forest cover (Schepaschenko et al. 2015b)

collection campaigns to produce high-quality training and validation data sets for different tasks related to the development of forest maps. For example, data on forest cover were collected by various experts using an interface like that shown in Fig. 1. Combined data from the Geo-Wiki database, in combination with several existing forest maps, have been used to develop a hybrid map of global forest cover (Schepaschenko et al. 2015b). More details are provided in Sect. 5.1. Other products include a high-resolution hybrid forest cover map of Ukraine along with a detailed tree species map (Lesiv et al. 2018c).

The "Human impact on forest" branch of Geo-Wiki focuses on the collection of the following forest and land use features: mature forest; plantations; fruit plantations; planted forest; clearcut, thinning; unpaved forest roads; paved roads; mosaic tree cover/cropland; and mosaic tree cover/urban. The "Drivers of forest cover change" Geo-Wiki branch allows users to record the following classes of land use change: no changes: stable tree cover, stable non-tree cover; tree cover loss: expansion of agriculture, shifting cultivation, urban/infrastructure expansion, mining, wildfire/windfall/dieback, timber harvest (without land use change); tree cover gain: reforestation, afforestation, tree crops.

3.2 LACO-Wiki

LACO-Wiki is a free platform for undertaking land cover accuracy assessment (https://laco-wiki.net). It contains the complete workflow from uploading a map for validation, creating a sample and interpreting the sample using VHR satellite imagery from Google Maps or Microsoft Bing Maps (or other imagery provided by a Web Map Service). An accuracy report is then produced, which contains the confusion matrix and the indicators of accuracy chosen by the user. Figure 2 provides an example of the visual interpretation process, illustrating validation of the GlobeLand30 land cover map in Kenya. The online

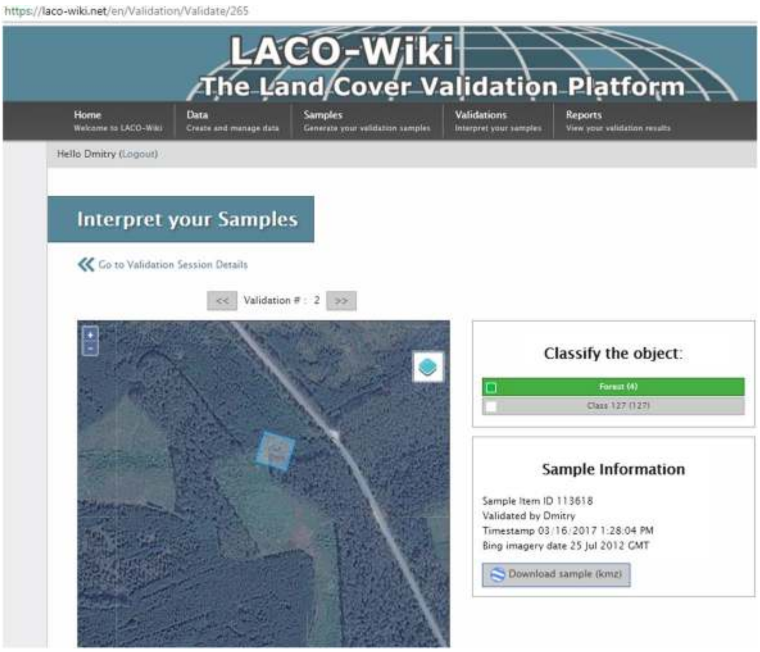

Fig. 2 An example of the visual interpretation of a sample unit using the LACO-Wiki tool

tool, the workflow and the Kenyan validation example are described in more detail in See et al. (2017).

Since the legend for visual interpretation is determined by the land cover map uploaded to the system, LACO-Wiki can be used for collecting data on forest cover, expressed as either forest cover classes or percentage forest cover, or any other features defined by the users, which are visible from VHR satellite imagery. LACO-Wiki also allows users to upload pre-defined sample locations, e.g., produced using a GIS, and undertake visual interpretation.

The vision of LACO-Wiki goes beyond that of just providing an online tool for accuracy assessment. It is also intended to be a repository for sharing land cover maps and the reference data sets generated as part of the accuracy assessment process (See et al. 2017). In this way, hybrid land cover or forest cover maps could be created from a mosaic of existing layers from the repository using a potentially much larger training data set than could be collected by individuals or organizations on their own.

3.3 Picture Pile

Picture Pile is a mobile and online application designed for the rapid classification of VHR satellite imagery and geotagged photographs. It is a generalized version of the Cropland Capture game (Sturn et al. 2015; Baklanov et al. 2016; Salk et al. 2016), which focused on visually classifying imagery for cropland using a simple question: Is there evidence of cropland? Users had the choice of yes, no or maybe, swiping the image in the direction of the answer on mobile devices or using the cursor keys on the browser version. In this way, it was possible to collect millions of interpretations of the presence/absence of cropland over a 6-month period.

Fig. 3 An example of the rapid interpretation of deforestation from a pair of images in picture pile

In Picture Pile, the concept is that piles of pictures corresponding to any subject area (not just cropland) could be visually interpreted in a rapid manner using the same simple question. The first campaign run provided users with pairs of satellite images from different time periods; the question they were asked was: "Do you see tree loss over time?" as shown in Fig. 3.

The idea behind this campaign was to validate the Hansen et al. (2013) tree loss and gain products for Tanzania and Indonesia. Preliminary results show that there are examples where Hansen indicates deforestation, but visual interpretation shows no tree loss and vice versa, i.e., no deforestation is indicated by Hansen et al. (2013), but visual interpretation shows clear patterns of forest loss. A new tool called Picture Paint is currently being developed that will take areas with deforestation as inputs from Picture Pile and allow users to shade those locations where deforestation has occurred. In this way, more accurate locations of where deforestation occurred can be recorded, which can be used to improve maps of deforestation and forest cover for specific time periods. Hence, Picture Pile and Picture Paint are two visual interpretation tools that can be used together to gather rapid and then more detailed forest observations.

3.4 Collect Earth

Collect Earth is a free and open-access software tool developed by the UN-FAO for the monitoring of land cover and land use (Bey et al. 2016). Collect Earth allows for the collection of plot-level information (e.g., a square of 0.5 ha) of current and historic land properties of a given location using various sources of remote sensing data. Combining the information collected for numerous plots through a systematic or randomized sampling design, Collect Earth outputs can then be used (1) for the development of statistics at national, regional or even global scale or (2) as a set of training and validation points for wall-to-wall mapping. To develop statistics with a low level of error requires considerable photointerpretation efforts, which rely on human capacity. For example, to characterize tree cover in drylands with less than 1% error, Bastin et al. (2017a) collected information at more than 200 000 points, which required the coordination of 236 operators in the photointerpretation effort. The list of recorded parameters includes: land cover type, land use category, land use change (2000–2015), year of changes, tree or shrub count, vegetation type, length of linear objects (vegetation, paved or unpaved roads), type and impact of disturbances and the accuracy of the assessment.

Collect Earth is built on Google Earth technologies and, in particular, two different tools: Google Earth Desktop and Google Earth Engine Code Editor. The interface of Collect Earth is completely included in the Google Earth Desktop. It provides access to all available satellite archives of VHR images, which are used for the photointerpretation of predefined plots. In parallel, for each plot, Collect Earth provides access to preprocessed satellite information at a high-temporal resolution computed using the Google Earth Engine Code Editor. In particular, it provides information on the normalized difference

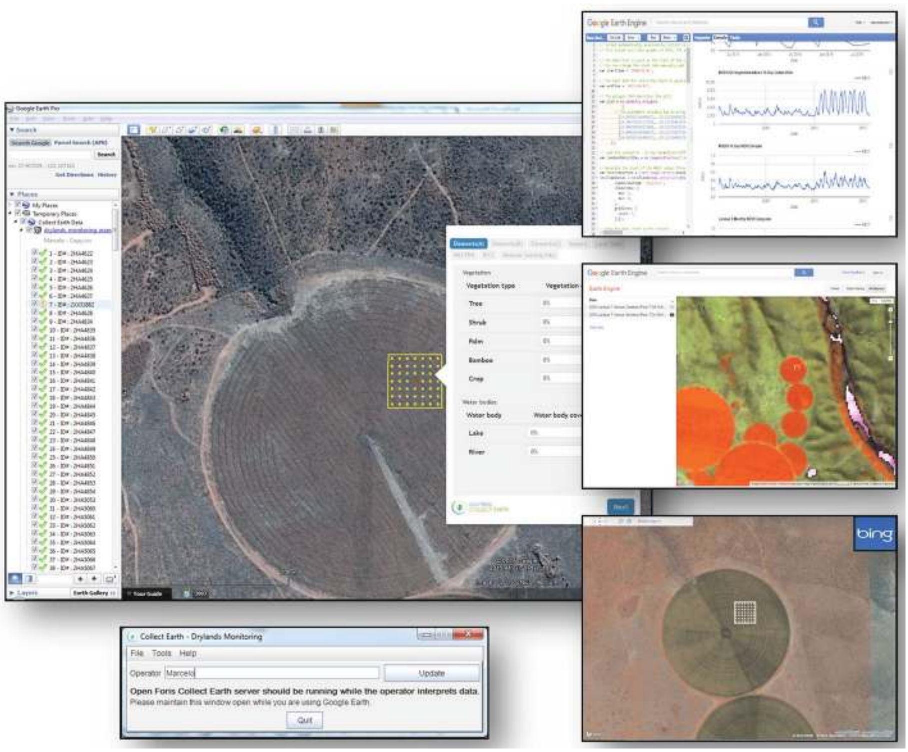

Fig. 4 An example of the rapid interpretation of land use and land use change using Collect Earth, combining VHR images available in Google Earth and Bing Maps with NDVI computed since the 2000s from Google Earth Engine Code Editor

vegetation index (NDVI), computed since the year 2000 from MODIS, and for Landsat and Sentinel 2, where available. Combining both high spatial and temporal resolution for land monitoring, Collect Earth allows the operator to collect a considerable amount of information about the land properties through augmented visual interpretation (Fig. 4).

3.5 Other Tools

Some tools for visual interpretation are not openly available, but some examples have been documented in the literature. For example, the VIEW-IT (Virtual Interpretation of Earth Web-Interface Tool) project was developed to collect land cover reference data including classes for woody and mixed woody vegetation in order to support ongoing research in land cover change (Clark and Aide 2011). The system is similar to Geo-Wiki in that users estimate the percentage of land cover in a 250 m MODIS pixel using VHR imagery from Google Earth. The tool was used to collect more than 46,000 reference samples across Latin America and the Caribbean with a team of 30 staff and students. The authors admit that the first version was meant to be a proof of concept with future developments to include expansion to global coverage, opening up to crowdsourcing, customized samples, grid sizes and data collection (similar to what is available in LACO-Wiki) and multiple interpretations of the same sample unit. Since the publication of that paper, the tool does not appear to have been opened up and the reference data have not been made openly available.

Focusing more on the forest domain, the UN-FAO complemented the Forest Resources Assessment (FRA) exercise in 2010 with a remote sensing survey (RSS) using an interface developed for interpretation of Landsat imagery (Lindquist et al. 2012). There were 13,066 sample sites in the RSS, each of which is a 20 km^2 area located at each 1 degree intersection of latitude and longitude, except in Canada and the Russian Federation where a different approach was used. In the framework of the TREES-3 project, the Joint Research Centre of the European Commission (JRC) took the responsibility for producing and verifying a large component of this global data set, particularly focusing on tropical forests. Using a segment-based classification and the commercial eCognition software, Landsat imagery from 1990, 2000 and 2005 was automatically classified to a legend that allowed the detection, at segment level, of tree cover loss and change between epochs. The individual segments were visually verified against Google Earth and other VHR imagery by both JRC staff and national experts, using a standalone tool developed in IDL (Simonetti et al. 2011). The results of the exercise (Achard et al. 2014) are available for free public download.[1]

A Web version of the verification/image interpretation tool described above was implemented as a research prototype in the context of the EuroGEOSS project, supported by open standards and application programming interfaces (APIs) (Bastin et al. 2012). This demonstrated the feasibility of Web-enabling a well-established validation process with significant policy impact, and offered the advantage that no imagery needed to be downloaded to the desktop. However, the standalone nature of the original IDL toolkit has proved to be particularly useful in areas where internet connectivity is limited or sporadic, and it is still available for free public download and use.[2] The JRC tools for mapping of forest change and loss have subsequently been improved and made more accessible—in

[1] http://forobs.jrc.ec.europa.eu/trees3/.

[2] http://forobs.jrc.ec.europa.eu/products/software/other.php.

particular, the classification step now uses entirely open-source tools and libraries (Simonetti et al. 2015). The entire workflow from image selection to validation is now embedded in a free and open-source toolkit named IMPACT.[3] An example of the analysis possible with IMPACT is documented in Szantoi et al. (2016), and the labeled data from that analysis is available through open OGC-standard Web Map and Feature Services hosted at JRC.

The Web-based version of the JRC land cover validation tool was adapted into a system that allowed the labeling of point samples using a combination of visual interpretation with inspection of NDVI signatures (Bastin et al. 2013). This approach was used by the Royal Society for the Protection of Birds (RSPB) and Birdlife in an exercise that labeled user-specified sample points in and around Important Bird Area (IBAs) in order to test the hypothesis that legal site protection reduces the loss of natural land cover (Beresford et al. 2013). This interface also delivered NDVI information, by overlaying the value for the sample location being interpreted at the time of acquisition on a graph of historic mean/standard deviation for the same area across the year. The point of this was for a user to see (a) whether the particular image they were looking at was anomalous or representative of the land cover at that location, and (b) the characteristic vegetation profile for that location over time. The NDVI information was derived from a web service based on JRC's eStation, which compiles and delivers environmental information from remote sensing across Africa. An administrative interface allowed sample locations to be uploaded and allocated to authorized labelers, and the resulting information could then be downloaded. The resulting ground-truth data set was reused to validate an experimental water classification by Pekel et al. (2014), and is available on request from the original researchers. This web tool and underlying database was taken offline in 2015 because of a lack of resources, but the codebase is archived in an open repository.

A system for object delineation and visual interpretation of VHR imagery from Google Earth has been developed by the Universite Catholique de Louvain (UCL). This system, which is targeted at experts, was developed to collect reference data for the development of land cover products, e.g., GlobCover (Bontemps et al. 2011) and the ESA-CCI (European Space Agency Climate Change Initiative) land cover time series (ESA CCI LC 2017), which have been produced by researchers at UCL in collaboration with other partners. Medium-resolution time series or high-resolution snapshot images are also at hand to facilitate the labeling process. The interface was recently simplified to allow experts in remote sensing and agronomy from the EU-funded SIGMA project[4] to collect binary cropland data at 4147 locations (Waldner et al. 2018). Unfortunately, the reference data that have been collected through this bespoke interface over several years have not been made openly available.

Earth Watchers is a software tool developed by Geodan Inc. in the Netherlands for involving students in change detection in the context of deforestation monitoring.[5] Students are assigned an area, which is a hexagon of around 1.6 km^2. Each week, a new processed radar satellite image is provided (although Landsat has been used in the past) and students raise an alert if they see evidence of change. The ten most likely sites of change are surveyed by a team on the ground, which documents their findings using photographs and video or they deploy UAVs for safety reasons. Any illegal activities are reported to the

[3] http://forobs.jrc.ec.europa.eu/products/software/impact.php.

[4] http://www.geoglam-sigma.info/.

[5] https://dfa.tigweb.org/about/?section=earthwatchers.

local authorities who have pledged their support to the project and to halt deforestation. The project is currently operating in Indonesian Borneo.

3.6 Comparison of Geo-Wiki, LACO-Wiki and Collect Earth

This section compares and contrasts the three main tools for visual interpretation of VHR imagery to which anyone can openly contribute: Geo-Wiki, LACO-Wiki and Collect Earth, based on a range of different features as outlined in Table 1. There are a number of similarities between the tools, e.g., the research teaching communities are a main target group for all of the tools. However, Collect Earth also targets organizations involved in official statistical reporting, while LACO-Wiki has been recommended as a validation tool for European Environment Agency member states. Geo-Wiki, through its crowdsourcing campaigns, targets a broader audience that includes citizens. Each system also has a mobile app although the Geo-Wiki Pictures app is now being replaced by ongoing developments in LACO-Wiki Mobile.

Overall, there are greater differences between the tools, in particular between Collect Earth and the other two. This is because users work directly in Google Earth Engine in Collect Earth so this means historical HR imagery is directly available along with other ancillary layers and scripts for processing the data, e.g., generation of NDVI profiles. Different types of information are collected with each tool as outlined in Table 1. Both Collect Earth and LACO-Wiki are customizable, while Geo-Wiki must be set up internally in response to research needs while both Geo-Wiki (to a limited extent) and LACO-Wiki allow users to design their sample online while samples must be generated outside of Collect Earth using a GIS package or scripts and then uploaded. At this stage, only Collect Earth is fully open, with code available in Github; this is not yet the case for Geo-Wiki and LACO-Wiki although the new mobile version of LACO-Wiki will be open source. Conversely, the data are not necessarily open from Collect Earth as this depends on the group or persons who use the tool for a particular purpose while the data from Geo-Wiki can either be downloaded from the website or can be found in PANGAEA (Fritz et al. 2017; Laso Bayas et al. 2017a). The validation data in LACO-Wiki are theoretically open through the licensing agreement that users agree to when registering in the system although individual users can currently keep the data private or share it more broadly. Finally, each of the systems has various support mechanisms including a user forum (Collect Earth), newsletters (Collect Earth and Geo-Wiki), a facebook group (Geo-Wiki) and contact via email (all three systems). Hence, it is clear from this comparison that each of these packages has different strengths and weaknesses, which are partly a function of how they were designed in response to user requirements.

4 Issues Related to the Quality of VHR Imagery and Visual Interpretation

The quality of visual interpretation of VHR imagery is a function of the quality of the satellite imagery and the interpretation procedure applied to the imagery. The interpretation procedure can involve experts or crowdsourcing, both of which can be problematic (See et al. 2013; Coillie et al. 2014). In this section, we consider issues that influence the quality of both of these components.

Table 1 A comparison of the three main open tools for visual interpretation of VHR imagery

Feature	Collect Earth	Geo-Wiki	LACO-Wiki
Main users	Research and teaching community, organizations involved in the verification or preparation of national statistics on land cover, land use and land use change for IPCC, UNFCCC and FRA reporting	Research and teaching community, citizens interested in science that want to participate in data collection campaigns that involve visual interpretation	Research and teaching community, any organization requiring land cover map validation, e.g., it is recommended to European Environment Agency member states for validation of VHR components as part of Copernicus land monitoring activities
Information that can be collected using the tool	Land cover type, land use category, land use change, year of changes, tree or shrub count, vegetation type, length of linear vegetation, type and impact of disturbances, accuracy of the assessment	Land cover, land use type; forest fragmentation, plantations, drivers of forest cover change (roads, agriculture expansion, shifting cultivation, etc.)	Land cover type, land use category and accuracy of the assessment can be customized so that any features represented as attributes in the map could be collected or validated
Role of GEE	Users work directly in GEE and have access to all data and scripts in GEE. Or they can write new/modify existing scripts, which requires some technical expertise	There is no direct access to GEE. Instead, there are tools embedded in the interface (or will be shortly in the case of LACO-Wiki) that ingest results generated by GEE; see example of NDVI tool below	
High-resolution imagery	Direct access to current and historical imagery such as Landsat is available in GEE	Current and historical HR imagery is available through Sentinel Hub as a WMS	
Imagery dates	The dates of the Google VHR images are recorded manually. Microsoft Bing Map dates are read automatically via an API		
Ancillary layers	Only those layers that are available in GEE, but users can upload their own layers	Any ancillary layer can be displayed as a WMS. Users must request the layer to be displayed	Users can specify the layers to be displayed from a WMS
NDVI time series	NDVI automatically generated for each plot photointerpreted. Generated for 2000 to present day for MODIS data, and for all available dates with no cloud cover for Landsat and Sentinel data	An NDVI tool is embedded in the interface. Users click on a location and can see NDVI values over time and mean values calculated from GEE	This feature will be implemented in 2019
Sample design	Users cannot generate a sample in Collect Earth, but scripts are provided on the Collect Earth website to generate a country-level sampling grid through the GEE code editor	A simple random sample can be created, but otherwise the sample is created using GIS and then hardcoded into the Geo-Wiki branch by developers	Users can generate different sample types (random, stratified, systematic) or upload a sample generated with a GIS

Table 1 (continued)

Feature	Collect Earth	Geo-Wiki	LACO-Wiki
Level of customization	Users can customize the interface for any specific data collection needs, including different data types and levels of spatial detail	Customization is currently not possible. Branches are created ad hoc to meet user needs	Users can customize a validation session to meet their needs (sampling design, data types)
Feedback and community support	There is an open forum for user queries and newsletters for subscribed users	Users can ask questions via email or discuss open issues via the Geo-Wiki facebook group. Newsletters are sent to subscribed users	
Code availability	Open access on GitHub	Not available	Not available but currently working on an open-source version of LACO-Wiki Mobile
Data access	The data collected using Google Earth belong to the group or persons who initiated the data collection campaign. Only they can decide if they share these data with others	The data can be downloaded from the Geo-Wiki website or from the PANGAEA repository	As part of the licensing, users agree to share their validation data. However, during individual sessions, users can keep the data private, share with individuals or share with everyone
Mobile app	Collect Mobile for Android	Geo-Wiki Pictures (Android and iOS) but now deprecated and will be replaced with LACO-Wiki Mobile	LACO-Wiki Mobile is currently being developed for Android and iOS as an open-source application

GEE Google Earth Engine; NDVI Normalized Difference Vegetation Index; API Application Programming Interface; WMS Web Map Service

4.1 Problems Associated with the Quality of VHR Imagery

Although the spatial coverage of VHR imagery in Google Earth and Microsoft Bing Maps continues to improve, visual interpretation may still be hampered by the actual quality of the imagery, which may lead to confusion in the resulting interpretation made by volunteers and experts. The most common reasons are image blurriness and the presence of clouds covering a scene. However, ubiquitous digital cameras have made the development of blur detection algorithms an active area of research (Tong et al. 2004; Li et al. 2016). These algorithms provide a quality score for an image, which allows a threshold to be specified that can be used to remove highly blurred images from an analysis. For example, the application of blur detection algorithms helped to detect around 2300 blurry images that were impossible to label correctly, even for experts (Baklanov et al. 2016, 2017). These images distorted the accuracy of the results in a crowdsourcing campaign due to high inconsistencies, i.e., volunteers and experts changed opinions when presented with the same blurry image, which affected the overall results when they were combined through a voting procedure.

VHR images from sources such as Google Earth and Microsoft Bing Maps come without a cloud mask, have very limited spectral information, and usually lack thermal bands that can be used for robust cloud detection (Zhu and Woodcock 2012). Thus, when working with VHR imagery from these sources, we only have a true-color RGB image. To handle these images, numerous approaches (Başeski and Cenaras 2015; Bai et al. 2016; Fan et al. 2017) of different complexity have been developed, which have an overall accuracy close to that when applying one of the algorithms that uses thermal bands.

The generalization of automated approaches from optical data is very dependent on sun-scene-sensor geometries (Barbier et al. 2011; Morton et al. 2014) and from specific interaction with object properties (e.g., the forest type) (Bastin et al. 2014), where this problem increases with spatial resolution. Hence this is a very important issue for the automated processing of VHR images. However, procedures for the correction of such geometries (Barbier and Couteron 2015) and the fusion of remote sensing metrics (Ploton et al. 2017) help to address some of these issues.

Finally, there are problems related to the comparison of interpretations of detailed information from VHR resolution imagery (e.g., tree count, tree cover) with ground observations. As raised previously and although this point has been debated in the literature (Schepaschenko et al. 2017; Bastin et al. 2017b), Bastin et al. (2017a) demonstrated that photointerpretation can lead to an error that is less than 10% in estimating the extent of forest at a global scale.

4.2 Approaches to Quality Assurance of Visual Interpretation of VHR Imagery

There are different approaches to quality assurance that have been applied to visual interpretation of VHR imagery, which includes comparison with in situ data/field measurements or other high-quality products such as a regional or national map, when available, comparison with an expert or “control” data set of visual interpretations and approaches for combining multiple observations at a single location.

In situ data from the Land Use/Cover Area frame Survey (LUCAS), which are collected every 3 years by Eurostat, have also been used as ground-truth data for the 2015 FotoQuest Austria campaign (Laso Bayas et al. 2016). Citizens were asked to go to specific locations across the Austrian landscape and collect information on land cover and land use with a mobile app. The results showed an agreement of up to 80% for high-level land cover and land use types in homogeneous areas.

Existing land cover maps have also been validated using a version of the Geo-Wiki platform that can be run offline and hence used more easily in countries with less reliable internet connections. Over 25,000 VHR Digital Globe images from Tanzania were classified by local volunteers for the degree of cropland and forests present. The land cover products included the ESA-CCI, GlobeLand30, FROM-GC and a regional product (Tanzania Land Cover 2010 Scheme II). Although the results reported in Laso Bayas et al. (2017b) were specifically focused on cropland, the results showed an overestimation of cropland by ESA-CCI and a large underestimation by the FROM-GC product. To ensure quality of the crowdsourced data, each location was interpreted by at least three different local people and combined using majority voting. A similar approach could be applied to forest cover data.

Geo-Wiki campaigns have made extensive use of an expert or control data set, i.e., a subset of the sample that is classified by a group of experts; this control data set is then used to calculate the performance of the crowd (See et al. 2013; Fritz et al. 2017; Laso Bayas et al. 2017a; Lesiv et al. 2018a). The information about performance can then be used to weight the data when used in subsequent applications, e.g., giving less weight to those interpreters who performed less well (e.g., Lesiv et al. 2018a). The control data set has also been used during campaigns to calculate a score based on both quality and quantity of interpretations, which was then used to determine the award of prizes or other incentives such as coauthorship.

The quality control of the data gathered through Collect Earth is not performed automatically; it should be implemented by the operator. In the study of Bastin et al. (2017a) on the extent of forest in dryland biomes, two main steps were implemented: a quality control and an uncertainty analysis. The quality control implied the reassessment of plots identified as potentially problematic, which were identified through the definition of several logical cross-control rules. For example, all plots classified as grassland reported to have $\geq$ 10% tree canopy were reassessed by a team of experts and corrected as necessary. The uncertainty analysis was performed accounting for (1) sampling error and (2) measurement error (i.e., the mismatch between ground truth and photointerpretation). In the study, the two were combined and propagated in the original data 100 times, meaning a random error was applied 100 times to the tree cover of each plot, following a normal distribution centered on the original value and with a variance equal to the sum of the two types of errors. The forest extent of dryland biomes was then recalculated 100 times from which the final error was calculated with the standard deviation.

Multiple interpretations at a single location have also been used to ensure quality. For this, a simple majority vote rule can be a good way to aggregate votes if volunteers are correct most of the time (Baklanov et al. 2016). For example, Foody et al. (2018) used a simple weighted average to combine interpretations from multiple participants to improve the overall accuracy, while in the study by Laso Bayas et al. (2017b), quality was estimated based on the consistency between the interpreters. However, there are numerous state-of-the-art vote aggregation methods (e.g., see the surveys by Hung et al. 2013; Chittilappilly et al. 2016), which could be employed to deal with incorrect visual interpretations but have not yet been applied to this specific field. Salk et al. (2017) also showed that majority voting can have its limitations in visual interpretation of cropland and that the use of a control data set is recommended.

5 Success Stories of Using VHR Data for Forest Observation and Assessment

5.1 Global Forest Mask

A number of global and regional maps of forest extent are available, but when compared spatially, there are large areas of disagreement between them. Moreover, until recently, there has been no global forest map available that is consistent with the national statistics from the UN-FAO FRA. Geo-Wiki has been used to validate existing forest extent maps and to collect training data for combining diverse data sources into a single forest cover product (Schepaschenko et al. 2015b; Lesiv et al. 2016). From these data, it was possible to produce a global forest map that is more accurate (at the target 1 km resolution) than the individual input layers and to produce a map that is consistent with UN-FAO FRA statistics. Geographically weighted regression (GWR) was employed to integrate eight different forest products into three global hybrid forest cover maps for the reference year 2000. Input products included global land cover (GLC2000, GLCNMO, MODIS LC, GlobCover) and forest maps at varying resolutions from 30 m (Sexton et al. 2013; Hansen et al. 2013) to 1 km, mosaics of regional land use/land cover products where available, and the MODIS Vegetation Continuous Fields product. The GWR algorithm was trained using crowdsourced data of visual interpretations collected via the Geo-Wiki platform, and the hybrid maps were then validated using an independent data set collected via the same system by experts. Three different hybrid maps were produced: two consistent with UN-FAO statistics, one at the country and one at the continental level, and a "best-guess" forest cover map that is independent of UN-FAO. Independent validation showed that the "best-guess" hybrid product had the best overall accuracy of 93% when compared with the individual input data sets. The global hybrid forest cover maps are available in a Geo-Wiki branch dedicated to biomass: http://biomass.geo-wiki.org.

5.2 Dryland Forest Assessment

Classical approaches employed to map tree cover at the global scale are generally based on medium-to-high-resolution satellite image processing, showing a typical spatial resolution of 10 to 250 meters. Such products are, however, known to produce very uncertain results in drylands (Sexton et al. 2016). Consequently, the UN-FAO has developed a new assessment of dryland forest resources based on a global photointerpretation effort coordinated with 236 operators, including researchers and country officials. Analyzing more than 210,000 0.5-ha sample plots through Collect Earth, this new assessment revealed that in 2015, 1327 million hectares of drylands had more than 10% tree-cover, and 1079 million hectares comprised forest. This estimate was 40–47% higher than previous estimates, corresponding to 467 million hectares of forest that have never been reported before. This means that previous efforts assessing the global forest extent were underestimating forest cover by at least 9% (Bastin et al. 2017a). This exercise has shown that a global photointerpretation effort coordinated between 236 operators can overcome, with some debated limitations (Schepaschenko et al. 2017; Bastin et al. 2017b), current flaws in state-of-the-art-automated mapping methods.

5.3 Landsat-Based Forest Loss and Gain

Landsat imagery provides the longest HR time series of land observations and has been used to estimate forest cover loss and gain (Hansen et al. 2013; Feng et al. 2016). To train their forest cover change algorithm, Feng et al. (2016) selected a stratified sample of points, which were visually classified as forest or non-forest cover by experienced image analysts. The decision was made based on Landsat time series images presented as multiple three-band combinations, e.g., near infrared, green, blue, and shortwave infrared, as well as auxiliary information including NDVI phenology from MODIS, HR satellite imagery and maps from Google Maps, and geotagged ground photos. Hansen et al. (2013) derived training data to relate to the Landsat metrics from image interpretation, including mapping of crown/no crown categories using VHR spatial resolution imagery such as Quickbird, and existing percentage tree cover layers derived from time series of Landsat data.

5.4 National Forest Reference Level: The Case of Papua New Guinea

Papua New Guinea submitted their national Forest Reference Level (FRL) to the UNFCCC in 2017 (Climate Change and Development Authority of Papau New Guinea 2017). The FRL is one of the elements to be developed by participating countries in the framework of REDD+ activity reporting, in agreement with decisions taken at several recent Conference of the Parties (COP) meetings. In their report, the Papua New Guinea governmental operators estimated their FRL for the year 2014 to 2018 in comparison with the reference period of 2001 to 2013. Carbon emissions for these periods were assessed from land use and land use change assessments using Collect Earth, which included deforestation, degradation and carbon stock enhancement, among others. The conversion to carbon emissions was obtained from national scientific literature and using the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006). This represents a good example of the nonscientific use of Collect Earth, which helped Papua New Guinea to report on LULUCF to the UNFCCC in a transparent fashion, demonstrating that developing countries can monitor their own carbon emissions.

5.5 Drivers of Forest Change

Global maps of forest loss show the scale and magnitude of forest disturbance, but they do not distinguish land use change (i.e., deforestation) from temporary loss of tree cover due to forestry or wildfires. Using visual interpretation of VHR satellite imagery, Curtis et al. (2018) developed a forest loss classification model to determine the spatial attribution of forest disturbance to the dominant drivers of land cover and land use change over the period 2001 to 2015. Their results indicate that 27% of global forest loss can be attributed to deforestation through permanent land use change. The remaining areas maintained the same land use over 15 years, and tree cover loss was attributed to forestry (26%), shifting cultivation (24%) and wildfire (23%).

6 Conclusions and the Future Perspectives

This review has shown that new sources of open satellite imagery have emerged over the last fifteen years, in particular HR imagery in the form of Landsat time series and Sentinel 2, as well as VHR imagery from Google Earth and Microsoft Bing Maps. This development has led to new tools for visual interpretation of VHR imagery such as Geo-Wiki, Collect Earth and more recently LACO-Wiki, which are collectively opening up visual interpretation of satellite imagery to crowdsourcing and nonscientific use, as well as providing new possibilities for research in the field of forest observation. Yet, the coverage of the Earth's surface by VHR imagery from freely open sources such as Google and Microsoft Bing Maps is not complete, limiting visual interpretation at these locations and potentially biasing the results from any probability-based sample. In fact, this number may be even higher in the northern latitude boreal forests where coverage by VHR imagery is even lower. However, the coverage is expected to continue to improve and there are instances where the coverage of VHR imagery from Google Maps can be complemented by that of Microsoft Bing Maps (Lesiv et al. 2018b). The incorporation of data from other new, emerging sources such as Planet may also help to fill in missing gaps in the future.

There should also be more joint efforts to bring together data sets based on visual interpretation from multiple sources, i.e., from the confidential data collected for individual projects that should be shared to the openly accessible data currently growing in size, which could contribute to a library of multipurpose reference data collections. Such an approach is already embedded in the philosophy of the LACO-Wiki system (See et al. 2017) but requires more coordinated efforts to achieve this at a global scale.

The future will also likely see more examples of online systems that allow for visualization of VHR imagery, particularly given the ease with which the imagery can now be accessed through Web Map Services, the growing archive of images available in Google Earth, which allows for some historical or change validation, and the trend in crowdsourcing and citizen science applications. We will also probably see a convergence in the functionality of the systems, particularly with regard to features that help with visual interpretation. More use of geotagged photographs and social media such as Twitter may also provide alternative sources of information that can aid visual interpretation efforts in the future.

Finally, it is anticipated that more VHR imagery will be opened up to the research community, which will allow for larger scale efforts in terms of automatic classification of VHR using the spectral information instead of just the RGB images from Google Earth or Microsoft Bing Maps, in particular deep learning approaches such as the use of Fully Convolutional Neural Networks (FCNs) applied to remote sensing (Maggiori et al. 2016; Fu et al. 2017; Baklanov et al. 2018a, b). These developments will only continue to improve the use of remote sensing data for forest observation in the future.

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