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Virtual constellations for global terrestrial monitoring

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ABSTRACT

Free and open access to satellite imagery and value-added data products have revolutionized the role of remote sensing in Earth system science. Nonetheless, rapid changes in the global environment pose challenges to the science community that are increasingly difficult to address using data from single satellite sensors or platforms due to the underlying limitations of data availability and tradeoffs that govern the design and implementation of currently existing sensors. Virtual constellations of planned and existing satellite sensors may help to overcome this limitation by combining existing observations to mitigate limitations of any one particular sensor. While multi-sensor applications are not new, the integration and harmonization of multi-sensor data is still challenging, requiring tremendous efforts of science and operational user communities.
Defined by the Committee on Earth Observation Satellites (CEOS) as a “set of space and ground segment capabilities that operate in a coordinated manner to meet a combined and common set of Earth Observation requirements”, virtual constellations can principally be used to combine sensors with similar spatial, spectral, temporal, and radiometric characteristics. We extend this definition to also include sensors that are principally incompatible, because they are fundamentally different (for instance active versus passive remote sensing systems), but their combination is necessary and beneficial to achieve a specific monitoring goal. In this case, constellations are more likely to build upon the complementarity of resultant information products from these incompatible sensors rather than the raw physical measurements. In this communication, we explore the potential and possible limitations to be overcome regarding virtual constellations for terrestrial science applications, discuss potentials and limitations of various candidate sensors, and provide context on integration of sensors. Thematically, we focus on land-cover and land-use change (LCLUC), with emphasis given to medium spatial resolution (*i.e.*, pixels sided 10 to 100 m) sensors, specifically as a complement to those onboard the Landsat series of satellites. We conclude that virtual constellations have the potential to notably improve observation capacity and thereby Earth science and monitoring programs in general. Various national and international parties have made notable and valuable progress related to virtual constellations. There is, however, inertia inherent to Earth observation programs, largely related to their complexity, as well as national interests, observation aims, and high system costs. Herein we define and describe virtual constellations, offer the science and applications information needs to offer context, provide the scientific support for a range of virtual constellation levels based upon applications readiness, capped by a discussion of issues and opportunities toward facilitating implementation of virtual constellations (in their various forms).

1. Introduction

Remotely sensed observations acquired from Earth orbiting spacecraft are fundamental to understanding Earth system functioning and the effects of natural and human-induced changes on the global environment (Cohen & Goward, 2004). Since the launch of the first Landsat sensor in 1972, active and passive remote sensing has provided critical input to Earth system models, ranging from atmospheric composition to the status of the terrestrial biosphere (Belward & Skøien, 2015). The scientific and technological progress in Earth observation over the last 40 years is unparalleled; however, the challenges faced by the Earth science community are immense: global climate has now entered a period of rapid change as humans are altering the composition of the atmosphere (McMullen & Jabbour, 2009; Woods, Heppner, Kope, Burleigh, & Maclauchlan, 2010), and scientists are faced with the task of assessing

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the risks associated with these changes, their feedbacks on the global carbon and energy cycle, and the consequences for life on Earth (Bentz et al., 2010; Kurz et al., 2008; Price et al., 2013).

The most recent report of the IPCC (2014) outlines the links between anthropogenic activity and observed changes in the climate system. These human activities include changes to global land cover and land use, with associated ramifications that range from the capacity of Earth systems to sequester CO_2 from the atmosphere and absorb solar energy (Pielke et al., 2002), through to the alteration of the natural disturbance regimes of forested ecosystems (Dale et al., 2001). The way in which land is used results in difficult trade-offs between meeting present day human needs (food, shelter, economic opportunity) while also maintaining the future capacity of the biosphere to continue meeting those same needs (Foley et al., 2005). Land use conversions are often made to accommodate human needs for agricultural production, living or commercial space, as well as industrial or transportation infrastructure. Depending on the type of conversion, permanent changes in land cover can have a range of impacts, such as a loss of carbon stocks as a result of biomass burning or conversion of forests to agricultural lands (Fearnside, 2000; Pielke et al., 2002) as well as changes to the provision of a broad range of ecosystem services (Naidoo et al., 2008).

The rapid nature and the scale of land-cover and land-use change (LCLUC) poses challenges to the remote sensing community, as a full understanding of anthropogenic impacts and their feedbacks on ecosystems will require frequent (Scheller et al., 2007) and comprehensive observations across large areas (Hansen et al., 2008; Laurance et al., 2012; Townshend et al., 2012). From regional and global monitoring perspectives, despite the progress made over the last several decades, contemporary scientific advancement remains limited by the data available to researchers and the trade-offs between spatial, temporal, spectral, and radiometric sensor characteristics that govern remote sensing instrument design (Wulder et al., 2008). For instance, high spatial resolution imagery typically results in a smaller image footprint, or spatial extent, thereby increasing the time it takes for a satellite to revisit the same location on Earth (Hilker, Wulder, Coops, Linke, et al., 2009; Hilker, Wulder, Coops, Seitz, et al., 2009). It is worth noting that reported temporal revisit of high spatial resolution sensors includes the use of pointable observatories. As an example, the revisit time for a given location can be about 4 days using off-nadir viewing (both cross-track and in-track), or 144 days if true nadir viewing is required (Wulder, Ortlepp, White, & Coops, 2008). While some deviation off nadir may be required to create more data collection opportunities, tolerance for off-nadir viewing is determined by the needs of a given application and by consideration of factors such as the level of geometric and illumination consistency required for automated applications over time, both for objects of interest (*i.e.*, trees), and between adjacent images (Wulder, White, et al., 2008; Wulder, Ortlepp, White and Coops, 2008). High temporal resolution sensors such as NOAA's Advanced Very High Resolution Imaging Spectroradiometer (AVHRR) and NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) have a more frequent revisit rate (daily) coupled with a wider imaging swath, resulting in wide-area coverage at a lower spatial resolution (Holben, 1986; Roy et al., 2008). Outside of government realms, there are successful examples of commercial satellite constellations, including DMC and BlackBridge RapidEye (Powell, Pflugmacher, Kirschbaum, Kim, & Cohen, 2007). Constellations (or swarms) of microsats (including cubesats) are also emerging (Hand, 2015; Butler, 2014). Generally of notably lower cost and operating at lower orbits with a small total satellite size and weight, these microsats have radiometric and geometric considerations that remain to be addressed (Butler, 2014). The presence of this wide range of sensors offers users with options for sourcing data, as well as many considerations to ensure compatibility and rigor in subsequent analyses.

One approach to help meet application and information needs while also mitigating the aforementioned challenges, as summarized above, is to combine sensors with similar characteristics into so-called *virtual constellations*. Satellite constellations have long been used to add value to Earth observations by combining sensors with complementary characteristics. For example, NASA's "afternoon constellation" (so-called "A-train") consists of satellites passing in the same sun-synchronous polar orbit within minutes of each other (http://www.nasa.gov/mission_pages/a-train/a-train.html). This formation flying allows near-simultaneous observations of a variety of parameters to aid the scientific community in understanding Earth–atmosphere interactions and advancing Earth system science. The value of the near simultaneous measures associated with the A-train has been recognized, and the potential inclusion of any new satellite in the A-train is now undertaken with specifically designed scientific objectives in mind (*e.g.* Stephens et al., 2002). Virtual constellations are similar in concept, but have come from more organic beginnings. Virtual constellations capitalize on existing capacities of current sensors and their orbits with the aim to identify and understand possible synergies of satellite observations from sensors with similar spatial, spectral, temporal, and radiometric characteristics in order to expand the scope of space-based Earth system science by producing a consistent and calibrated set of Earth observations to meet the needs of a particular domain area. The Committee on Earth Observation Satellites (CEOS) defines virtual constellations as a "set of space and ground segment capabilities that operate in a coordinated manner to meet a combined and common set of Earth Observation requirements." Herein, we broaden this definition to include virtual constellations in which the sensors themselves may have disparate characteristics and observations, but they offer complementary information that is of synergistic value. In this paper, we review the potential of virtual constellations for LCLUC and describe the concept, motivation, characteristics, and forward-going opportunities for the development of virtual constellations targeted at monitoring LCLUC. In so doing, we characterize three different types of virtual constellations according to their application-readiness. We discuss the potential of virtual constellations for improving and complementing medium spatial resolution (pixel resolution of 10–100 m) data sets, addressing spatial versus temporal trade-offs, as well as overall benefits for land surface observations. Our overarching objective is to elucidate the potentials of virtual constellations for LCLUC and identify key research priorities that could support implementation and expand opportunities for virtual constellations to contribute toward enhanced global monitoring capacity.

2. Land-cover and land-use change mapping context for virtual constellations

LCLUC is the complex result of a combination of resource scarcity, market opportunities, policy intervention, and changes in social organization and attitudes (Rindfuss, Walsh, Turner, Fox, & Mishra, 2004; Lambin, Geist, & Lepers, 2003). In recent years, the study of LCLUC has moved from simplistic representations of change to recognition of a complex co-evolution of natural and social systems across different spatial and temporal scales (Lambin et al., 2003; Lepers et al., 2005). While significant progress has been made in reducing LCLUC uncertainties, much remains to be learned about interactions between changes in vegetation properties on one side, and carbon sequestration, provision of ecosystem services, maintenance of biodiversity, and ecosystem degradation on the other (McKinley et al., 2011; Rittenhouse & Rissman, 2012). For instance, initial research has focused on *land-cover conversions* (*i.e.*, the complete replacement of one cover type by another) as a major contributor to land carbon emissions, but in recent years the importance of more subtle *land-cover modifications* and ecosystem degradation has increasingly been recognized (Lambin et al., 2003; Houet et al., 2009). Both land-cover conversions and modifications can be difficult to detect in the presence of phenological and climate related interannual changes in vegetation (Singh, 1989), yet their impact on ecosystems and carbon cycling is considerable (Foley et al., 2005). A comprehensive understanding of LCLUC therefore requires observations and modeling at a range of spatial and temporal scales (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003).

More coarse spatial resolution sensors (≥300 m) have been used predominantly for global to regional analysis of land systems (Friedl et al., 2002), due to their wide-area coverage and high revisit frequency. One major reason for the broad acceptance of the MODIS sensor in the user community is the provision of standardized reflectance composites (Schaaf et al., 2002) and higher-level products (Justice et al., 2002), combined with free data access and quality assessment (Roy et al., 2002). Notwithstanding these advantages, pixels with this spatial resolution (*i.e.*, ≥300 m) are often composed of mixtures of different land covers that differ in their socio-economic and ecological function (Boschetti, Flasse, & Brivio, 2004; Pflugmacher et al., 2011). By comparison, medium resolution (10 to 100 m sided pixels) observations provide a synoptic characterization of large areas at a level of detail informative of, and upon, management, reporting, and decision making (Wulder, White, et al., 2008). While these medium resolution observations are more sensitive to data availability issues and clouds, land surface mapping over large areas (Masek et al., 2006, 2008; Townsend et al., 2009) has become increasingly feasible for the broader user community with the development of standardized surface reflectance datasets (Masek et al., 2006) and automated cloud masking algorithms (Zhu & Woodcock, 2012). In recent years, these observations have been integrated with high (pixels sided 1 to10 m) and very high (<1 m) spatial resolution satellite data to enable monitoring of urban development (Ban, Hu, & Rangel, 2010), or integrated with light detection and ranging (lidar) data to inform international forest monitoring needs such as REDD (Reducing Emissions from Deforestation and Forest Degradation) (De Sy et al., 2012).

Arguably, the most common data utilized to map LCLUC are from Landsat satellites (Cohen & Goward, 2004). The 30 m spatial resolution of Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) data, combined with a spatial extent of 185 x 185 km per scene have proven utility for monitoring land surface parameters over time, offering insights at human scales (Wulder, White, et al., 2008). With observations reaching back to 1972, the Landsat program also provides the longest record of remotely sensed data over land and is therefore well suited for mapping anthropogenic changes of the terrestrial biosphere. While the success of Landsat for global vegetation mapping is undisputed, scientific understanding of landscape dynamics can be limited by the revisit cycle of the satellite and the related acquisition plan (Wulder, Masek, Cohen, Loveland, & wWoodcock, 2012).

Based upon the Landsat orbital characteristics and imaging swath there is an opportunity to obtain an image for any given location every 16 days with a single sensor. Due to the on-board recording and downlink capacity of Landsat-8 (Roy et al., 2014) there is now an opportunity to collect about 725 scenes per day, representing most of the Earth's terrestrial surface. This level of imaging is beyond the observation and sensor design specifications and is well above what has been historically collected (Wulder & Coops, 2014), in some ways making acquisition planning obsolete. With the currently operating Landsat sensors, there is a collection opportunity every 8 days, which has been the case since the launch of Landsat-7 in 1999 (with both Landsat-5 and -7 operating concurrently, until the failure of Landsat-5 in early 2012). However, data acquisition characteristics combined with cloud conditions often results in an effective lengthening between two clear sky observations (Fig. 1).

There is a geographic dependency of image availability based upon acquisition planning and the presence of persistent cloud cover (Arvidson, Goward, Gasch, & Williams, 2006). For instance, atmospheric contamination is particularly important across tropical and sub-tropical regions (Ramankutty, Foley, & Olejniczak, 2002), where lack of clear pixels due to cloud cover make the use of optical remotely sensed data difficult (Hilker et al., 2012, Fig. 1) even for generating cloud reduced composites. Higher levels of cloud cover also impact the ability to geolocate imagery, especially when the use of GCPs is required. Phenology likewise impacts the availability and suitability of imagery, with shorter growing seasons and the frequent presence of unseasonal snow and ice at higher latitudes. Somewhat compensating for the shorter growing season at higher latitudes is the overlap of imaging paths, which results in more views per unit area of Earth's surface with increasing latitude (White & Wulder, 2013). Accordingly, the development and updating of land cover and change maps using medium spatial resolution data sets over large areas is primarily limited by the frequency of temporal repeat visits, latitude, sensor- and period-specific acquisition conditions, as well as atmospheric contamination including cloud, shadow, haze, and smoke.

Once an image has been acquired, cloud and related shadow remains the primary driver of image quality and usability. Fig. 1 illustrates an estimate of clear sky observations based on mean annual cloud fraction derived from the MOD35 cloud mask (Ackerman et al., 1998; Frey et al., 2008) and the total number of Landsat observations derived from the degree of overlap in the WRS-2 path rows. The figure highlights the need for additional observations, particularly in the tropical and boreal regions. Depending on the specific application, the actual number of useful observations per year (Fig. 1A) is also limited considerably by length of the growing season and availability of daylight in higher latitudes. This is particularly relevant for the boreal regions of Eurasia and North America (Fig. 1B), where the number of clear sky observation gets reduced to less than 5 across much of the region when constrained by growing season. Note that for the purpose of this study, growing season length was approximated as the number of days with mean daily air temperature greater than 5 °C. Daily estimates of air temperature were obtained from NOAA's Gridded Climate Datasets, http://www.esrl.noaa.gov/psd/data/gridded/tables/daily.html for 2013 at 2.5° spatial resolution.

3. Virtual constellations: definition and forms

The main objective of a LCLUC virtual constellation is to improve the temporal revisit frequency of medium-resolution sensors (CEOS, 2006). Principally, this can be accomplished either by combining medium-resolution observations from sensors of similar spatial, spectral, temporal, and radiometric characteristics or alternately by complementing the finer spatial resolution data with the higher temporal revisit frequency of coarser spatial resolution sensors, including MODIS (Gao, Masek, Schwaller, & Hall, 2006), AVHRR (Lunetta, Lyon, Guindon, & Elvidge, 1998), and the upcoming Sentinel-3. While virtual constellations can greatly benefit Earth system science by providing new opportunities for observations with high cost efficiency, there are trade-offs and limitations associated with combining different sensors and platforms to accomplish existing and new science goals. Spacecraft and sensors are typically designed for specific scientific objectives and measurement requirements, and as a result, use of such data for purposes they have not been designed for may lead to sub-optimal performance. Challenges include orbital considerations, the signal-to-noise-ratio of combined observations, and differences in the number, width, and placement of spectral bands, among other issues (CEOS, 2006).

Virtual constellations are driven by the application need, and may be categorized by the level to which the different data sources used in this constellation require processing before they can be combined in a constellation approach. We suggest defining these processing requirements in terms of “Application Readiness Levels” (ARL):

1. ARL-1 virtual constellations combine sensors whose data are incompatible because the measurements are based on different principles (for instance constellations of passive and active systems). While data sources from such constellations cannot be easily combined on a per pixel basis, processed results or derived

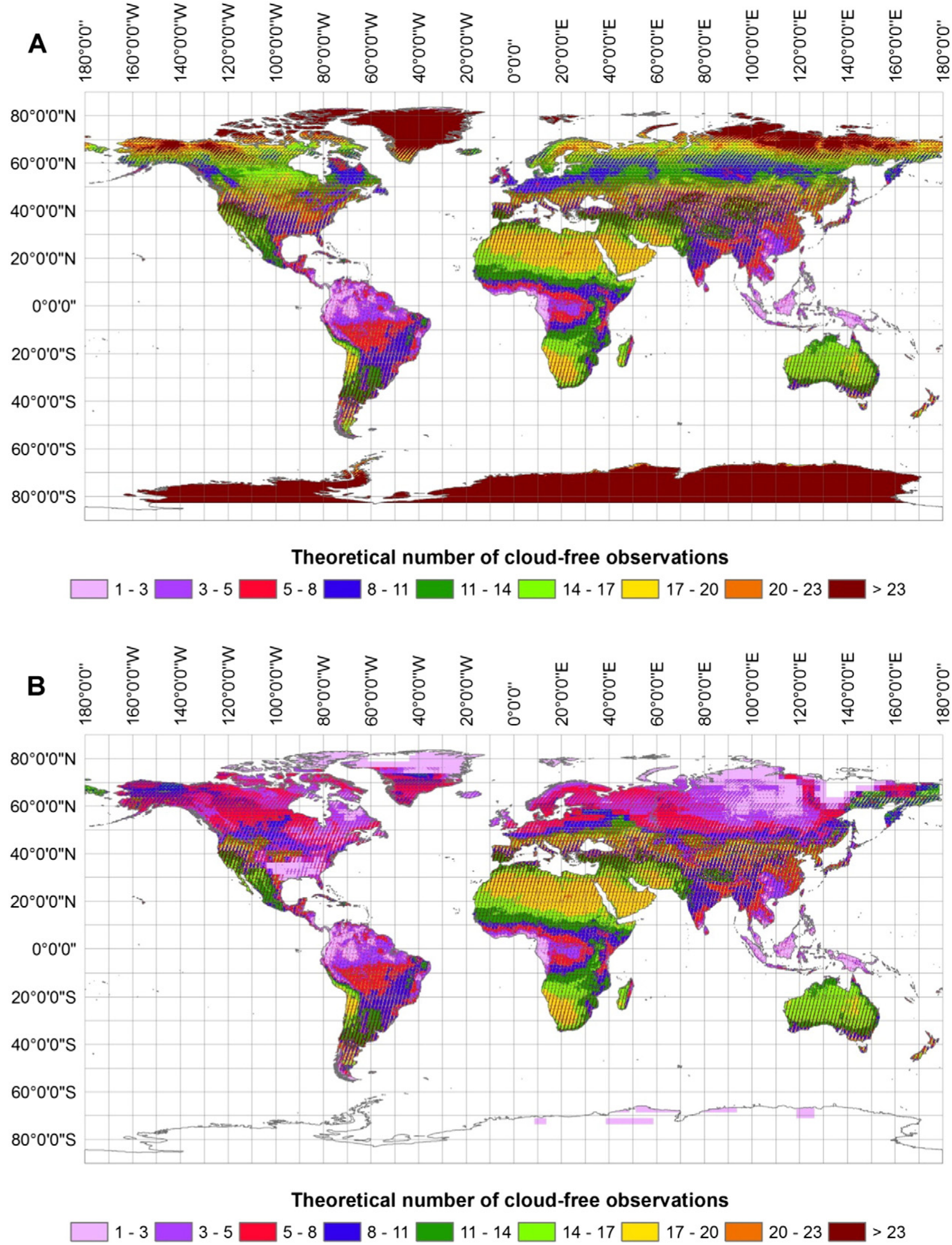

Fig. 1. Approximate number of cloud-free Landsat observations per year (inset A), assuming the 2013 mean annual cloud fraction as estimated from MOD35 (Ackerman et al., 1998; Frey et al., 2008) and the WRS-2 Path Rows with a 16-day revisit cycle (descending nodes only). Approximate number of cloud-free Landsat observations within the growing season (inset B). The actual number of useful observations may be further limited by the length of the growing season and availability of daylight, particularly in higher latitudes. Growing season was approximated as number of days with mean daily air temperature >+5 °C.

products from each data source can provide complementary information that would not be possible with either sensor alone. ARL-1 virtual constellations have the potential to provide substantial improvements to conventional data products, for instance through the combination of two- and three-dimensional datasets (Hudak, Lefsky, Cohen, & Berterretche, 2002).

2. ARL-2 virtual constellations combine sensors that have either fundamentally different spectral or spatial characteristics but that share a common measurement principle, for instance passive optical remote sensing. ARL-2 includes principally compatible sensors, but some transformation of data values may be required. Importantly, the resulting data product is still at the level of basic, pixel-level radiometry, that is, reflectance values are matched. An example of processing for an ARL-2 level is the blending of data from sensors with complementary spatial, spectral, and temporal characteristics, such as Landsat and NASA's MODIS (Gao et al., 2006).
3. ARL-3 virtual constellations combine sensors with similar spatial and spectral characteristics. In the simplest case, data from sensors with very similar characteristics may be matched with no or minimal processing requirements. For example the cross-calibrated TM and ETM+ sensors on board Landsat-5 and -7 (Chander, Markham, & Helder, 2009) can be used interchangeably for certain applications (*e.g.*, Kennedy, Yang, & Cohen, 2010; Wulder, Masek, et al., 2012). Minimal processing in this context implies minimal spectral alignment or spatial resampling of the otherwise compatible reflective bands. Examples for ARL-3 type compatibilities also include sensors from different platforms and space agencies that share important characteristics in at least a portion of the spectral bands (*e.g.* Sentinel-2, Landsat sensors, SPOT-4/5).

The degree to which sensors are compatible would determine the approach by which data products are generated via virtual constellations (Goward et al., 2012). Table 1 details the type of LCLUC information products that would be associated with each of these ARLs. Fully compatible sensors (ARL-3) can be merged at the radiometric level or used interchangeably as inputs to algorithms, with only minor adjustments required for differences in bandpass or bidirectional reflectance distribution function (BRDF). In contrast, data from sensors with different measurement modalities (ARL-1) may be combined to retrieve biophysical variables, but will be merged relatively late in the processing chain. For example, optical reflectance and radar backscatter can be used synergistically with lidar to map forest biomass (Montesano et al., 2013). Note that the compatibility between historic systems and archival data is also considered as an important component of the various ARLs. For the following sub-sections, we reverse the order of presentation for the various ARL, organized to begin with the simplest case (ARL-3).

3.1. Sensors that have similar spectral and spatial characteristics (ARL-3)

Combinations of similar sensors allow improvement of revisit frequencies at no or minimal loss of spatial and spectral detail; however, the resulting increase in temporal resolution is moderate. Arguably, the most commonly applied virtual constellation is that of different sensors from the Landsat series of satellites, particularly TM (Landsat-4 and -5) and ETM+ (Landsat-7) data (Teillet et al., 2001). The ETM+ and OLI sensors offer several enhancements over TM sensors, including reduced signal-to-noise (SNR), improved geodetic accuracy, and reliable calibration (Masek, Honzak, Goward, Liu, & Pak, 2001); however, the failure of the Scan-Line Corrector of ETM+ in 2003, has somewhat limited the use of ETM+ for land-cover mapping and change detection applications (Wulder, Ortlepp, White, & Maxwell, 2008). Nonetheless, the continuity of spatial and spectral characteristics between the TM, ETM+, and most recently OLI (Roy et al., 2014) sensors allows for a near-seamless integration of these different data types for LCLUC purposes (Chander, Markham et al., 2009; Muñoz-Villers & López-Blanco, 2008).

Several countries have placed satellites in orbit that are in principle compatible with Landsat sensors (Goward et al., 2012), including the French Satellite Pour l'Observation de la Terre (SPOT), the Indian Remote Sensing (IRS) satellite, and the Japanese Advanced Land Observing Satellite (ALOS) (Goward, Williams, Arvidson, Irons, & Irish, 2009). However, as reviewed by Powell et al. (2007), apart from Landsat, very few Earth-observation systems independently meet the requirements that are essential for mapping LCLUC (Singh, 1989), specifically: a systematic acquisition strategy (Arvidson et al., 2006), consistent and calibrated radiometric quality (Markham & Helder, 2012), and long-term global archives (Goward et al., 2006; Wulder, Masek, et al., 2012). Systems that do meet these criteria include the IRS ResourceSat Advanced Wide Field Sensor (AWiFS), the China–Brazil Earth Resources Satellite (CBERS) (Goward et al., 2012) (Table 2). The spatial resolution of AWiFS is only about half that of Landsat (56 m at nadir); however, this disadvantage is compensated for by a nominal swath width of 730 km (four times that of Landsat), allowing for a 5-day revisit cycle (Fig. 2A). The IRS sensors have a demonstrated potential to support large-area remote sensing applications with accuracies comparable to Landsat (Powell et al., 2007), however, akin to SPOT, AWiFS lacks spectral coverage in the blue, and thermal infrared (TIR) regions (Powell et al., 2007; Table 2) which limits the ability to consolidate multispectral reflectance measurements (Cohen et al., 2002; Healey, Cohen, Zhiqiang, & Krankina, 2005) and reduces the options for change detection algorithms that can be applied (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 2004; Hansen & Loveland, 2012). In addition, considerable differences exist in the configuration and functioning of Landsat and AWiFS, particularly the spectral sensor configuration (radiometry of 10-bit AWiFS versus 8-bit Landsat) and sampling footprint (Goward et al., 2012). Arguably the most challenging limitation for using AWiFS data in a virtual constellation is data availability. In contrast to Landsat data (Wulder, Masek, et al., 2012), AWiFS data, like SPOT data, are neither free nor readily accessible at the present time. Basic access to data is a fundamental requirement for data to be incorporated into LCLUC monitoring programs (Goward et al., 2012; Hansen & Loveland, 2012), with the nature of access being a key consideration for a data-driven virtual constellation strategy. Despite these challenges, AWiFS (previously) and DMC (more recently) have been used as key imagery inputs, along with Landsat data, in the NASS Cropland Data Layer (CDL) crop type maps (*e.g.*, Hansen & Loveland, 2012). Proposed to start in 2015, Satellite Pour l'Observation de la Terre (SPOT) 1–5 imagery more than 5 years old is to be made freely available for non-commercial use through the SPOT World Heritage Program (https://theia.cnes.fr/rocket/#/search?collection=SpotWorldHeritage). The SPOT family of satellites has acquired nearly 30 million images worldwide since 1986. The free access to these SPOT data will be beneficial for retrospective LCLUC analyses.

INPE (Instituto Nacional de Pesquisas Espaciais, Brazil) has provided CBERS data free of charge to end users in South America and China since 2004 (Fonesca et al., 2014) and in 2007, this policy was extended to end users in African countries. Since 2004, CBERS data have been freely available to end users elsewhere on the globe as well, but only via the internet. Initially CBERS observations were acquired over Brazil and China exclusively. Later agreements allowed for receiving stations outside of Brazil and China. While *ad hoc* in nature, the capacity to extend downlinks to other ground stations has been demonstrated. The number and distribution of ground stations still does not enable systematic, globally distributed coverage of CBERS data, so in a virtual constellation context, the integration of CBERS observations would be spatially constrained. CBERS is in a sun-synchronous orbit at an altitude of 778 km, resulting in a 24-day revisit time and a swath width of

Table 1
Examples of LCLUC information needs addressed by virtual constellations with different "Application Readiness Levels" (ARLs).

LCLUC domain	Virtual constellation
Land cover type I (*e.g.* forest, cropland, etc.)	ARL-3
Land cover type II (*e.g.* forest type, crop type)	ARL-3/ARL-2
Annual land cover change monitoring	ARL-3/ARL-2
Near-real time change indicators (fire, deforestation)	ARL-2
Forest degradation/land-use intensification	ARL-1
Carbon monitoring (*e.g.* REDD+)	ARL-1

Table 2
Spectral and spatial characteristics of the main LCLUC ARL-3 virtual constellation candidate instruments.

Attribute	Landsat TM, ETM+		Landsat OLI		Sentinel-2		CBERS-2 (CCD)		AWiFS	
	Spectral bands (μm)	Resolution (m)	Spectral bands (μm)	Resolution (m)	Spectral bands (μm)	Resolution (m)	Spectral bands (μm)	Resolution (m)	Spectral bands (μm)	Resolution (m)
Visible	0.45–0.52	30	0.45–0.51	30	0.43–0.45	60	0.45–0.52	20		
	0.52–0.60	30	0.53–0.59	30	0.55–0.58	10	0.52–0.59	20	0.52–0.59	56
	0.63–0.69	30	0.64–0.67	30	0.64–0.67	10	0.63–0.69	20	0.62–0.68	56
NIR	0.76–0.90	30			0.70–0.71	20	0.77–0.89	20	0.77–0.86	56
					0.73–0.75	20				
					0.77–0.79	20				
					0.78–0.90	10				
			0.85–0.88	30	0.86–0.88	20				
					0.93–0.95	60				
SWIR					1.37–1.40	60				
	1.55–.175	30	1.57–1.65	30	1.57–1.65	20	1.55–1.75	80	1.55–1.70	56
	2.08–2.35	30	2.11–2.29	30	2.10–2.28	20				
Architecture	Cross-track scanner		Pushbroom		Pushbroom		Pushbroom		Pushbroom	
Swath width	185 km		185 km		290 km		113 km		737 km	
Revisit	16 days		16 days		10 days		26 days		5 days	

113 km. The sensors on board CBERS-2 and CBERS-2B, launched in 2003 and 2007, respectively, have higher spatial resolution (20 m, Table 2) than Landsat in the visible and near-infrared bands (Powell et al., 2007). With rapid development and short launch intervals, there are a number of CBERS sensors with some variability to observation characteristics. This variability in observation characteristics can impact CBERS' utility for change detection and image classification methods (Coppin et al., 2004) as well as agricultural water use (via transpiration modeling), as well as cloud screening (Roy et al., 2014). More recently, CBERS-4, which has similar characteristics to CBERS-2, with the addition of SWIR and TIR bands, was launched (Dec 2014; http://database.eohandbook.com/database/missionsummary.aspx?missionID=393). Fig. 2 demonstrates the extent to which virtual constellations of both AWiFS and CBERS will increase the number of cloud-free observations in tropical regions considerably, thereby providing new opportunities for mapping seasonal changes in vegetation cover and aseasonal degradation of forest canopies across the Amazon region. Ongoing research and development with new CBERS-4 measures will offer additional insight into opportunities for sensor integration.

Significant improvements in LCLUC mapping are expected from the Sentinel-2 mission of the European Commission's Copernicus Program, which will acquire medium-resolution optical images globally, providing enhanced continuity of SPOT- and Landsat-type data. The Sentinel-2 mission aims at providing an operational multi-spectral Earth-observation system that complements the Landsat and SPOT observations toward improved data availability for users (Drusch et al., 2012). The Sentinel-2 mission is based on a twin satellite configuration (Sentinel-2A and 2B) that will be deployed in a polar sun-synchronous orbit with 14.3 cycles per day, and a reference altitude of approximately 786 km (Gatti & Bertolini, 2013). Launched approximately 12 months apart, the satellites will carry a payload with visible, near infrared (NIR), and SWIR sensors (13 spectral bands) with a spatial resolution between 10 and 60 m (Table 2). One of the strengths of the Sentinel-2 mission is the relatively large swath, allowing a 2–3 day revisit time at mid-latitudes, and five days at the equator for two satellites. The European Space Agency (ESA) announced in November 2013 free and open access to all Sentinel satellite data during the operational phase of the satellite missions (ESA [European Space Agency], 2013). This policy change is formally the responsibility of the European Commission, with an open data policy established for the Copernicus Program (http://www.copernicus.eu/sites/default/files/library/Regulation_377_2014_Copernicus_3April2014.pdf). Sentinel-2 data products (Level 1C)

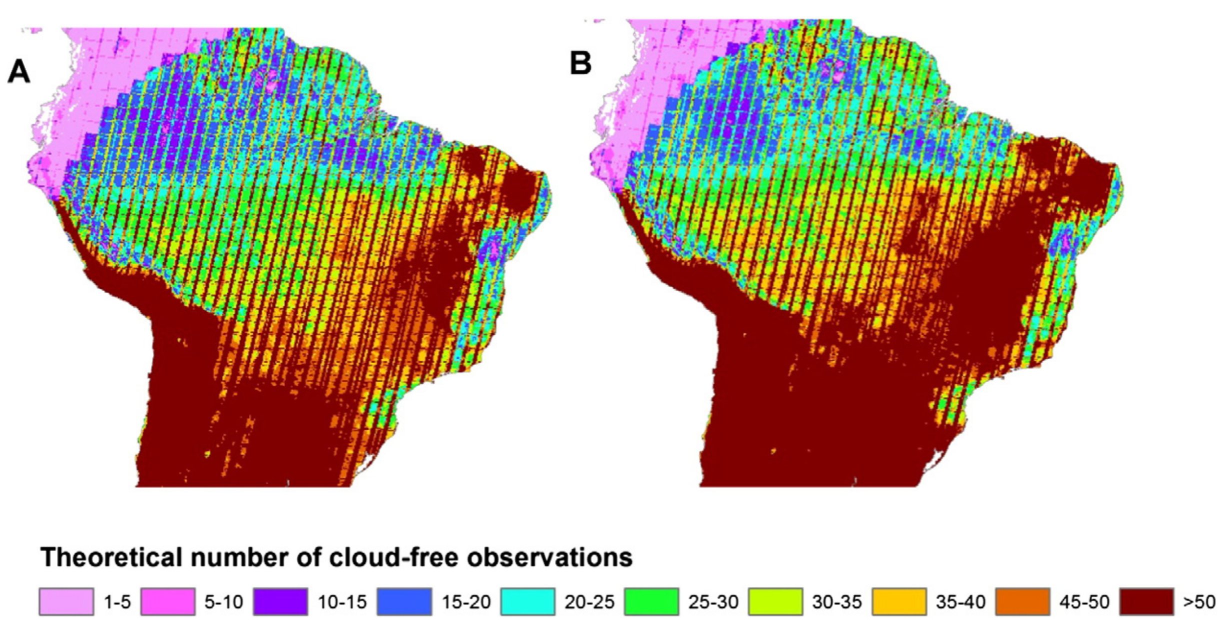

Fig. 2. Approximate number of cloud-free observations acquired per year over Brazil from a virtual constellation of (A) Landsat and AWIFS and (B) Landsat, AWIFS, and CBERS.

will be delivered as ortho-rectified top-of-atmosphere reflectance datasets in UTM-UPS/WGS84 projection and tiled into 100 km x 100 km segments following the US-MGRS (US-Military Grid Reference System) grid approach. Surface reflectance products will be available via a user-operated processing toolkit. Surface reflectance products will be available on a 5-day basis to the end-user. An ARL-3 virtual constellation of Landsat with Sentinel-2 would increase the number of available observations considerably (Fig. 3A–B) while providing a similar level of radiometric quality and spectral coverage. Such data will be particularly beneficial for phenological studies and the number of

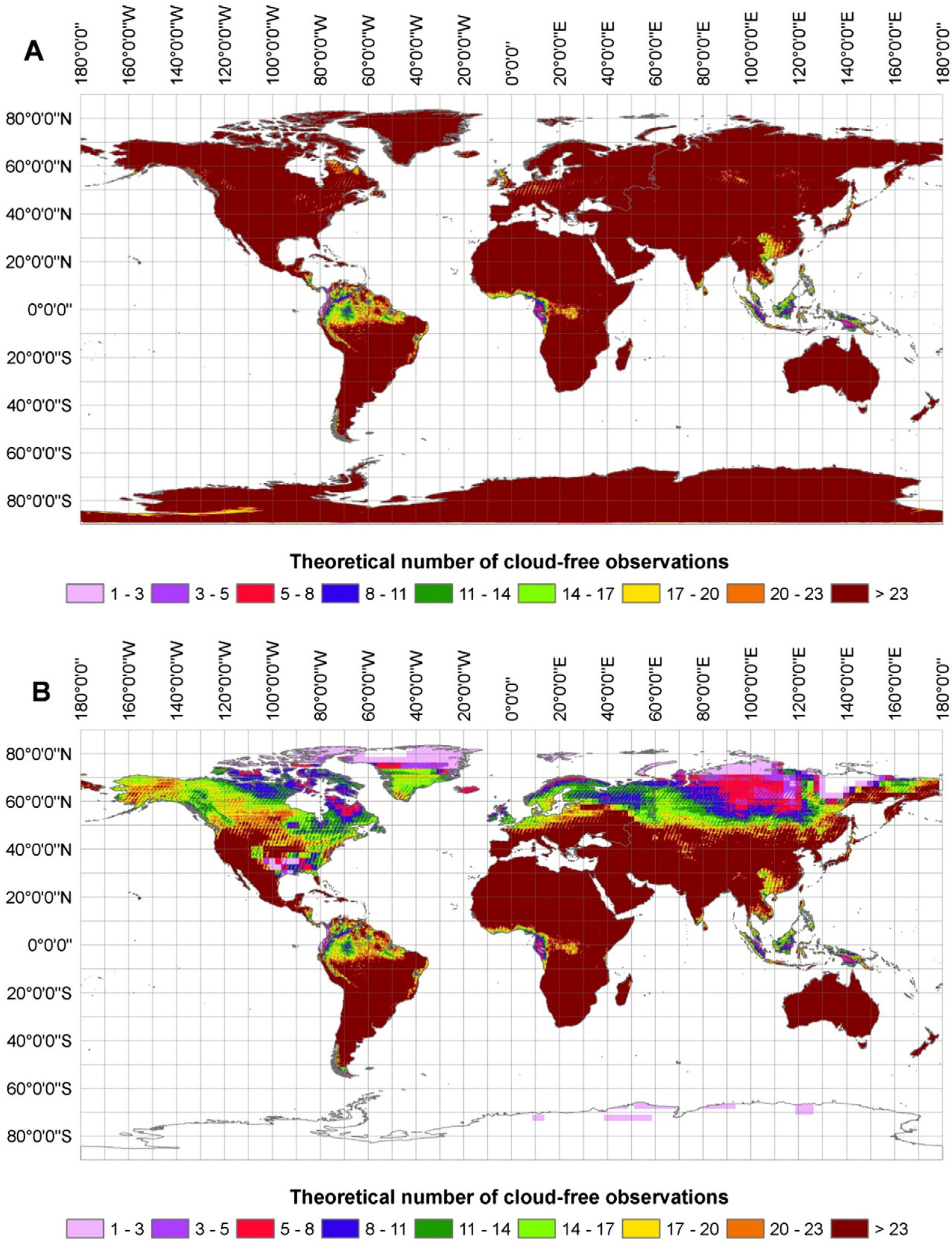

Fig. 3. Approximate number of cloud-free observations to be expected from a virtual constellation of Landsat and both Sentinel-2 instruments (descending nodes only) for the year (A) and the growing season (B).

observations available during the growing season in higher latitudes (Fig. 3B). Once collected it is intended that the data is to be available as a rolling archive for a period of up to four months (https://sentinel.esa.int/documents/247904/349490/S2_SP-1322_2.pdf), with intentions to place the data off-line and less available to users. Discussions are ongoing internationally to enable mirroring of the data and facilitating greater availability. Collecting and downlinking of over 800 gigabytes per day is a highly complex technical and logistical activity. The additional storage and dissemination load that results from the large number of channels over fine spatial resolutions with a high radiometric-bit depth cannot be underestimated.

The ability to detect changes in land cover depends not only on the number of available clear sky observations but also the measurement noise inherent to the system. In addition, when retrospective analyses of historic changes are desired, modern sensors need to be combined with older sensor data that often have broader and fewer spectral bands (Hostert, Roder, & Hill, 2003; Pflugmacher, Cohen, & Kennedy, 2012) as well as with different radiometric resolution (*e.g.*, evolving from 6 to 8 to 12 bits over time). While the number of clear sky observations from ARL-3 virtual constellations can be approximated (Figs. 1–3), noise levels of virtual constellations are much harder to determine. Accuracies of virtual constellation surface reflectance depend on: the signal-to-noise ratio and calibration accuracy of each component sensor and related error propagation; each sensor's spatial resolution and geolocation accuracy; the accuracy of estimating atmospheric and bi-directional reflectance effects; spatial, spectral, temporal, and radiometric mismatches in the combination of satellite systems. As a result, performance may vary in space and time; however, despite these dependencies, ARL-3 virtual constellations are likely to increase the ability for mapping changes in surface parameters significantly, as the total number of available cloud-free observations—and not measurement noise—is typically the most limiting factor for the accuracy of vegetation parameters (Hilker et al., 2012). Statistical significance of changes in surface properties may be assessed using approaches that consider the unequal numbers of observation and variances (Satterthwaite, 1946; Welch, 1947). Recent work by Whitcraft, Vermote, Becker-Reshef, and Justice (2014) and Whitcraft, Becker-Reshef, and Justice (2015) has an agricultural focus, describing the measurement context and needs for this domain. A follow-up evaluation characterizes the independent and combined revisit capacity for sub-100 m spatial resolution optical satellites (Whitcraft, Becker-Reshef, Killough, & Justice, 2015). The authors find that no currently operating system is able to provide the measurement frequency required to result in cloud-free data within an eight-day period. Multi-agency, multi-mission, hypothetical constellations are simulated to generate, for comparative purposes, the likelihood of an 8-day cloud free measurement. While gaps remain, Whitcraft, Becker-Reshef, Killough, et al. (2015) demonstrate that constellations can improve the likelihood of meeting required measurement targets when compared to the single-satellite scenario. Ultimately, in the context of LCLUC, increasing the likelihood and frequency of cloud-free observations within an 8-day target window would arguably be the greatest advantage and promise afforded by ARL-3 virtual constellations.

3.2. Sensors that have different characteristics but a common measurement principle (ARL-2)

In situations where greater temporal density of measurements is required, data needs of LCLUC may be met by virtual constellations of sensors with differing but complementary spatial and temporal characteristics. These ARL-2 virtual constellations require a model-based application to allow matching of pixel information and blending of coarse and medium spatial resolution data (*e.g.*, Gao et al., 2006). Such methods allow for an increase in temporal resolution, noting that there will be a reduction of pixel level variance (as the fine temporal resolution is informed by the lower spatial resolution data source). Regarding the detection of change, some of the limitations associated with the blending procedure may be mitigated by preparing a change mask from a finer spatial resolution image pair that represents a season which in turn can be assigned to a within-season change date using the more coarse spatial resolution data (Hilker, Wulder, Coops, Seitz et al., 2009). To this end, Schmidt, Lucas, Bunting, Verbesselt, and Armston (2015) used *a priori* knowledge (derived from a Landsat-based information product) of clearing events to constrain their temporal analyses. In their study, the authors used the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM; Gao et al., 2006) to build a blended dense time series (8-day interval) dataset for a 12-year period (2000–2011). The authors used this data to construct an NDVI time series and with that detected stand-replacing disturbance events with an accuracy of 94%. Events were accurately dated to within 40 days of their actual disturbance date.

Among the most relevant coarse resolution (>250 m) sensors (Table 3) for the purposes of applications concerning terrestrial vegetation are the AVHRR (Lunetta et al., 1998) and MODIS (Townshend & Justice, 2002) sensors. The AVHRR sensor has been in orbit since 1978 (Fontana et al., 2012) and provides daily observations at a spatial resolution of 1 km with 4 to 6 spectral bands depending on the sensor type (James & Kalluri, 1994). While AVHRR provides a long heritage of freely available surface reflectance observations (Loveland et al., 2000), the sensor is limited by its spectral characteristics, calibration, and (for global products) uneven geographic sampling, which essentially limits long-term land cover classifications to analysis of red and NIR reflectance (Loveland et al., 2000; Young & Wang, 2001). Note that Table 3 is intended to be representative of candidate instruments and is not intended as an exhaustive list of satellites and specifications. For observational context and an exhaustive list of satellite and specifications, see Belward and Skøien (2015) and related supplemental data.

MODIS provides 36 spectral bands, 7 of which are commonly used for terrestrial applications (Vermote, Kotchenova, & Ray, 2011). Depending on the spectral channel of interest, MODIS has spatial resolutions of 250 m, 500 m, and 1 km at nadir, with near daily global coverage since 2000. Data from both MODIS sensors have been extensively used for coarse resolution LCLUC at regional and global scales (Friedl et al., 2010) and to complement finer spatial resolution Landsat observations. Acerbi-Junior, Clevers, and Schaepman (2006) used wavelet analysis to combine Landsat observations with 500 m resolution data from the MODIS to classify land cover types in the Brazilian savanna. Muchoney et al. (2008) used regression trees to fuse Landsat and MODIS data based on the 500-m 16-day MODIS BRDF/Albedo land surface characterization product to monitor forest cover in the Congo Basin.

Most image-based data-fusion algorithms do not generate calibrated outputs of spectral radiance or reflectance. However, STARFM and the more recent Spatial and Temporal Reflectance Unmixing Model (STRUM) (Gevaert & Garcia-Haro, 2015) are examples of ARL-2 algorithms that yield modeled surface reflectance at a 30 m spatial resolution, through the blending of MODIS and Landsat surface reflectance data. Based on STARFM, Hilker, Wulder, Coops, Linke, et al. (2009) developed a change detection model that allows disturbance detection at the temporal resolution of MODIS but with the spatial detail that more closely resembles Landsat. The algorithm was used to accurately (93%) map disturbances > 1800 m^2 (or 2 Landsat pixels) across a large area of west-central Alberta, Canada (Gaulton, Hilker, Wulder, Coops, & Stenhouse, 2011).

Other potential sensors for consideration in an ARL-2 constellation include ESA's MERIS (MEdium Resolution Imaging Spectrometer) instrument (Curran & Steele, 2005) as well as NASA's SeaWiFS sensor (Tucker et al., 2005). MERIS was launched aboard ENVISAT in November 2001 and collected data until its unexpected loss in early 2012. SeaWiFS was operational between 1997 and 2010. Both the MERIS and SeaWiFS sensors were originally designed for ocean color applications and, as a result, do not include SWIR or TIR bands, thus the capacity of these sensor's to discriminate among certain land cover classes (particularly

Table 3
Spectral and spatial characteristics of the main LCLUC ARL-2 virtual constellation candidate instruments.

	Landsat TM, ETM+		Landsat OLI		Sentinel-2		MODIS		AVHRR		SeaWIFS		MERIS		VIIRS		Sentinel-3	
	Spectral bands (µm)	Resolution (m)	Spectral bands (µm)	Resolution (m)	Spectral bands (µm)	Resolution (m)	Spectral bands (µm)	Resolution (m)	Spectral bands (µm)	Resolution (m)	Spectral bands (µm)	Resolution (m)	Spectral bands (µm)	Resolution (m)[b]	Spectral bands (µm)	Resolution (m)	Spectral bands (µm)	Resolution (m)
Visible	0.45–0.52	30	0.45–0.51	30	0.43–0.45	60	0.45–0.47	500			0.40–0.42	1100	0.41–0.42	300	0.40–0.42	750		
	0.52–0.60	30	0.53–0.59	30	0.55–0.58	10	0.54–0.56	500			0.54–0.56	1100	0.51–0.52	300	0.44–0.45	750	0.54–0.56	500
	0.63–0.69	30	0.64–0.67	30	0.64–0.67	10	0.62–0.67	250	0.58–0.68	1090	0.66–0.68	1100	0.62–0.63	300	0.48–0.49	750	0.65–0.67	500
NIR					0.70–0.71	20									0.55–0.57	750		
					0.73–0.75	20									0.66–0.68	750		
	0.76–0.90	30			0.77–0.79	20			0.73–1.00	1090	0.74–0.78	1100	0.76–0.78	300	0.74–0.75	750		
			0.85–0.88	30	0.78–0.90	10	0.84–0.88	250							0.85–0.88	750	0.86–0.88	500
					0.86–0.88	20									1.23–1.25	750		
					0.93–0.95	60												
SWIR			1.36–1.38	30	1.37–1.40	60									1.37–1.38	750	1.36–1.38	500
	1.55–.175	30	1.57–1.65	30			1.63–1.65	1000	1.58–1.64[a]	1090					1.58–1.64	750	1.58–1.64	500
	2.08–2.35	30	2.11–2.29	30			2.10–2.15	1000							2.23–2.28	750	2.25–2.28	500

[a] Not available on every AVHRR sensor.
[b] At nadir.

different forest types) is therefore limited (Zurita-Milla, Clevers, Van Gijsel, & Schaepman, 2011). Launched in 2011, the Visible Infrared Imaging Radiometer Suite (VIIRS) is a sensor on board the Suomi National Polar-Orbiting Partnership, designed to advance capabilities of AVHRR and provide continuity with MODIS (Table 3; Justice et al., 2013). Operational data products (Environmental Data Records or EDRs) have been generated by NASA and NOAA and include surface reflectance and vegetation indices. Currently these VIIRS products are undergoing a refinement and validation phase (*e.g.*, Vermote, Justice, & Csiszar, 2014). The upcoming Copernicus Sentinel-3 mission (projected to be launched in late 2015; http://spaceflightnow.com/launch-schedule/) will provide another opportunity for forming ARL-2 virtual constellations with medium and coarse-resolution sensors. Significantly, Sentinel-3 will be the only coarse-resolution optical platform with a morning viewing time, thus providing some degree of continuity with systems such as the Terra MODIS sensor. As in the case of ARL-3 constellations, ARL-2 constellations can improve the likelihood of cloud-free observations, which is a key limiting factor for LCLUC applications. As an active area of research, the fusion of data from these aforementioned sensors has an increasingly strong scientific foundation that can inform the future development of ARL-2 constellations.

3.3. Sensors that have disparate characteristics, but offer complementary measures or information products (ARL-1)

Finally, new opportunities for Earth system science also emerge from combining observations from "incompatible sensors" (sensors with different measurement modalities). To date, spaceborne active remote sensing systems are predominantly synthetic aperture radar (SAR) sensors, with no current spaceborne lidar systems in orbit. Interferometric SAR, lidar, and to some extent SAR backscatter systems, provide complementary information on three-dimensional vegetation structure, such as biomass (Kaasalainen et al., 2015). ARL-1 virtual constellations represent the most challenging type of virtual constellation to implement.

Observations from an ARL-1 virtual constellation may be used to enhance land cover characterizations. For example, SAR backscatter data has been combined with optical imagery to reduce classification error rates, when compared to error rates of single-source classifications (Haack & Slonecker, 1994; Solberg, Jain, & Taxt, 1994). The most common radar wavelengths suitable for vegetation mapping are X-band (3.1 or 3.5 cm wavelength), C-band (5.65 cm), S-band (12 cm), L-band (24 cm) and P-band (30–60 cm) (Balzter, 2001). Several radar systems are available and may be potential candidates for ARL-1 virtual constellations (Mitchell et al., 2014) including instruments by European, Japanese, Canadian, and American Space Agencies; additionally, Belward and Skøien (2015) note the presence of SAR instruments launched by Russia with access and applications utility remaining to be determined. The Advanced Synthetic Aperture Radar (ASAR) instrument flew aboard ESA's ENVISAT until the satellite's loss in early 2012 and extended the mission of the previous Active Microwave Instrument (AMI) SAR instruments flown on the ERS-1 and ERS-2 satellites. ASAR provided C-band observations between 30 m and 1000 m ground resolution. Similarly, the Canadian RADARSAT-1 and -2 satellites are advanced Earth observation systems equipped with a C-band SAR and launched in 1995 and 2007, respectively. A big advantage of C-band SAR lies in its historic and future data continuity: Envisat ASAR, ERS, and Radarsat have acquired compatible C-band data for more than 20 years, and the Copernicus Sentinel-1 (launched 2014) will ensure data continuity into the near future. Backscatter from C-band SAR mostly results from interactions with tree canopy leaves, needles, and small secondary branches, whereas C-band backscatter from tree trunks is small due to minimal canopy penetration (Kasischke, Melack, & Dobson, 1997). Thus, C-band backscatter is less sensitive to forest structure when compared to the longer wavelengths of L-band and P-band instruments.

PALSAR (Phased Array type L-band Synthetic Aperture Radar) provides L-band frequency observation at 10 and 100 m spatial resolution and a swath width of 250 to 350 km (Rosenqvist et al., 2014). The first instrument system flew aboard the Advanced Land Observing Satellite (ALOS) satellite and provided data between 2006 and 2011. A second instrument with improved spatial resolution and revisit time was launched in 2014 aboard ALOS-2. The Shuttle Radar Topography Mission (SRTM) obtained interferometric synthetic aperture radar (InSAR) data onboard the Space Shuttle Endeavour during an 11-day mission in February of 2000 (Fatoyinbo & Simard, 2013).

While beyond the scope of this communication, it is worth noting that SAR data (C-, L-, and X-band) are also interoperable in the data domain, with some level of interoperability possible. The similarity of measures between SAR instruments allows for increased interoperability capacity over mixing measures of differing wavelengths. Moreover, research into synergies between SAR and lidar data is increasingly common (Nelson et al., 2007), particularly for forest biomass estimation (Hyde, Nelson, Kimes, & Levine, 2007; Sun et al., 2011; Tsui, Coops, Wulder, Marshall, & McCardle, 2012; Kaasalainen et al., 2015). Likewise, there is increasing interest in the integration of optical and SAR data (Byun, Choi, & Han, 2013) and information products (Hyde et al., 2006). An example application of an ARL-1 virtual constellation for forest monitoring is provided by Lehmann et al. (2015), who present an approach for integrating forest presence/absence masks derived from Landsat and ALOS-PALSAR data. While there may be good agreement for single-date characterizations of forest presence/absence from SAR and optical data, there are significant differences in the characterization of forest change (such as focused on deforestation and afforestation) that may compromise the full interoperability of these data sources in the context of carbon accounting (Lehmann et al., 2015).

Finally upcoming satellite missions will continue to advance radar capabilities. In 2020, ESA is planning to launch a P-band SAR satellite in 2020 dedicated to measuring forest biomass for the assessment of terrestrial carbon stores and fluxes (Le Toan et al., 2011). BIOMASS will feature a P-band sensor that will provide P-band backscatter and polarimetric InSAR (Pol-InSAR) data to measure forest biomass and its change between 70° N to 56° S at a spatial scale of 100–200 m over its 5-year mission lifetime. The US and India are collaborating on the NASA-ISRO Synthetic Aperture Radar (NISAR), a dual S- and L-band sensor to be launched around 2020.

Challenges for ARL-1 virtual constellations incorporating radar and optical data include issues with data continuity and availability, which often may require combinations of multiple sources for each component of the virtual constellation (*i.e.*, multiple sensors providing optical and radar measures). Nonetheless, the combination of optical and radar data may provide new opportunities for mapping of land cover changes (Laurin et al., 2012) as well as estimation of canopy biophysics and energy input, particularly in tropical regions with persistent cloud cover throughout the year (Treuhaft, Law, & Asner, 2004). Combining optical and SAR data can help with reducing data gaps in optical systems (Reiche, Verbesselt, Hoekman, & Herold, 2015) and improve land surface characterizations if both instrument data are available for a specific observation period. For instance, Solberg et al. (1994) combined Landsat TM images with SAR and optical sensor data and demonstrated distinct improvements in land cover classification accuracies compared to optical sensors alone. As such ARL-1 virtual constellations may also enable results that would not be possible using either sensor's data exclusively. Similarly, Kaheil and Creed (2009) combined ERS-2 SAR, Landsat TM, and airborne lidar data to classify dry and wet vegetation types using support vector machines and discrete wavelet transformations.

The need to use radar data to mitigate cloud cover in optical data is reduced given sufficient additional ARL-1 measurements (*e.g.*, Whitcraft et al., 2014). Modern systems have greater on-board storage and downlink capacity, such as demonstrated by the increased daily acquisition of Landsat-8 (Roy et al., 2014), enabling a greater data yield on a per satellite basis. Landsat-8 is operating near an "always-on" mode for terrestrial ecosystems, with well over 700 images collected per day (Wulder & Coops, 2014). Radar and optical data are not interoperable, that is one cannot be used in place of the other, as the data are representative of different surface conditions due to the wavelengths sensed and the mode (active versus passive) utilized.

With regards to the use of radar in large area LUCUC applications, challenges remain due to the impacts of both physical conditions such as topography and moisture, and technical elements related to the high level of training and expertise required to utilize these data. Topography is well known to impact radar backscatter but can be corrected for to some degree (*e.g.* Atwood, Andersen, Matthiss, & Holecz, 2014); less predictable is the impact of environmental conditions upon the nature of the returned microwave signal. Yatabe and Leckie (1995) report that due to environmental conditions, such as recent rainfall, harvested areas cannot be consistently detected using C-band SAR, with rugged terrain also impacting detection. The authors also found that improved outcomes are found using different microwave wavelengths, although environmental conditions continued to have an effect. The use of multi-date imagery or interferometry is suggested to improve detection outcomes by Smith and Askne (2001) who also note that data choice trade-offs include the likelihood of getting cloud free optical data and the greater cost and complexity of using multi-temporal SAR data.

Spaceborne lidar systems specifically designed for vegetation measurements have not yet been implemented. However, a potential candidate for virtual constellations is the spaceborne lidar data is the Geoscience Laser Altimeter System (GLAS) on board the Ice, Cloud, and land Elevation Satellite (ICESat) (Harding, 2005). GLAS's primary objective was to measure ice sheet mass balance, but GLAS data are, to some extent, also useful for studying vegetation structure (Duncanson, Niemann, & Wulder, 2010; Fatoyinbo & Simard, 2013; Harding, 2005; Lefsky et al., 2005; Popescu, Zhao, Neuenschwander, & Lin, 2011). GLAS provides lidar data at a footprint of about 64 m, with spots separated by nearly 170 m along the spacecraft's ground track (Abshire et al., 2005). Lefsky (2010) and Simard, Pinto, Fisher, and Baccini (2011) developed global forest height maps based on the fusion of GLAS data with MODIS satellite imagery. Lefsky (2010) developed least squares regression models to estimate Lorey's height for each GLAS waveform using the waveform extent and the height of the 10th and 90th percentile of waveform energy. Simard et al. (2011) utilized the measure of the distance between the signal beginning and the ground peak for each GLAS waveform. Lefsky (2010) and Simard et al. (2011) then extrapolated these height estimates to produce wall-to-wall canopy height maps. Lefsky (2010) used image segmentation to derive forest "patches" from monthly composites of 500 m MODIS spectral data. Forest patches ranged from 1–900 pixels with an average of 100 pixels (25 km^2). Simard et al. (2011) used a regression tree method to extrapolate GLAS values globally based on a range of climate and MODIS products. The CHMs resulting from these two studies were subsequently compared and evaluated using small-footprint airborne laser scanning data by Bolton, Coops, and Wulder (2013).

The Global Ecosystem Dynamics Investigation Lidar (GEDI) is scheduled for deployment on the International Space Station (ISS) in 2019 (http://science.nasa.gov/missions/gedi/). GEDI will collect lidar waveform observations over 14 parallel tracks at a 25 m footprint size. The GEDI measurements will provide systematic measurements of vegetation canopy top heights and the vertical distribution of canopy elements to address science questions related to forest carbon and carbon change. These data will provide a robust sample of global forest biomass with sufficient resolution to avoid terrain-induced bias. It is worth noting that these measures will be limited to the extent of the orbit of the ISS, which extends to approximately 50-degrees north and south latitude, thereby excluding much of the northern boreal forest. Airborne lidar has been demonstrated as a valuable information source and surrogate for field plot data (Wulder, White, et al., 2012), which can be used to calibrate and validate spatial models driven by remotely sensed data (*e.g.*, Mora et al., 2013). It is envisioned that spaceborne lidar measures can be used in a similar fashion (*e.g.*, Margolis et al., 2015) to provide estimates of attributes such as height and biomass and to production of wall-to-wall maps useful for management, reporting, or modeling purposes.

4. Discussion

In the preceding sections we have outlined and demonstrated that there is great scientific potential associated with the use of virtual constellations to map and characterize LCLUC at medium spatial resolutions (~30 m). Virtual constellations—as defined by CEOS—are about coordinated capabilities for both space and ground segments, implying a potentially complex path to success that may be encumbered by institutional inertia, bureaucracy, and a lack of political will. Clearly, virtual constellations are much more than the fusion of complementary observations or information products. First and foremost, virtual constellations are opportunities to deploy and coordinate the use of Earth-observing sensors in a way that increases observation frequency and data accessibility while reducing unnecessary redundancy and costs, and that ultimately increases the use and application of these data to address user information needs and advance Earth system science. Indeed the increased use of these data in an operational context is one of the keys to ensuring long-term continuity of these Earth-observing systems (National Research Council, 2013). While the potential of virtual constellations to increase observation capacity is compelling (Figs. 1 and 3), when considered specifically from a cost-benefit perspective, most existing constellation opportunities are currently underutilized (Goward et al., 2012). Major limitations exist in terms of data compatibility and availability both of which are difficult to overcome (Kajii, 2010). Of the 350 active missions currently supported by CEOS, 245 (70%) have some form of open data policy (http://www.ceos-datapolicy.org/). Recent adaptation of open data policies by both the European Commission as well as the Japanese space agency (JAXA) are crucial steps for more common acceptance of the virtual constellation concept and for the more widespread use of satellite data in the future (ESA, 2013). As presented in Wulder, Masek, et al. (2012), free data is only part of the equation, with ease of access and portability of imagery into applications similar of importance. Free data that is difficult to access, such as via an awkward data delivery portal or the lack of web-based access entirely, limits data product utility and uptake by users. Ground systems that prepare imagery to an analysis ready level further promote user uptake by reducing pre-processing requirements while also ensuring a common initial level of data quality.

The increasing number of space agencies and satellite operators poses new challenges and opportunities to CEOS and the Earth-system science community as virtual constellations require not only coordination, but also the definition and adoption of minimum standards and rules that satellite operators will adhere to. At the same time, an increasing number of sensors will expand the possibilities for virtual constellation usage. However, timing of mission launches and coverage will likely remain problematic in the near future, as there is no easy way to reconcile mission-specific objectives with requirements to adhere to minimum CEOS standards (CEOS, 2006). Such standards can provide extremely useful, albeit non-binding guidance as to how to achieve and maintain compatibility with existing satellite systems.

As compatibility between similar sensors is most easily accomplished, an ARL-3 virtual constellation has the greatest likelihood of implementation in the near future. Indeed, this is the virtual constellation model that is being most actively pursued by CEOS, which has established a working group on a Land Surface Imaging virtual constellation (Goward et al., 2012). Numerous examples exist in the literature that demonstrate the potential for the combined use of sensors with similar characteristics (*e.g.* Geneletti & Gorte, 2003; Zhou, Civco, & Silander, 1998), but there is currently no coordinated effort across agencies that allows for the routine production of global datasets for virtual constellation sources. This may improve with the European Sentinel-2 mission (Malenovský et al., 2012), which has been designed with compatibility to Landsat in mind (Wulder, Masek, et al., 2012).

Recent trends point toward the possibility of innovative approaches for ARL-3 constellations. The commercial remote sensing industry has expanded dramatically in the last few years, with a major push toward constellations of smaller satellites (<200 kg). These systems do not necessarily prioritize radiometric quality and calibration to the degree of the "heritage" Landsat-type systems, but these sensors may be effectively incorporated into a virtual constellation using vicarious calibration techniques (Kamel et al., 2012; Chander, Saunier, Choate, & Scaramuzza, 2009). In this context, having at least one well-calibrated system on orbit supports this type of disaggregated architecture. In addition, incorporation of commercial imagery into virtual constellations faces issues associated with licensing agreements and cost.

Unlike ARL-3 constellations, ARL-2 constellations are not limited by data availability, as both MODIS and AVHRR data archives are freely available with both sensors providing daily observations. Due to the data volume generated, applications that seek to combine these types of data have thus far have been limited to local and regional studies (Hilker, Wulder, Coops, Seitz, et al., 2009; Schmidt et al., 2015). Nonetheless, the increase in the number of data fusion models over the past several years (Gao et al., 2006; Hilker, Wulder, Coops, Linke, et al., 2009; Gevaert & Garcia-Haro, 2015) demonstrates the interest in these types of observations for mapping vegetation parameters and improving Earth system modeling.

Arguably the largest range of possibilities—and challenges—are associated with ARL-1 virtual constellations. These types of constellations may not be easily implemented if complex analyses are required, which indicate a need for highly qualified technical staff with rare skill sets, to derive compatible data products. Their use will therefore likely be limited to specific topic areas or applications. One promising field is the combination of lidar and passive optical systems for mapping global biophysical processes and vegetation growth (Duncanson et al., 2010). The potential of such virtual constellations has been demonstrated in a research context, but significant efforts will still be required to achieve the level of acceptance needed to fully leverage the possible benefits from coordinated use of satellites within and between agencies.

There are several cautions and considerations that must precede the making of any forward-going recommendations, as it must be noted that the design and implementation of any form of virtual constellation could be complex, and would unfold gradually over a number of years. Our aim has been to discuss the complexities and opportunities, while providing a vision of a more integrated future of land imaging. The endgame for virtual constellations that offer enhanced integration and capacity for LCLUC monitoring are systematic, timely, and robust information products. We have framed those needs and offer thoughts toward further development and possible implementation. As noted above, there are ongoing inter- and intra-government activities (*e.g.*, within national space programs and via CEOS and GEO) that are wrestling with these same topics. Considerations to greater integration are the complexities, costs, and non-measurement based interests that must also be acknowledged. Nations build and launch satellites for a number of reasons, ranging from development of industrial capacity and support and cultivation of technology sectors within and outside of government, through to engendering national prestige (Belward & Skøien, 2015).

Virtual constellations have two critical responsibility centers, the first is related to mission development (*e.g.*, NASA, ESA) and the second is related to ground systems and the provision of data to end users (*e.g.*, USGS). At the mission development phase, constellation concepts are considered and missions are defined with interoperability in mind (*i.e.*, with similar or same radiometry, with similar or same imaging modes, with coordinated orbit strategies, with similar or same data format, with compatible ground segments for reception, archiving and catalogue structure, data handling, data structure, with similar or same background and or foreground mission operation strategy, harmonized data policies, etcetera). In the realm of data provision are considerations to ensure data compatibility, integration, data fusion, and data processing (including data assimilation and processing, algorithm development, definition of high level products using different data sets, documented error and level of uncertainties for high level products, stringent definition of standards and protocols for interoperability and complementarity, etcetera).

At its greatest extreme, the level of coordination required to enable a virtual constellation would involve a full end-to-end system of co-developed and deployed space assets, in conjunction with purpose-developed ground and information systems, delivering integrated and robust analysis-ready products. The opposite extreme could be very little or no coordination, with fully independent programs and sensors, and data that are serendipitously similar and freely available (the current status quo). More tenable perhaps is a level of coordination and integration that allows for maintenance of national strategic interests and responsibility centers, while also minimizing unnecessary redundancy and coordinating potentially incompatible acquisition priorities. For example, at a minimum, a virtual constellation in which mission space segments are coordinated would ensure the compatibility of fundamental data products and the harmonization of data acquisition to maximize global coverage. Such is the model that is currently unfolding between Landsat and Sentinel-2.

The coordination of missions and related data streams toward the development of some determined fundamental data products could be recommended for further consideration and development. Such an approach would fulfill national bottom-up imperatives for meeting a given information need supported by space-based observations as well as image and data products suitable for national consumption. From an international benefits and top-down benefits point of view, these measures—from a global perspective and via coordination—will also be interoperable with the sum of the observations and data products greater than the parts. In short, the top-down perspective is aimed at satisfying bigger picture objectives and aligning with the recommendations of responsible coordinating bodies (*e.g.*, CEOS) with the bottom-up element justifying and engendering national agency support. In fact, 2014 saw the re-initiation of the Land Surface Imaging (LSI) Virtual Constellation Working Group within CEOS, charged with generating a viable Implementation Plan to support coordination of land imaging satellites and data sets in the future.

The recent announcements from the US government to establish a new program for Sustained Land Imaging indicate that notions of virtual constellations are under development. Rather than the historic *ad hoc*, mission-to-mission funding of Landsat (Wulder, White, et al., 2008), a multi-decadal land imaging program has been initiated (Foust, 2015). The program includes a space element, as well as an integrated ground program to produce image and data products, mirroring the key elements of a virtual constellation as indicated above. Based upon early reports, to shorten development times and reduce risk, Landsat-9 is proposed as a rebuild (as possible) of Landsat-8 with a planned launch no later than 2023. Also included in the program is an activity for technology development and systems innovation. Building upon the lessons learned from the technology development stream, alternate imaging technologies or system architectures could be possible for Landsat-10 (envisioned to be launched in 2030). These launch dates can also be interpreted within the context of the recent and forthcoming launches of the Sentinel-2 satellites (Drusch et al., 2012), with the first of the series successfully launched on June 23, 2015, with the second launch anticipated to follow approximately a year to 18 months later. At the time of writing Sentinel 2A has collected and successfully downlinked development and test datasets as elements of the scheduled 3 month commissioning phase with data collection and dissemination expected thereafter.

5. Conclusions

Facing rapid and complex changes to global ecosystems, virtual constellations provide an opportunity to coordinate the acquisition and dissemination of EO data in a way that enables scientists and decision makers to maximize the use of these data and related investments. Virtual constellations are more than just a framework of best practices for data integration and fusion; rather, they are formalized systems, designed to address specific scientific and operational information needs. They involve not only sensors and measurements, but also data policies and archives. Herein we have diverged from the official definition of virtual constellations offered by CEOS to include a broader suite of possible forms for virtual constellations, specifically targeted at capturing LCLUC information. Characterized by their application-readiness, we proposed three types of virtual constellations: sensors with similar spectral and spatial characteristics (*e.g.*, ARL 3; Landsat and Sentinel-2); sensors with different characteristics, but a common measurement principle (*e.g.*, ARL 2; Landsat and MODIS); and sensors with disparate characteristics, but complementary information (*e.g.*, ARL 1; Landsat and lidar). As identified, a key rationale for our definition of virtual constellations is toward an improved, on-going, and operational capacity for global monitoring of LCLUC at 30 m spatial resolution. While ARL-3 virtual constellations are of greatest interest and priority, we also offer opportunities supported by a wide range of scientific literature that do not require the direct integration of calibrated reflectance measurements. The recently announced Sustainable Land Imaging program of the United States is an example where information drivers are used to rationalize and drive measurement needs, with the emphasis moving from research and capacity development, toward utilization of known capacity in an operational fashion. Operational programs still have the opportunity for technology development and injection, but are based upon an expected core of standard measurements and delivery mechanisms that allow users to build science and applications. With an information needs focus aimed at a variety of societal benefit areas, measurements from a range of satellites and data types are required. Virtual constellations composed of differing application readiness levels provide the mix of data capture options required to relate surface conditions and dynamics at required spatial and temporal scales.

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