The Future of Earth Observation in Hydrology

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Abstract. In just the past five years, the field of Earth observation has progressed beyond the offerings of conventional space agency based platforms to include a plethora of sensing opportunities afforded by CubeSats, Unmanned Aerial Vehicles (UAVs), and smartphone technologies that are being embraced by both for-profit companies and individual researchers. Over the previous decades, space agency efforts have brought forth well-known and immensely useful satellites such as the Landsat series and the Gravity Research and Climate Experiment (GRACE) system, with costs typically on the order of one billion dollars per satellite and with concept-to-launch timelines on the order of two decades (for new missions). More recently, the proliferation of smartphones has helped to miniaturise sensors and energy requirements, facilitating advances in the use of CubeSats that can be launched by the dozens, while providing ultra-high (3-5 m) resolution sensing of the Earth on a daily basis. Start-up companies that did not exist five years ago now operate more satellites in orbit than any space agency, and at costs that are a mere fraction of traditional satellite missions. With these advances come new space-borne measurements, such as real-time high-definition video for tracking air pollution, storm-cell development, flood propagation, precipitation monitoring, or even for constructing digital surfaces using structure-from-motion techniques. Closer to the surface, measurements from small unmanned drones and tethered balloons have mapped snow depths, floods, and estimated evaporation at sub-meter resolutions, pushing back on spatio-temporal constraints and delivering new process insights. At ground level, precipitation has been measured using signal attenuation between antennae mounted on cell phone towers, while the proliferation of mobile devices has enabled citizen-scientists to catalogue photos of environmental conditions, estimate daily average temperatures from battery state, and sense other hydrologically important variables such as channel depths using commercially available wireless devices. Global internet access is being pursued via high altitude balloons, solar planes, and hundreds of planned satellite launches, providing a means to exploit the Internet of Things as an entirely new measurement domain. Such global access will enable real-time collection of data from billions of smartphones or from remote research platforms. This future will produce petabytes of data that can only be accessed via cloud storage and will require new analytical approaches to interpret. The extent to which today's hydrologic models can usefully ingest such massive data volumes is unclear. Nor is it clear whether this deluge of data will be usefully exploited, either because the measurements are superfluous, inconsistent, not accurate enough, or simply because we lack the capacity to process and analyse them. What is apparent is that the tools and techniques afforded by this array of novel and game-changing sensing platforms present our community with a unique opportunity to develop new insights that advance fundamental aspects of the hydrological sciences. To accomplish this will require more than just an application of the technology: in some cases, it will demand a radical rethink on how we utilise and exploit these new observing systems.

1 Introduction

The capacity to observe the hydrosphere from the vantage point of space has redefined not only our perspective of Earth as an interconnected system, but also how we describe the dynamic processes that occur above, on and beneath its surface. 2017 marks the 60th anniversary of the launch of Sputnik 1, a polished metal sphere of less than 60 cm diameter that became the first man-made object placed into orbit. Although only broadcasting dual-frequency radio transmissions over a short 21-day period (until the batteries ran out), Sputnik had an indelible impact on humanity's perception of space, triggering the "space-race" and heralding in a new era of Earth observation (EO). Space was to become the new frontier. While the earliest satellite systems had a military reconnaissance focus, the value of space-based sensors for monitoring weather and climate was quickly recognised (Nordberg, 1965). Several meteorology focused systems were launched in the years following Sputnik, including the Television and InfraRed Observation Satellite (TIROS 1) in 1960, Nimbus 1 in 1964 and the Environmental Science Services Administration (ESSA-1) satellite in 1966. However, it would be 15 years post-Sputnik before the first civilian focused digital multispectral sensors were launched on-board the inaugural Landsat 1 mission in 1972, a program that has continued uninterrupted for more than four decades (Wulder et al., 2008), providing an unrivalled record of terrestrial change and dynamics. Since these early satellite missions there have been considerable and dramatic advances in remote observation platforms and the types of measurements available from them. Evolving from early pan-chromatic and red-green-blue (RGB) or R-G-near-infrared (NIR) imagery (De Wulf et al., 1990), sensor technology has expanded to include multi- and hyper-spectral visible to near-infrared bands (VNIR) (Houborg et al., 2015), multi-band thermal (Roberts et al., 2012), multi-channel microwave emissions (Njoku and Li, 1999), as well as radar and lidar techniques (Mace et al., 2009), all of which have advanced and redefined our knowledge and understanding of the Earth system.

From a hydrological sciences perspective, remote sensing has driven process insights and provided new and independent datasets that span the range of water cycle components. Recent studies such as Lettenmaier et al. (2015) provide a retrospective assessment of these developments and the progress of satellite observations in hydrology, complimenting earlier reviews of Schmugge et al. (2002) and Tang et al. (2009). In addition, process focused contributions have examined remotely sensed evaporation (Kalma et al., 2008; Wang and Dickinson, 2012), soil moisture (Njoku and Entekhabi, 1996; Wagner et al., 2007), precipitation (Kidd and Huffman, 2011), surface waters (Alsdorf et al., 2007) as well as terrestrial water storage changes using more recent gravity-based methods (Rodell and Famiglietti, 1999; Swenson et al., 2003). Leveraging the spatial coverage of satellite data, a number of research efforts have also taken advantage of extended temporal sequences of these observations to compile long-term global datasets (Miralles et al., 2011; Liu et al., 2011a; Beck et al., 2017). Such satellite-derived products provide an independent means of examining hydrological system dynamics and response (McCabe et al., 2005; Brocca et al., 2014), and offer the opportunity for an assessment of trends and variability in water cycle components (Zhang et al., 2016c; Kidd, 2001; Liu et al., 2012; Miralles et al., 2014).

Considering the multitude of discipline specific papers detailing diverse remote sensing applications in hydrology that have been published over the last few decades[1], it is apparent that Earth observations have played an undeniable role in advancing the state of hydrological science. However, while reviewing this role is instructive and important, our intent here lies principally in foreshadowing the emergent opportunities that more recent and near-future observational developments might have in advancing and redefining our understanding of the terrestrial system and its interlinked processes. To do this requires expanding our review beyond just space-based sensors, especially since satellite remote sensing represents just one aspect of EO. Indeed, some of the earliest attempts at mapping and monitoring the Earth surface were conducted from hot-air balloons, progressing to fixed wing planes and high-altitude reconnaissance aircraft such as Lockheed's U-2 "spy-plane": the

[1] A search on SCOPUS using the terms "remote sensing hydrology" returns over 4,300 unique contributions (June 1st, 2017).

geopolitical repercussions of which, when combined with the rejection of Eisenhower's "open-skies" initiative, precipitated a tactical shift to space-based sensing, and ultimately to the space-race. Interestingly, while EO developments have largely been defined by finer and finer spatio-temporal resolutions or an increasing number of resolvable bands, we are also witnessing something of a devolution in the choices available from our observing platforms. That is, some of the earliest approaches (balloons, fixed-wing aircraft, etc.) are being reimagined through technological advances in system design, power management, autonomous operation and the accuracy of navigational controls and communication infrastructure.

The overriding intent and purpose of this contribution is to introduce and explore some of these emergent technologies and observational approaches, highlighting new and innovative sensing platforms that are either still reaching maturity in terms of their applications potential, or are yet to be fully embraced (or even recognised) by the larger user-community. Another is to motivate some discussion on how we, as a scientific community, might better utilise available information and analytical resources, while also exploring the rapidly changing landscape of traditional space agencies in the light of recent commercial ventures in space-based observation. At the least, this research synthesis will present to the reader details on the ever-increasing number of observational tools and techniques that have the scope and potential to deliver new and powerful insights to our discipline.

2 Overview of Space Based Earth Observing Systems

The United States, European, Chinese, Japanese, Canadian, Indian and other national space agencies operate a large number of satellite systems that deliver a diverse range of measurement types and/or spatial and temporal coverage to the science community. Including the International Space Station (ISS) and systems operated jointly between the U.S. and international agencies, NASA alone has eighteen major Earth science missions currently in orbit, while the European Space Agency (ESA) has eleven EO missions in operation and a range of future satellites in advanced stages of planning and launch readiness. Other Earth observing instruments from various international agencies operate on-board small satellites and CubeSats, as well as being mounted within the ISS. The petabytes of data gathered by these missions have supported tens of thousands of scientific investigations, practical applications, and breakthroughs in our understanding of the planet. There have been launch and instrument failures along the way, but the vast majority of large space agency missions have met their baseline objectives. There are many examples of successful joint international missions that have reduced the costs and risks associated with launching a satellite to the contributing countries, while increasing collaboration and data uptake. Unfortunately, attempts to coordinate multi-platform observing systems in recognition of shared goals (e.g. holistic water cycle measurement) have been less effective: although NASA's A-train may serve as a partial counter-example to this claim (Stephens et al., 2002). Obstacles to greater cooperation generally include scientific competitiveness, technological secrecy and political considerations, differing visions and needs, and the lack of an authoritative coordinating organization. All this is to say that there remain considerable challenges and barriers to overcome before an holistic and collaborative EO strategy can be realised.

While EO in all its forms is the focus of this synthesis paper, it is worth reviewing the somewhat narrower perspective of satellite-based remote sensing, given its central role in delivering hydrological observations. As detailed in Fig. 1, the last few decades have seen the launch of thousands of satellites, with over 4,000 placed into orbit during this time. Of these, nearly 1,460 are operational, with the largest proportion comprising systems that form the backbone of the global communication network. Earth observing satellites, which include those operated by government, military, civilian and commercial sectors, comprise around 25% of the operational satellites in space, representing some 360 unique platforms. While national governments operate the majority of the EO based systems (57%), recent years have seen an increasing number of both commercial and civilian platforms being launched: a trend that is expected to continue into the future (see Sect. 4).

Figure 1. The state of play in space today. Estimates are based on the Union of Concerned Scientists satellite database, updated from 1/1//2017 (see http://www.ucsusa.org/nuclear-weapons/space-weapons/satellite-database). In terms of the sectors operating Earth Observing systems (right panel), another 5% include shared systems between those listed.

2.1 Problems, Challenges and Knowledge Gaps

The past 25 years have seen astonishing advances in our ability to observe hydrological phenomena, driven in part by the maturation of satellite remote sensing, surging computing power and data storage capacity (Lettenmaier et al., 2015). Global measurements of rainfall, soil moisture, snow cover, groundwater storage change, surface water elevation, and other water cycle variables could scarcely have been imagined when the race to space began in 1957, and the innovators and agencies who shepherded these developments deserve to be commended. Nevertheless, as detailed in Table 1 and discussed throughout this section, there remain critical gaps in our hydrological measurement and analysis capabilities. Snowfall, snow water equivalent, evaporation, deep soil moisture, groundwater depth and storage, water consumption, and water quality remain elusive targets, despite hopes that satellite missions to be recommended by the 2017 edition of the U.S. Decadal Survey for Earth Science and Applications from Space (see http://sites.nationalacademies.org/DEPS/esas2017/) may address some of these retrieval challenges. As is proposed herein, continuous, holistic water budget observation would be superior to the current paradigm of asynchronous measurement of individual variables. However, apart from requiring a paradigm shift in how we undertake much of our research, achieving this also requires a breakthrough in observation cost efficiency, such as cheap, reusable rockets, or some other game-changing innovation. In Sect. 3, we explore some of these shortcomings and suggest improvements, highlight existing opportunities and identify some new innovations that may be on the EO horizon.

Table 1. Hydrological variables and the current and planned satellite remote sensing missions that can be used to estimate them. We note that this list is not necessarily comprehensive and that there are possible trade-offs between resolution and accuracy that are not explicitly accounted for.

To date, only a handful of terrestrial hydrology focused EO missions have been designed and launched by national and international space agencies. These were enabled by a shift towards more user-oriented missions over the last two decades, which allowed scientists to press for their data needs and helped steer missions from their earliest design (Lettenmaier et al., 2015). As a result of this engagement, there has been an increase in the range of hydrological variables that can be retrieved from space, spanning far beyond the snow cover extent, land cover and topographic products of early satellite remote sensing research. Key elements of catchment and continental scale water balances are now routinely derived from the available suite of EO satellites. While this unprecedented wealth of data has brought about major advances in the study of large-scale hydrology, there remain gaps that need to be filled to increase our understanding of the hydrosphere, as well as issues that need to be addressed to ensure continued progress in our system knowledge. Here we detail some of these, with the aim of providing context and motivation for many of the new techniques and observation platforms on the EO horizon:

1. **Satellite Retrieval and Interpretation Challenges.** A fundamental challenge in EO are the limitations imposed by only measuring the spectral signature of solar, Earth emitted and reflected radiation, and using this information to retrieve a desired geophysical parameter (GRACE being an exception to this description). This issue can be extended to a perception in the literature that geophysical variables are directly obtained from EO, whereas the reality is that complex retrieval models, with their various simplifications, parameterizations, and non-unique solutions, are almost always employed to transform the satellite measurement into a specific variable of interest. For some variables, this conversion is quite straightforward (e.g. NDVI), while for others, the retrieval model may have underlying assumptions or require ancillary data that contribute significantly to retrieval error (e.g. soil moisture, evaporation). Bearing in mind that the utility of Earth observations lay not just in their capacity to reveal insights on the hydrological cycle, but also in their potential to

benchmark the climate models that we use to project hydrological response, an important issue emerges when one considers the dependency of EO datasets on their underlying models. In some cases, climate models and the retrievals against which they are benchmarked may share model assumptions and/or ancillary data. This interdependency can extend to the use of model climatologies or reanalysis forcing data in the generation of EO-based datasets (Mueller et al., 2013; Liu et al., 2011b). Given that "independent" satellite observations increasingly serve as indicators of climate change, or are used to detect trends in hydrological processes (see following point), it becomes critically important that a complete understanding, description and accounting of both the model and component forcing that underlie the production of EO data is provided.

2. **Data Homogeneity and Harmonization.** The capacity to develop long-term remotely sensed hydrologic records has proven useful across a range of applications, including: (a) studying trends in the terrestrial water cycle (Miralles et al., 2014), (b) improving simulations of hydrological, eco-physiological and biogeochemical models (Beck et al., 2017), (c) examining the social science implications of water availability (Müller et al., 2016), and (d) benchmarking the hydrology in land-surface and atmospheric models (Mueller et al., 2013), amongst numerous other examples. The development of long-term records demands the continuity (although, not necessarily replication) of previous successful missions, which for space agencies with static budgets, may come at the expense of more innovative exploratory missions. In addition, given the limited lifetime of satellite missions, these long-term records can only be achieved by merging datasets based on various sensors. As a consequence of this merging, observed inter-annual fluctuations may reflect discontinuities in the constellation of satellites, rather than actual hydro-climatological signatures (Liu et al., 2012). Efforts to harmonize satellite data represent a critical need, not just for more effective data assimilation or direct use of Earth observations in hydrological models, but to better understand any underlying physical process. To support such efforts, information on the accuracy of hydrological retrievals is required, which requires a departure from simple sensor precision and ground validation statistics, towards more appropriate error analysis and statistical equivalence that may reflect the artefacts of multi-sensor merging strategies (Su et al., 2016).

3. **Engineering and Operational Constraints.** If a satellite is to rotate around the Earth at the same speed that the Earth rotates around its axis, then it must be placed above the equator in a geostationary position, approximately 35,786 km above mean sea level. At that altitude, and with current technologies, visible and NIR frequencies can be measured at high temporal resolutions (minutes), but only at spatial scales on the order of kilometres (GOES-16 and Himawari-8 can be tasked to capture sub-areas of a full-disk at a frequency of 30 seconds). Lower altitude (~700 km) satellites generally operate in polar orbits, allowing them to image a large part of the Earth surface, but at a coarser revisit time of one to several days. Such orbital limitations impede the ability to observe fast weather and hydrologic processes over the diurnal cycle at the needed high spatial resolutions (sub- to 10's of meters). One way to leverage the higher-resolutions achievable from lower-orbits and overcome the temporal repetition (cadence) issue, is through the use of more than one satellite i.e. constellations: a topic that is explored further in Sect. 3.4. Related in part to the satellite orbital characteristics, sensors and platforms are often poorly-designed to provide data over regions where hydrological observations are the scarcest and most needed (e.g. tropics, poles, mountainous regions and urban areas), which limits the potential to close the hydrological balance at continental scales and advance our understanding of these processes. Finally, many hydrological variables require observations in the microwave portion of the spectrum (from Earth emitted radiation), but current technology limits antenna size and therefore spatial resolution (excepting synthetic aperture radar) and impedes the mounting of microwave sensors in geostationary satellites. Increased spatial resolution is necessary to help disentangle Earth emissions from heterogeneous land and atmospheric conditions (cloud and moisture variability, wet and dry surface areas, different vegetation classes, effects of topography, etc.). Optimising the desired spatio-temporal combination against the physics based constraints of orbiting systems is one area where emerging EO technologies (see Sect. 3) may offer a solution.

4. **The Need for Comprehensive Sensing.** A number of unsuccessful missions (e.g. OCO, Glory, Landsat 6) have demonstrated the often capricious nature of space based observation. Such mission failures (or instrument failures, as in the case of the SMAP radar) highlight that even with massive investment and allocation of resources to satellite programs, there is no guarantee of mission success, reflecting an inherent risk of single instrument platforms. This third challenge relates to the scientific community's penchant to focus on using a single sensor to retrieve a single geophysical variable. Such 'stove-piping' of both science teams and retrieval algorithm development has impeded the progress of more comprehensive approaches to estimating global-scale hydrologic datasets. Indeed, there are numerous satellite systems that are currently in orbit, or in advanced stages of planning, that we seem ill-prepared to exploit (e.g. hyperspectral sensing), while at the same time, we rely on other sensors or variables that are often used well beyond the intent or purpose for which they were designed (e.g. NDVI). This may be a consequence of too much data, and too little cross-disciplinary interaction. Either way, the result is a plethora of variables that are being routinely collected by satellite systems, but which remain largely under-utilised by the community. As a manifest illustration of this issue, the current international Programs of Record (POR) includes over 700 existing or planned (approved) sensors for EO. It is more likely than not that most investigator or operational programs will use only a few of these. Rather than employing a piece-meal approach to EO, we require a comprehensive and consistent strategy that informs across a range of hydrological processes and responses.

5. **The Decline of Evaluation Infrastructure.** Finally, although the number of EO systems available for hydrological monitoring seem to be increasing, one of the most concerning aspects threatening the very foundation upon which much of our process understanding and conceptual developments derive, is the decline of *in situ* networks, especially since the 1980's (Fekete et al., 2012). Distinct from the issue of poor spatial representation of ground-based monitoring that discriminates collections in the developed versus developing nations, this is a negative trend that has been replicated across many regions of the world, from the United States (Lanfear and Hirsch, 1999) to the pan-Arctic (Shiklomanov et al., 2002). From a long-term monitoring perspective, one particularly worrying aspect of this decline is the demise of gauging stations (and other measurements) containing greater than 30 years of continuous records, which has been witnessed in the U.S. (see water.usgs.gov/nsip/history.html) and almost certainly seen in other parts of the world and for other hydrological variables (Lorenz and Kunstmann, 2012). Without long-term and well maintained *in situ* networks, the challenges of disentangling the fingerprints of climate changes and its impact on hydrological systems becomes far more difficult (Hidalgo et al., 2009). While there have been encouraging activities that draw focus to the importance of *in situ* collections at catchment, regional and even global scales (Zacharias et al., 2011; Dorigo et al., 2011; Stahl et al., 2010), sustained community effort is required. The importance of a robust and operational *in situ* network is an often under-recognized element of satellite research programs and initiatives. Indeed, it is not outrageous to posit that there are few conceptual advances or process insights resulting from space-based observations that have occurred independent of using ground based monitoring. Technologies that strengthen and support this endeavour are immediately required.

To resolve many of these issues will require comprehensive programs that conceive EO as being based upon a variety of complementary platforms (i.e. satellite arrays that include nano-satellites, commercial aircraft based sensors, long-deployment UAVs, high-altitude balloons, etc.; see Fig. 2 and Sect. 3), blended and merged with models in ways that are more informative than just using conventional data assimilation approaches. The community has already developed hyper-resolution land surface models that have been applied at 30 m scales over continental domains (Chaney et al., 2016), as well as approaches for integrating land surface models with satellite retrievals to obtain time consistent data sets (Coccia et al., 2015), or using diverse data to challenge hydrological simulations (Koch et al., 2015; Stisen et al., 2011). Other approaches beckon, especially the opportunities being facilitated by cloud computing and data analytic techniques (see Sect. 3.8). The emerging hyper-resolution

trend (Wood et al., 2011; Bierkens et al., 2015) requires hyper-resolution forcing data, together with observations of the diurnal cycle of critical hydrological variables in order to prevent spatial and temporal inconsistencies between observations and models: a demand that we seem ill-prepared to meet.

To face these challenges, we have to recognize and accommodate the physics of EO, space agencies need to invest in new technologies (e.g. the development of nano-satellites and next-generation antenna) and ensure continuity of critical platforms, and they also need to support the community to develop improved retrieval models and encourage the use of measurements from a variety of sensors. All of this will require open and easily accessible data systems: something that to date has not been streamlined or optimised in the most efficient manner. What emerges from this brief summary is that it is not necessarily technological limitations that are inhibiting progress or advances. The challenges as listed seem largely scientific in nature, and reflect the need for a paradigm shift in how EO data is collected, disseminated and utilised: a topic that is examined further in Sect. 3.

2.2 Hydrology Specific Data Needs

Some of the issues identified above are general to Earth observation as a discipline, rather than specific to the field of hydrology. For this reason, we shift the discussion to focus on some of the key data needs and knowledge gaps per water cycle variable. While the following is focused on satellite-based retrievals and does not explicitly detail other observation systems, the issues are not platform specific. In compiling this (deliberately concise) list, we perpetuate a previously recognized limitation of our community's approach to EO i.e., the fixation on single component retrieval, whereby we measure one water cycle variable at a time, and ignore the interdependencies and relationships inherent in observed responses (López et al., 2016). Here, by at least acknowledging the issue, we seek to excuse ourselves from perpetuating it.

Precipitation. Satellite retrieved rainfall was first inferred using visible and thermal infrared observations (Lethbridge, 1967), providing an estimate of rainfall volume (Kidd and Huffman, 2011). With the launch of microwave sensors such as the Advanced Microwave Sounding Unit-B (AMSU-B) and the Special Sensor Microwave Imager (SSMI), a shift towards more direct measurement was taken. Evolutions on these early missions are reflected in the dedicated Tropical Rainfall Measuring Mission (TRMM) and the latest Global Precipitation Mission (GPM), both of which use a combination of radiometers and high-resolution radar measurements. Precipitation is highly variable in both time and space, so accurate representation demands a platform that reflects these spatio-temporal constraints. Unfortunately, while advances have been made, current capability still falls short in this regard. Microwave instruments on low Earth orbits limit repeat overpasses to once per day or longer. Although algorithms have incorporated infrared retrievals from geostationary satellites to fill the temporal gaps, these can introduce considerable uncertainty. Furthermore, measurement resolutions over land are typically greater than 5 km x 5 km, and are not anticipated to improve dramatically after GPM, presenting a further challenge for those seeking hyper-resolution hydrological modelling. So, while remote sensing observations of precipitation have greatly improved our understanding of its global magnitude and variability, there remain critical knowledge gaps. Other long-standing issues include the detection of snowfall, drizzle and extreme events (Rios Gaona et al., 2016) and the fact that lower-frequency microwave channels often fail to discriminate between the scattering by ice in the clouds and that by the surface, while higher frequency channels require the extraction of the background emission, which is not trivial. An additional challenge is rainfall retrieval at higher latitudes, where snowfall is the largest contributor to annual precipitation, yet remains unsampled by the oblique orbits of TRMM or GPM. All of these issues are amplified by the disconnect between satellite data and traditional gauge-based measurements, which have well recognized problems of poor distribution, wind-induced under-catch, elevation bias in gauge placement, and numerous other measurement complications (Lorenz and Kunstmann, 2012; Steiner et al., 1999). While ground-based polarimetric radars offer high temporal and spatial resolutions, they are only generally available in developed

countries (Heistermann et al., 2013), have relatively poor coverage in mountainous areas, and their merging with satellite observations has often proven cumbersome (Lee et al., 2015). Nevertheless, due to their spatial and temporal continuity, ground radar data are considered the gold standard where they do exist. Further efforts to archive, harmonize, reprocess and provide access to the global network of radar data are needed before the potential value of this data source can be fully realized[2].

Evaporation. Monitoring the second largest flux in the continental hydrological cycle has proven to be especially challenging, whether from ground-based approaches or from space. A range of techniques to derive evaporation from remote sensing data exist (Anderson et al., 2004; Wang and Dickinson, 2012; Ershadi et al., 2014; Fisher et al., 2008; Zhang et al., 2016a; Bastiaanssen et al., 1998). However, given the inability to observe this water flux in any direct way, all such approaches rely on rather complex empirical or process-based models, often requiring significant ancillary information and site-specific parameterisations. Moving forward, improvements are needed in both retrieval algorithms as well as satellite measurements. Large scale satellite-based evaporation estimates generally have a resolution that is too coarse for critical applications such as drought assessment, water management or agricultural monitoring, although there are regional to local scale exceptions to this (Anderson et al., 2013; Cammalleri et al., 2014). To achieve the required high resolution over large spatial domains, equally high-resolution observations of surface-level temperature and radiation budget components are required, together with improved representation of the hydrometeorology required to force many of these models (Ershadi et al., 2013). While current generation geostationary satellites can provide retrievals between 1-2 km in the visible-to-infrared spectrum, available global operational data products only offer coarse degree-scale resolutions, presenting a critical drawback for efforts targeting the production of global estimates (McCabe et al., 2016; Miralles et al., 2016). Finally, one of the key issues to advance the development of evaporation models is our representation of the vegetation components inherent in partitioning between evaporation and transpiration. The emergence of new remote sensing data sets (see Vegetation section below) that move beyond the relatively simplistic NDVI or LAI approaches that are currently employed, may provide a path forward to achieving needed model improvements.

Soil moisture. Over the years, several algorithms have been formulated to derive soil moisture from low microwave frequencies, resulting in numerous data products being developed since the late 1970's. These datasets have demonstrated their utility in hydrological applications at different scales, and have become a valuable tool for the climate community after merging into multi-decadal, -satellite and -sensor (active and passive) records (Liu et al., 2012). With algorithm developments for active scatterometer based retrievals (Naeimi et al., 2009) enabling soil moisture products from the Advanced Scatterometer (ASCAT) (Wagner et al., 2013), together with the launch of soil moisture dedicated missions such as the Soil Moisture and Oceans Salinity (SMOS) mission in 2009 and the Soil Moisture Active Passive (SMAP) mission in 2015, the retrieval of soil moisture from space has taken on a new dimension. Current research strives to improve the accuracy of retrieval algorithms (Mladenova et al., 2014), understand the spatial representativeness of the observations (Dorigo et al., 2015), increase the spatio-temporal resolution (Jha et al., 2013; Merlin et al., 2010), optimally ingest observations into hydrological models (Reichle et al., 2007), and explore the blending of different sensors (Liu et al., 2011b). The coarse resolution of passive based retrievals remains a challenge, but advances in antenna technology may provide improvements on this. Shallow retrieval depths also limit the determination of root-zone moisture profiles and dynamics, although modelling approaches seek to improve deeper-soil representation (Das and Mohanty, 2006; Li et al., 2010). Despite the failure of the SMAP radar after only three months of operation, the performance of SMAP's passive retrievals has recently been evaluated with encouraging results (Pan et al., 2016). Likewise, the SMOS mission continues to provide valuable insights and an expanding range of derived products (Mecklenburg et al., 2016). Although no SMOS follow-on mission is planned at this time, the future of satellite remote sensing of soil moisture remains bright, with the newly launched Sentinel-1 series from the European Space Agency (ESA) carrying

[2] See http://eumetnet.eu/activities/observations-programme/current-activities/opera/ for an example of such an initiative

high-resolution radars that have proven capabilities to deliver soil moisture at less than 1 km resolution and near-real time (Paloscia et al., 2013).

Runoff. Of all the hydrological variables, the one that typically draws the most attention from a water management perspective is river runoff. However, runoff is inherently local and difficult to determine from coarse-resolution space observations. While some efforts have focused on using GRACE to derive long-term mean discharge for large rivers, most initiatives to date have been limited to running hydrological models of different complexities using satellite-derived digital elevation models, river height, inundation extent or simply satellite-based precipitation. The long-awaited Surface Water and Ocean Topography (SWOT) mission (now planned for 2021) is set to measure surface water bodies and to infer river discharge. SWOT will carry a radar altimeter capable of deriving two-dimensional images of surface water height, with a vertical accuracy of about 1 cm averaged over 1 km^2 across a 120 km swath. This will deliver a substantial advance over previous altimeters used for hydrological applications that report only one-dimensional heights (Calmant and Seyler, 2006). However, while river height, width and slope will be derivable from SWOT, the calculation of river discharge will still rely on algorithms that account for the unknown channel depths and flow velocities. Any algorithm that has a requirement of *in situ* data for calibration limits its applicability in ungauged regions, where discharge measurements from space are the most needed. Moreover, estimates of discharge will correspond to the particular time of the SWOT overpass, which may not match the desired timing, especially in applications related to the detection and monitoring of flash floods that require both high spatial and temporal resolution.

Groundwater and terrestrial water storage. Gravimetric remote sensing represents one alternative to conventional electromagnetic sensing techniques for estimating water storage variables. Since 2002, GRACE has been measuring temporal anomalies in the Earth's gravity field, from which changes in terrestrial water storage (the sum of groundwater, soil moisture, surface water, snow and biomass water content) can be inferred (Tapley et al., 2004). Combined with auxiliary model- or observation-based information, satellite gravimetry provides the only viable remote sensing approach for consistently estimating changes in groundwater storage (Rodell et al., 2007). However, GRACE's coarse spatial (>150,000 km^2) and temporal (monthly) resolution and data latency (typically 2-4 months) have limited its value for operational applications and decision-making, absent any model-based downscaling (Zaitchik et al., 2008). The GRACE Follow-On mission (to be launched in 2018) is expected to improve upon the retrievable resolution somewhat (>100,000 km^2). In spite of these limitations, the GRACE mission has proven to be one of the outstanding examples of non-traditional EO applications in hydrology, and serves as a reminder that process understanding is best achieved utilising a range of complementary observation platforms.

Vegetation. Given the strong links between vegetation and multiple elements of the water cycle, there is understandable focus from the hydrological community on capturing plant response and dynamics at high spatial and temporal resolutions. Vegetation features are most clearly extracted from the VNIR, with sensors such as MODIS and Sentinel-2 providing unprecedented detail on plant-spectrum response. It could be argued that too much emphasis has been placed on relatively simplistic broadband-derived optical or near-infrared vegetation indices such as the Normalized Difference Vegetation Index (NDVI), at the expense of other indices and portions of the electromagnetic spectrum (Houborg et al., 2015). For instance, microwave observations of Vegetation Optical Depth (VOD) offer a close proxy of the water content and hydrological functioning of vegetation (Liu et al., 2011a; Liu et al., 2013), without the limitations of clear-sky conditions or the impacts of signal saturation in dense canopies and sun-sensor geometry issues. While research efforts have produced long-term records of VOD that hold considerable potential to improve understanding of land water fluxes and carbon storages (Liu et al., 2015), they are seldom employed in diagnostic studies of the hydrological cycle. In some ways, there seems to be a disconnect between the vegetation and water research communities that has led to the mis- or under-use of observable vegetation metrics. Solar

induced fluorescence (SIF) (Meroni et al., 2009) is one example of this disconnect. Observations of fluorescence by the Japanese Greenhouse gases Observing SATellite (GOSAT) have mapped photosynthesis at the global scale (Frankenberg et al., 2011). Due to the synchronization of photosynthesis and transpiration through the stomatal conductance, SIF data could in principle be utilised to enhance our understanding of transpiration and evaporative stress (Alemohammad et al., 2016), but relatively little research has focused on examining this apparent link. Data from the Orbiting Carbon Observatory-2 (OCO-2) spectrometer, and the TROPOspheric Monitoring Instrument (TROPOMI) on-board Sentinel-5 Precursor (to be launched in 2017), will enable some of these ideas to be explored further, forerunning the first SIF-dedicated mission, the FLuorescence EXplorer (FLEX) from the European Space Agency (ESA) (launch scheduled in 2022). While earlier SIF datasets had resolutions that were not particularly well suited for hydrological applications, OCO-2 and TROPOMI present improved spatial detail (3 km and 8 km, respectively), and in the case of TROPOMI, a near daily revisit time.

Snow and permafrost. Terrestrial snow and frozen soils represent an important yet poorly-represented component of the global water cycle. While the retrieval of two-dimensional snow cover extent is a mature research field (Hall et al., 1995), the retrieval of snow depth, density or water equivalent (SWE) is usually of greater interest to hydrologists, since these form key elements of model initialisation and forecasting of runoff, drought and flood prediction (Bormann et al., 2013). Unfortunately, retrieving these and related cryospheric variables remains a major challenge, particularly for mountainous regions, where spatial variability is high and seasonal snow depth may reach tens of meters. Microwave sensors can be used for SWE and snow depth observations, but current systems lack optimal combinations of frequencies and resolutions. Although active microwave sensors can improve retrieval resolution and may be better suited for snow monitoring in mountainous regions, the maturity of active-based products has not reached the same level as passive approaches. However, even passive microwave-based SWE retrieval can suffer from signal saturation due to a deep snowpack, with commonly used Ku- and Ka-band microwave emission signals saturating at around 200 mm SWE. Given the importance of monitoring wet-snow properties for hydrology, synthetic aperture radar (SAR) retrieval approaches have been proposed, since passive approaches are not sensitive to dry snow parameters. Gravimetric techniques represent another alternative to microwave based measurement approaches for snow depth (Baur et al., 2009), but the approach is limited by the large spatial and coarse temporal characteristics of such sensors (Niu et al., 2007). In light of the non-selection of ESA's CoreH2O as an Earth Explore mission, there remains a need for high-resolution active microwave sensors with high revisit times to more effectively capture the dynamics of wet-snow in diverse terrain. Apart from snow covered surfaces, understanding the dynamics of frozen soils has become an increasingly important topic in hydrology, given the observed warming in many cold regions and the role that permafrost may play in changing river discharges, particularly in Boreal areas (Woo et al., 2008). Permafrost properties include key state variables such as ground temperature, as well as thickness of the active layer, spatial patchiness and ice content. While there has yet to be a dedicated permafrost mission, EO data can be used to obtain permafrost-related features, such as the evolution in micro-topography, rock glaciers, thermokarst and deformation. For instance, ESA's SMOS satellite has been used to detect the onset of soil freezing (Rautiainen et al., 2016) with encouraging results, while the SMAP mission would have provided key insights into permafrost processes, particularly the freeze/thaw state, which acts as a proxy for monitoring methane and carbon release (Heimann and Reichstein, 2008), forest productivity (Kimball et al., 2001) and sub-surface flow processes (Bayard et al., 2005). ESA's Sentinel 1 mission (Sabel et al., 2012), together with InSAR data (Liu et al., 2010), may present as possible platforms from which permafrost characteristics can be retrieved, advancing our knowledge of this increasingly important variable and our understanding of cold regions hydrology.

Water vapour. A general drawback of current satellite observations for hydrological applications is their inability to provide vertical profiles of the atmospheric state with a high enough temporal resolution to allow tracking of the fate and transport of water vapour. Water dynamics in the lower atmosphere are determined by complex interactions between the land surface and

the free atmosphere, which are mediated by the diurnal cycle of the atmospheric boundary layer (ABL, from the surface to 2–5 km above). Diurnal processes like air entrainment into the ABL act as key drivers of evaporation, convective rainfall or near-surface humidity. Therefore, understanding the connection between the surface and atmospheric branches of the hydrological cycle relies on adequately monitoring heat and moisture exchanges in the ABL over large spatial domains. However, this requirement demands the availability of temperature and humidity observations at fine time steps (e.g. hourly) and over high vertical and horizontal resolutions. Presently, low orbiting sensors capable of providing vertical information, such as the lidar in the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO), the radar in CloudSat, or the hyperspectral sounder in the Atmospheric Infrared Sounder (AIRS), can only provide data at daily (or much longer) temporal resolutions. Existing geostationary satellites, on the other hand, have frequent temporal sampling, but wider spectral bands and coarser vertical resolutions. Until these capacities are resolved in a single platform (or in a constellation of smaller satellite systems) the lack of any high spatio-temporal resolution data to monitor the evolution of the ABL will continue to constrain our ability to monitor diurnal cycles of atmospheric water fluxes from space.

Water quality. Compared with other hydrology related variables, relatively little focus has been directed towards characterising inland surface water quality from space. Changes in the Earth's natural environment, whether from global warming, land use and land cover changes, or other anthropogenic causes, can significantly deteriorate freshwater quality (Whitehead et al., 2009). Given the limited availability of *in situ* water quality measurements, remotely sensed datasets offer a means to fill this knowledge gap, with temperature, suspended sediment, dissolved organic matter and chlorophyll of particular interest. Lake and stream temperatures, which directly impact freshwater habitats, are very sensitive to climate changes (van Vliet et al., 2013). Although land surface temperature products generated from sensors such as MODIS and Landsat are quite well developed, large-scale water temperature datasets are less common. Since estimating water temperature requires delineating water bodies, a MODIS-based water mask has been developed for this purpose (Carroll et al., 2009). However, resolving such information remains challenging for water bodies with surface areas that have large seasonal or inter-annual variations, or whose cross-sections fall below retrievable resolutions. Suspended sediment and chlorophyll concentrations can be measured using VNIR data from Landsat, Sentinel-3, MODIS, and AVHRR, or with hyperspectral sensors (Brando and Dekker, 2003). Research on the use of physically based algorithms that monitor these properties is required, with high spatial and spectral resolution observations needed to advance such efforts (Odermatt et al., 2012). The Hyperion mission has contributed to sensing such variables with high accuracy (Giardino et al., 2007), but was decommissioned in late Feb, 2017. With no dedicated water quality mission planned, there is interest in the proposed Plankton, Aerosol, Cloud, and ocean Ecosystem (PACE) satellite to advance terrestrial water quality monitoring (even though its primary focus is on oceans), but the future of this satellite remains uncertain in light of the recent 2018 US budget announcement.

Section 2 has focussed predominantly on our space-based observing platforms and identified some of the issues hindering developments in our characterisation of the hydrological cycle. In order to drive continued advances in our system understanding, it is paramount that we exploit a comprehensive and holistic EO strategy, both with data that we currently have, as well as that which is only just emerging. To explore this concept and the opportunities being provided by a combination of new technologies, sensor innovations, and advanced analysis techniques, a presentation of some emerging monitoring systems and approaches that may leverage, support or even supplant the traditional notion of EO is presented in the following section.

3 Emergent Platforms, Capabilities and Technologies

A few decades from now, historians may reflect on today's remote sensing capabilities the way we regard transportation in the early 20th century, i.e. most of the major modes were already in existence, but huge improvements in quality, cost and

production efficiency, accessibility, and safety were yet to come. The improvements will be spawned and nurtured as before by government research investments, individual ingenuity, as well as private sector involvement. In this section we briefly summarize both the near- and mid-term plans of government space agencies and draw attention to a range of recent innovations that will augment and possibly disrupt the traditional concept of large orbital missions in the near, middle, and long-term. Later, in Sect. 4, we review the commercialization of space, which will be essential in driving down orbital insertion costs and thus enabling the predicted efficiency and accessibility improvements for many of the technologies described below. In previewing some of the observation platforms that will be described below, Figure 2 provides a concept of what a new Earth observing "System of Systems" might comprise.

Figure 2. An Earth observing "System of Systems" for revolutionizing our understanding of the hydrological cycle. This multi-scale, multi-resolution observation strategy is not really a concept, as the technology exists and is largely in place now. Supporting traditional space based satellites, there are now a range of orbital options from commercial CubeSats to demonstration sensors on-board the International Space Station. Beyond orbiting EO systems, technological advances in hardware design and communications are opening the skies to stratospheric balloons and solar planes, as well as an explosion of UAV-type platforms for enhanced sensing. At the ground level, the ubiquity of mobile devices are expanding traditional in-situ network capacity, while proximal sensing and signals of opportunity are opening up novel measurement strategies.

3.1 Future Agency Missions

In forecasting the range of future hydrology related satellite missions, it is not feasible to comprehensively list the entirety of national space agency plans in this brief overview. Realising this, we use U.S. agency missions as guidance for comparable space programs in Europe, China, Japan and elsewhere. While the specifics might vary, there are some generalities that remain true. For example, space agencies typically discuss plans for their flagship Earth observing missions 10-15 years out, accept proposals and approve the formulation and science definition teams for missions 5-10 years out, and begin assembly 3-5 years out. While NASA Venture class and smaller missions as well as bolt-on instruments typically have more compressed timelines, it is clear that the time horizons from mission concept to launch are long, rather than short.

Some hydrology relevant flagship missions currently approved and in various stages of development include the GRACE Follow On, WCOM, SWOT and ICESat-2. The joint NASA and German Aerospace Center (DLR) GRACE Follow-On mission, with a launch window between December 2017 and February 2018, will extend the unique monthly record of terrestrial water storage anomaly observations that have been provided by GRACE since 2002 (Tapley et al., 2004; Rodell et al., 2017). In addition to the K-band microwave ranging system used to measure changes in distance between its twin satellites with extreme precision, GRACE Follow-On will use an experimental laser ranging system and design improvements that together are expected to increase the spatial resolution from roughly 150,000 km^2 to 100,000 km^2 at mid-latitudes. China's Water Cycle Observation Mission (WCOM), targeted for launch around 2020, aims to measure soil moisture, snow water equivalent, soil freeze-thaw, atmospheric water vapour, and precipitation, amongst other variables. This is to be accomplished through accurate, simultaneous active and passive microwave measurements across a wide frequency range, obtained by three on-board instruments: 1) an L-S-C tri-frequency Interferometric Microwave Imager with 15-50 km spatial resolution, consisting of a 9 x 6 m mesh reflector and a one-dimensional thinned array as the feed; 2) a Polarized Microwave Imager covering 7.2 to 90 GHz with a 1.8 m diameter reflector antenna for conical scan; and 3) an X-Ku dual-frequency polarized scatterometer with 2-5 km spatial resolution and 1000 km swath for snow water equivalent and freeze-thaw mapping. NASA's SWOT mission, scheduled for launch in 2021, will return accurate surface water elevations over 90% of the globe at least twice every three weeks, enabling estimation of river runoff as well as surface water storage. SWOT will employ a wide swath, Ka-band radar interferometer to resolve 100 m wide rivers and 250 m^2 lakes, wetlands, or reservoirs with a height accuracy of 10 cm and a slope accuracy of 1 cm/km. Recent runoff data are currently available from only a fraction of the world's rivers,

due mainly to closed data policies outside of a few developed nations. SWOT will fill a major void in our observational capabilities. NASA's ICESat-2, while primarily focused on precise laser altimetry for ice sheet mapping, will also prove valuable for monitoring surface water elevations (Jasinski et al., 2016), particularly before the launch of SWOT. Other missions, such as NOAA's Suomi National Polar-orbiting Partnership (Suomi NPP; launched in 2011) Joint Polar Satellite System 1 (JPSS-1; scheduled for launch near the end of 2017), and future missions in the JPSS series are mainly geared towards atmospheric measurements, but all will carry Visible Infrared Imaging Radiometer Suite (VIIRS) instruments, which collect visible and infrared imagery useful for monitoring snow cover and vegetation as an input to retrieval algorithms for numerous hydrological variables. ESA's Sentinel-4 Earth observing mission (planned for launch in 2019) and its Sentinel-5 successor, will focus on air quality monitoring. ESA also plans two Earth Explorer missions related to hydrology: 1) the Biomass mission (planned for launch in 2021) will carry a P-band synthetic aperture radar for the purpose of estimating forest biomass, but which may also be useful for inferring root zone soil moisture; and 2) the Fluorescence Explorer (FLEX) mission, which will map vegetation fluorescence to quantify photosynthetic activity and should help to constrain transpiration rates. In addition to these large missions, NASA's Venture class ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) (scheduled to be deployed aboard the ISS in 2018), will measure vegetation temperatures with the aim of constraining transpiration estimates and better understanding plant response to stress.

The 2017 edition of the Decadal Survey in Earth Sciences is intended to guide the prioritization and selection of major U.S. Earth observing satellites for the next ten years. While the 2007 edition (National Research Council, 2007) recommended specific mission architectures, the new edition is expected to recommend observables and to leave mission and instrument design to the agencies and proposing institutions. At the time of writing, it is unknown what hydrological observables will be prioritized, but based on the missions that were included in 2007 (but did not enter NASA's mission queue due to a second or third tier ranking), we speculate that snow water equivalent will be a priority. Referring to Table 1, evaporation is another variable that may be targeted due to its importance, lack of a current, dedicated mission, and existence of a demonstrated retrieval approach. Deep soil moisture could also be on the list, although soil moisture algorithms that make use of wavelengths longer than L-band (e.g. P-band at 40 cm) are not yet mature (Moghaddam et al., 2007).

While there are impressive and innovative sensing platforms scheduled for launch in the next 5-10 years (or in advanced stages of planning) across international space and government agencies, there are emerging parallel opportunities for both investigator driven and commercially led activities that have the potential to reshape the EO landscape in hydrology. A selection of these are explored below.

3.2 Unmanned Aerial Vehicles (UAVs)

One of the most exciting recent advances in near-Earth observation lies in the field of Unmanned Aerial Vehicles (UAVs), also referred to as Unmanned Aircraft Systems (UAS) or Remotely Piloted Aircraft Systems (RPAS). Often used interchangeably, or simply referred to as a drone, the terms encompass the remote or semi-autonomous operation of an airborne vehicle. In a way, these new observation platforms represent a "hook in the sky" from which to deploy a range of sensors. The application of UAVs for remote sensing has offered new opportunities to map, monitor and understand the environment in unprecedented detail (Anderson and Gaston, 2013), particularly at the scale at which traditional field-based observations can be made, but also covering a greater spatial extent with a unique top-down view. The key advantages of UAV-based remote sensing is their capacity to: 1) collect ultra-fine resolution imagery (defined here as 1-20 cm pixel size); 2) acquire data on-demand at critical times and with high temporal resolution at costs affordable to an individual investigator; 3) carry multiple sensors (both active and passive), across the electromagnetic spectrum; 4) be employed for calibration and validation of satellite products; 5) complement, extend or potentially replace field surveys (especially in areas that are difficult to access);

and 6) provide a scaling tool between field and satellite data. Most importantly, this rapidly emerging technology offers the opportunity to reveal new insights into hydrological, geomorphological, atmospheric, and biotic processes, and represents a game-changing sensing platform.

In a recent contribution, Vivoni *et al.* (2014) reviewed the application of UAVs for ecohydrology and suggested that UAV remote sensing can fundamentally change how ecohydrologic science is conducted. This same is true for hydrology. At the most basic level, UAVs can provide turn-key solutions of ultra-high resolution RGB imagery using consumer-grade cameras. Recently, multispectral and thermal sensors have gained traction and are increasingly being deployed by scientists. While lidar and hyperspectral sensors are still in an early operational phase, rapid progress is being made. One of the breakthrough technologies to the success of UAVs for mapping applications is structure-from-motion (SfM) and dense image matching (Turner et al., 2012). SfM is based on photogrammetric principles and generates detailed 3D point clouds from overlapping and multi-view photography. UAV platforms are ideally suited to fly overlapping flight lines, and collect hundreds of images during dedicated campaigns. Using SfM approaches, extremely rich 3D information on the terrain, vegetation, buildings, geology, etc. can be extracted cheaply and efficiently by the end-user. For hydrological applications, SfM provides information on micro-topography and can be used to generate digital terrain models (DTMs) and digital surface models (DSMs) at unprecedented detail. Apart from their natural affinity to application in precision agriculture (Zhang and Kovacs, 2012) and for vegetation health and stress monitoring (Zarco-Tejada et al., 2012; Zarco-Tejada et al., 2013), a number of recent contributions have demonstrated the utility of UAVs in hydrological process studies, with snow depth retrieval (Vander Jagt et al., 2015), flood mapping (Feng et al., 2015), irrigation monitoring (Bellvert et al., 2016) and evaporation estimation (Hoffmann et al., 2016) all being explored.

Figure 3. **Employing a UAV to retrieve high-resolution multispectral information on the land surface for hydrology and related applications over an Australian rangeland site located near Fowler's Gap in New South Wales. Retrieved products include: a) a false-colour infrared image; b) a reconstructed digital surface model using visible imagery and structure-from-motion techniques; and c) an optimized soil adjusted vegetation index (OSAVI) derived from the 4-band multispectral image. Images were captured using a MicaSense/Parrot Sequoia sensor on-board a 3DR Solo quadcopter. The UAV was flying at a height of 40 m, providing a ground sampling distance of approximately 3 cm. Imagery provided by the University of Tasmania's TerraLuma Research Group.**

New UAV based sensor technologies are likely to drive further advances in hydrological process description and understanding. For example, advances in sensor manufacturing have now enabled production of frame-based hyperspectral snapshot systems that are much smaller than a typical consumer grade compact camera. Similar miniaturisation processes are being applied to thermal sensors and laser scanners. These recent developments offer opportunities to the hydrologic community by offering the combination of multiple sensors that acquire data simultaneously. The acquisition of 3D information on terrain and vegetation, together with hyperspectral and thermal imagery, was previously a highly specialised task for very experienced airborne remote sensing crews. Now, this multi-sensor capability is already available for UAV platforms, providing unprecedented information for remote sensing applications. However, as with any new technology, UAV deployment comes with challenges as well as opportunities. One potential threat to the success of UAV remote sensing is that innovations are primarily driven from a technological rather than scientific perspective. While new airframes and sensors are evolving at an impressive pace, research is required to deliver rigorous processing workflows and to generate accurate and robust end-products that are meaningful. There is a real risk that new sensors and products may produce little more than "pretty pictures" without a thorough understanding of sensor performance, precision and calibration. Semi-automated processing workflows are needed to ensure accurate geometric, radiometric, and spectral corrections. These workflows will have to cope with a data deluge of hundreds to thousands of images that typical flight campaigns generate, but developments in cloud-computing (Sect. 3.8) may provide a solution to the currently long processing times. Furthermore, as the need (or desire) for ultra-high resolution imagery increases, there will be a push to extend UAVs beyond visual line of sight (BVLOS) in order to

cover larger areas. Visual line of sight is a current legal limitation of UAV operation in many countries, which effectively limits the size of the study area to an order of 1 km^2, making the retrieval of information over larger catchments a laborious and time-consuming process. Improvements in technology and safety will ultimately make BVLOS operations feasible, but it will take time for regulatory bodies to keep pace with advances in technology.

Even though UAV remote sensing requires expertise in piloting, sensor operations, calibrations, and image processing workflows, it is now possible for small groups and even individual end-users to collect their own ultra-high resolution multi-sensor EO data: a capability that even a decade ago, was the purview of space agencies and highly specialised airborne data providers. In the not too distant future, fully autonomous systems are anticipated. Although current applications are some way off being completely autonomous, the ultimate goal of the UAV is analogous to the image capturing capability of the space-based satellite: a self-propelling, powered, self-contained and independent data collection system. So long as the needed developments in UAV science can keep pace with the rapid technological innovations, these innovative observation platforms are well placed to deliver needed advances in hydrological understanding.

3.3 Stratospheric Balloons and Solar Planes

UAVs are not the only non-orbiting remote sensing systems driving progress in hydrological observation: they are just one of the latest. Aerial weather balloons have been used for more than a century to remotely monitor terrestrial systems. Some of the earliest uses of balloons were to carry observers over battlefields throughout the 1800s and even during World War I, providing an unparalleled logistical and military planning tool. Today, balloon designs enable a low cost, stable platform for intriguing hydrologic and related remote sensing applications (Chen and Vierling, 2006). Apart from providing soundings of atmospheric temperature, pressure, and humidity, along with a variety of other meteorological variables, a range of enhanced measurement capabilities are also possible. Vierling et al. (2006) constructed a tethered balloon consisting of meteorological instruments, GPS receiver, thermal infrared camera, and a video camera, all operating in real time with data downlinked to a receiving computer. A more recent and novel application was the use of a mobile laser scanning lidar attached to a tethered balloon to acquire topographic elevation measurements (Brooks et al., 2013; Hauser et al., 2016). Costing approximately $100,000, the approach yielded a point-cloud of elevation measurements accurate to about 5 cm and spanning an approximately 75 m swath along the balloon's trajectory. Another system was developed by Shaw et al. (2012), who retrofitted a tethered balloon with red and infrared imaging capabilities for less than $1000, providing an approximately 12 cm spatial resolution in a 64 m wide imaging swath from a legally restricted flying height of 50 m.

Like balloons, aircraft based remote sensing has existed since the earliest developments of powered flight. Since more traditional aerial methods are well-known and easily accessible via the peer-reviewed literature (Green et al., 1998), we focus here instead on a more speculative but intriguing sensing future. Consider the recent around-the-world piloted flight of the Solar Explorer 2 (2016), an entirely solar powered airplane weighing 2,300 kg and having a 72 m wingspan. Covered in more than 17,000 photovoltaic solar cells, the craft achieved a maximum flight leg lasting almost five full days and nights. While this experimental system cost more than $200M, it highlights the future possibilities of having unmanned aircraft flying uninterrupted over fixed locations, without the need for landing. Back of the envelope calculations, assuming an average velocity of 75 km/hr and a maximum piloted altitude of 8,500 m, suggest that a similar unmanned plane equipped with an imaging sensor capable of 20 km swath widths could observe areas of 300 km by 120 km in a single day: enough to sense the extent of the Sierra Nevada Mountains and their snow packs in about three days.

Unsurprisingly, improved Earth observation is not the only motivation driving the exploration of balloons and solar-powered platforms. A number of Silicon Valley technology companies have well developed plans to use unmanned systems to deliver

broadband internet coverage to poorly connected regions of the globe. Google's Project Loon (https://x.company/loon/) is perhaps the most advanced of these and is based on the idea of using stratospheric winds to navigate and control an interconnected network of high-altitude balloons. Using this approach, the project aims to provide internet access to both developed and developing communities. With a similar goal in mind, Facebook's Project Aquila (Zuckerberg, 2016) is a parallel effort exploring solar powered aircraft. Aquila's aim is to have a fleet of planes flying at between 18,000–27,000 m that would stay aloft for months at a time, using on-board lasers to transmit and receive information to users below. A first unmanned flight was completed in late June 2016, lasting for 96 minutes (Gomez and Cox, 2016), but many technical barriers remain to be overcome. While these examples are focused on providing communications infrastructure to the estimated 2 billion people currently without internet access (representing an untapped revenue stream relative to the largely saturated market in most developed countries), there are clear opportunities for leveraging such systems for enhanced EO. Harnessing a fleet of high-altitude balloons or aircraft with an array of lightweight sensor packages provides a platform not just for opportunistic sensing, but also for evaluating new technology, calibration and validation of satellite systems and supporting large scale test-beds for product assessment: the last representing an often ignored (or under-funded) element of space based Earth observation. Leveraging the advances in technology behind the commercial development and production of these systems may provide scientists with direct access to their own airborne platforms, offering capabilities to individuals or research teams that are currently beyond the scope or reach of most. While such future platforms remain somewhat speculative, these early developments are not just exciting: they represent real pathways towards an enhanced Earth observation strategy.

3.4 The Rise of the Cubesat

The demand for increased spatial and temporal resolution is one of the underlying drivers of sensor and platform development, with the assumption being that enhanced resolution will improve the monitoring, characterization and understanding of terrestrial ecosystems. Till recently, there has been a rather incremental improvement in observing system specifications. Current agency based high spatial resolution satellites, such as the Landsat series or Sentinel-2 platforms, provide spatial detail at the 10-100 m resolution, but are constrained by the temporal frequency of acquisitions (5–16 days). When considering the influence of cloud cover on the visible, shortwave infrared and thermal infrared portions of the spectrum, data continuity and availability can be severely impeded (Roy et al., 2008). While deploying two identical sensor systems, as with Sentinel-2A and -2B (Drusch et al., 2012), represents significant progress towards improving the temporal resolution, acquisition of near-daily high-resolution imagery can only currently be met via the expensive tasking of commercial multi-sensor satellite systems such as RapidEye and WorldView (Houborg et al., 2015), and only then on an area-limited basis.

One way in which enhancements in revisit time and large area availability can be realised is via the launch of a larger number of replicate sensor systems. In the past, such attempts have been hindered by the high mission costs of the type of large satellites favoured by space agency missions. For instance, Landsat-8 (which is around the size of a large car), had an estimated cost of $855M to build and launch, so producing multiple versions (not including associated launch costs) is not a realistic proposition. The 2014-2020 budget for the European Copernicus Earth observation program, which includes the Sentinel missions, is estimated at approximately €4.3B, but does not include multi-satellite constellations beyond the Sentinel-2 pair (Denis et al., 2016). Here the key limitation in the replication of multiple sensing platforms relates to the satellites size and the associated price tag. One possible solution to this constraint that has seen some impressive real-world results is an obvious one: make satellites smaller and lighter and they become cheaper to launch. Such an approach is behind the CubeSat concept, introduced by Stanford University and the California Polytechnic State University in 1999 (Puig-Suari et al., 2001). CubeSats have provided the foundation upon which the recent surge in the development and launch of constellations of compact (i.e., 0.1 – 10 kg) pico- and nano-satellites (Bouwmeester and Guo, 2010; Selva and Krejci, 2012) can largely be attributed. A single-unit (1U) CubeSat, measuring 10 x 10 x 11.35 cm^3 and typically weighing less than 1.33 kg, forms the base level building block

for a range of larger configurations. Indeed, CubeSats can be configured in a variety of sizes, increasing as integer multiples such as 3U, 6U or 12U, to expand observation capacities and potential applications (Hevner et al., 2011). The advances driving CubeSats have not occurred in isolation, nor are they solely a product of economies of scale. The economics of space observation is changing rapidly, due to a combination of sensor miniaturization (allowing the development of standardized smaller satellites comprised of commercial off-the-shelf (COTS) components) and their deployment as secondary payload on commercial and public launch platforms (Woellert et al., 2011). The emergence of reusable rockets is also a major driver in the cost reduction of actually placing infrastructure in orbit, making the launch of investigator led CubeSats a feasible proposition (see further details in Sect. 4.2).

Regardless of the driving forces behind their emergence, CubeSats represent a cost-effective observation strategy that provides a unique opportunity for the implementation and demonstration of technological innovations, serving as potential test beds for advanced visible-infrared sensing systems (to date, the power requirements of active sensors currently limit their integration) or even as direct replacements to larger satellite missions (see e.g. NASA's CubeSat Launch Initiative; (NASA, 2016a) and Small Spacecraft Technology Program (NASA, 2016b)). NASA's Jet Propulsion Laboratory (JPL) is actively exploring the CubeSat potential, with new on-board processing and sensor technology testing being conducted on planned CubeSat missions (Edberg et al., 2016). From a hydrological perspective, JPL's RainCube (Haddad et al., 2016) that is scheduled for launch in 2017, will act as a demonstration mission for the use of Ka-band radar for precipitation retrieval. Another JPL project is the CubeSat Infrared Atmospheric Sounder (CIRAS), that seeks to match some of the temperature and water vapour profiling capabilities of the AIRS instrument (Aumann et al., 2003), but on a considerably smaller platform. Driving these efforts is the opportunity to leverage the significantly reduced cost, relative to conventional satellites, that makes launching constellations or swarms of CubeSats economically feasible. They also represent an inherent risk minimisation strategy: a systems failure on a sole-satellite configuration is mission ending, while multiple failures could occur within a constellation and still retain its mission capability. Such an approach has the potential to revolutionize monitoring capacity from space, not just from a hydrological perspective, but across disciplines and sectors.

A number of commercial companies are leading the way in exploiting this observation strategy, most notably Planet (formerly known as Planet Labs; www.planet.com) who, with more than 150 3U CubeSats launched since 2013, manages the world's largest constellation of satellites in orbit (Planet Team, 2017). Planet's flock of "Doves" are capable of capturing RGB and near-infrared imagery at 3-5 m ground sampling distance (GSD), providing near-daily global coverage based on a full constellation of nano-satellites. This emerging resource provides new and exciting opportunities for a wide range of applications seeking to exploit high-resolution clear sky imaging. One recent example using these data is the retrieval of high resolution Normalized Difference Vegetation Index (NDVI) for precision agriculture (Houborg and McCabe, 2016), but there are clear applications in land cover and land use change detection, environmental monitoring and numerous other fields of interest (see Fig. 4). The CubeSat approach features in other commercial enterprises, such as the planned Astro Digital Landmapper-HD constellation, that comprises twenty 6U CubeSats capturing five spectral bands at a GSD of 2.5 m every 3-4 days (www.astrodigital.com). Likewise, Planetary Resources (www.planetaryresources.com) envisions a programmable constellation of ten 12U CubeSats, delivering visible to near-infrared (400-900 nm) hyper-spectral and mid-wave (3-5 μm) thermal infrared data at 10-15 m GSD for any spot on Earth on a weekly basis. With the cost of a CubeSat ranging anywhere from a few tens of thousands upwards (including launch costs), the prospect of investigator or community driven missions becomes a realistic proposition.

Figure 4. Multi-scale capabilities of state of the art sensing optical satellites. Image illustrates the expanding resolution options available from both commercial and government satellites. A) Planet CubeSat at 3 m ground sampling distance over the Tawdeehiya Farm in Al Kharj, Saudi Arabia. Center pivot irrigated fields dot the landscape, with dimensions approaching 800 m. The inset in A) is zoomed to show the resolution advantages offered by the next generation of sensing solutions over B) Landsat-8 at 30 m, with C) Sentinel-2A at 10 m and D) Planet imagery at 3 m providing enhanced details. All images are false colour representations of NIR, Red and Blue in RGB bands. Sentinel-2A and Landsat-8 images were acquired on December 4th, 2016, while the Planet data were captured on December 5th, 2016.

Instead of launching constellations (i.e. a large number) of independent satellites into space, others have advocated the concept of a dense network of distributed space missions working in cooperation, where sensing systems coordinate to achieve a monitoring task in much the same way as a distributed sensor network collects information on the ground (Barnhart et al., 2009). Using satellite-on-a-chip or printed circuit board approaches, such low-cost, sub-kilogram options have obvious potential for hydrological and related sensing. While the next generation of CubeSats has the potential to revolutionize Earth observation, data from such platforms should ideally complement, and not necessarily replace, the high quality imagery that is currently acquired by conventional large satellite missions. To harness the potential and exploit these technological advances demands preparation (Dash and Ogutu, 2016) and this will only be realised through synergistic exploration and leadership from government space agencies, the science community, and increasingly the private sector. An underlying assumption here is that space junk will not continue to accumulate to the point of becoming an intolerable risk to launching satellites to low Earth and geosynchronous orbits: though that dystopia would actually enhance the importance of the sub-orbital alternative technologies described throughout this section. Whether intrinsic barriers (e.g. payload launch) or a divergence of commercial motivation versus scientific research interests will inhibit this exciting and much needed development in EO are topics that are explored further in Sect. 4.2.

3.5 Mobile Phones and Citizen Science

While space-based and near-Earth sensing platforms are revealing entirely new avenues of EO, there are technologies closer to home that are also revolutionising how we can monitor, sense and interact with the environment around us. Smartphones have transformed entire societies, from the most developed countries to regions where a regular source of electricity or freshwater is still lacking. Data from 2013 estimated that there are 7.3 billion mobile subscriptions globally, with 3.2 billion of these linked to smartphones[4] (see Fig. 5). Undoubtedly this number has increased in the last few years. Given their ubiquity, they present as ideal platforms from which to harness the possibilities of remote sensing hydrologic and related variables, as well as providing a means of information exchange. In Africa, one of the world's fastest growing regions for mobile phone subscribers (numbering more than 330 million as of mid-2016[5]), mobile banking has allowed Kenya to lead the world in mobile money via its M-PESA system (Aker and Mbiti, 2010), while the delivery of information via text-messaging has improved the economic outcomes of subsistence farmers through simple knowledge of market prices (Wyche and Steinfield, 2016). Other approaches have exploited mobile camera capabilities combined with smartphone applications to monitor soil, vegetation and land use changes (Herrick et al., 2017). In this sense, a person with a smartphone can become a remote (or at least proximal) sensing platform capable of providing information on the environment around them. This concept of harnessing widely accessible technology and the users deploying it is broadly referred to as "citizen science", and has the potential to reshape how information is both collected and interpreted (Buytaert et al., 2014).

But simple image-capture examples belie the potential that mobile devices have in providing a distributed measurement network. Plug-in and Bluetooth technologies linked to smartphones enable potentially billions of users to become "sensors" for measuring actual hydrological events. As an example of the immediate potential of this sensing platform, iBobber is a $100

[4] https://www.ericsson.com/mobility-report
[5] http://interactive.aljazeera.com/aje/2016/connecting-africa-mobile-internet-solar/connecting-africa.html

baseball-sized fishing bob that measures water depths and temperatures and has GPS location capabilities (see http://reelsonar.com; noting that there are other similar devices available on the market). Fishermen everywhere could be recording water depths for river hydraulic models and for total storage in lakes. In a more focused manner, teams of lay-scientists could be easily trained to use such low-cost devices to provide remotely sensed water depths in cost effective ways, e.g., a leisurely riverboat excursion or simple fishing pole cast from the shoreline to yield water depths. It is not hard to envisage numerous other smartphone-enabled devices that auto-upload their measurements to the internet. Indeed, it is the ubiquity of smartphones that enables the imagining of new hydrologic measurements.

Figure 5. Worldwide global system for mobile communication (GSM) coverage for the year 2013. The GSM network does not include the growth of related 3G or 4G networks. The image is derived from Figure 2 in Overeem et al. (2016).

However, there are (at least) two challenges with such "citizen science": 1) making certain that the measurements are accurate; and 2) connecting the hydrologic researcher with the smartphone users. Both challenges are solvable using standard methods employed in hydrological sciences. For instance, data assimilation and other statistical approaches can ensure that measurements collected from disparate platforms are appropriately integrated in hydrologic models. In terms of engagement or outreach, cross-disciplinary interaction between the social and physical sciences could facilitate the implementation of strategies to effectively engage citizen science. One application where smartphones have already demonstrated their potential for environmental monitoring is their use as thermometers. Overeem et al. (2013b) showed that thousands of smartphone battery temperatures uploaded to a central database through an Android application could be employed to estimate daily mean air temperatures in eight major cities around the world with reasonable accuracy. Their results show the potential of "crowd-sourcing" for real-time temperature monitoring in urban areas, where dedicated temperature measurements by meteorological services are typically lacking. Recent reviews have further illustrated the success of a number of crowd-sourcing projects, detailing the use of mobile video and imagery to capture and analyse flash-flooding, debris flow and flow velocities (Le Coz et al., 2016), precipitation events (Allamano et al., 2015) as well their application in atmospheric and climate sciences (Muller et al., 2015), detailing an exciting avenue of enhanced data collection.

Importantly, crowd-sourcing in hydrology is not solely about smartphones. De Vos et al. (2016) report on an effort to source rainfall data from personal weather stations in Amsterdam, exploiting the proliferation of low cost stations designed for home-based meteorological collection. Even in this single-city focused example, more than 60 inhabitants were found to operate personal weather stations equipped with tipping bucket rain gauges within the Amsterdam metropolitan area, significantly increasing the sole rain gauge operated by the Royal Netherlands Meteorological Institute (KNMI) at Amsterdam's Schiphol Airport. While there are undoubtedly issues associated with poor siting considerations, (lack of) maintenance and (interrupted) connectivity that would need to be accounted for, the utility of such additional hydrological monitoring is obvious. Indeed, the De Vos et al. study highlighted the additional information on the space-time variability of rainfall over a densely populated area that could be retrieved with reasonable accuracy and reliability from such a citizen network. A larger scale example includes the Community Collaborative Rain, Hail and Snow Network in the United States, (https://www.cocorahs.org/), which receive approximately 20,000 daily rain-gauge reports from citizen scientists across North America (Reges et al., 2016). In a particularly novel application of exploiting existing networks of data, Rabiei et al. (2016) inferred rainfall by utilising a vehicles GPS location together with sensors attached to the cars windscreen wipers. Many late-model vehicles employ infrared (or optical) sensors to determine rainfall intensity in order to automatically adjust the wiper-rate, offering the possibility of providing distributed records of rainfall: albeit limited to the road-network.

The use of non-traditional sources of information to infer, improve or inform upon our hydrological understanding, as well as to expand the distribution and spatio-temporal representation of existing networks, is a rapidly growing field that presents clear potential. The topic is explored further in the section below, which details related examples of opportunistic sensing.

3.6 Signals of Opportunity

The modern world is full of sensors, from the cars we drive, to the mobile phones (and cameras) we carry in our pockets. We are in the age of the Internet of Things (IoT), where every day physical devices are connected to the network, sensing the world around us. Although related to the concept of "citizen science" that was introduced in Sect. 3.5, we couch the present discussion under the context of "opportunistic sensing": the concept of utilising signals from often unrelated measurements to inform upon hydrological processes. Inferring hydrological properties by making use of signals of opportunity is a growing area of research.

Telecommunication engineers have known for a long time that radio signals propagating from the transmitting to receiving antennas of microwave links used in cellular communication networks are attenuated by rainfall. By using this knowledge, researchers have been able to translate this electromagnetic "noise" into a hydrometeorological "signal" (Messer et al., 2006; Leijnse et al., 2007). Indeed, it turns out that for the radio frequencies typically employed in such cellular networks, the signal attenuation is nearly linearly related to the average rainfall intensity. The attenuation can be inferred from the transmitted and received signal levels, which are operationally stored by telecommunication companies at regular time intervals (typically 15 minutes or less) to monitor network quality. As these links typically have lengths of a few kilometres and are installed at just a few tens of metres above the ground, they can be considered as path-averaged rain gauges, well suited for hydrological applications. Several thousand such links across the Netherlands have recently been used to produce 15-minute rainfall maps of comparable quality to those obtained from gauge-corrected ground-based weather radars (Overeem et al., 2013a; Overeem et al., 2016). In addition to rainfall monitoring over urban areas[7] (where network densities are generally high), this technique offers much potential for high-resolution measurement in areas where the density of ground-based monitoring networks (i.e. gauges or radars) is typically low, such as in developing countries (Doumounia et al., 2014; Gosset et al., 2016).

Given their spatial and temporal advantage, there is a long history of using radio occultation measurements via the Global Positioning System (GPS) of satellites to infer atmospheric variables and profiles (Kursinski et al., 1997) for use in numerical weather prediction. More recent work has sought to expand the type of measurements that can be inferred between satellite links and ground stations. For example, Barthès and Mallet (2013) describe the use of an Earth-space link in the Ku band to measure rainfall, leveraging several hundred telecommunications satellites transmitting in this frequency to infer periods of rainfall via signal propagation through the troposphere. Such information is not only useful for hydrological applications, but also for ground validation of satellite-based rainfall retrievals.

While improved representation of rainfall is of importance to hydrological studies, soil moisture plays an equally significant role in many process investigations. The use of proximal remote sensing techniques to measure soil water content and soil properties at depths deeper than current remote sensing capabilities (i.e. greater than 5 cm) represents an area of considerable interest. One of the best example of opportunistic proximal sensing is the Plate Boundary Observatory (PBO) H_2O initiative, which uses reflected GPS signals to estimate soil moisture (Larson et al., 2008), snow depth (Larson et al., 2009), and vegetation growth (Small et al., 2010). Some of the advantages of this technique include the provision of temporally continuous data at scales (~1,000 m^2) that fill a gap between point measurements and satellite remote sensing footprints, and that cloud

[7] See http://www.nature.com/news/mobile-phone-signals-bolster-street-level-rain-forecasts-1.21799

cover and labour are not issues. Another approach that seeks to bridge the point-to-footprint scale divide is the COsmic-ray Soil Moisture Observing System (COSMOS) (Zreda et al., 2012), which provides an increasingly rich dataset for calibration, validation, and evaluation of remote sensing products and land surface models. Comprising a growing network of more than 200 cosmic-ray neutron probes at fixed installations across six continents, these data represent a valuable source of independent information from which a range of hydrological responses may be inferred or assessed (Jana et al., 2016; Montzka et al., 2017).

A recent addition to the COSMOS program has been the use of mobile "rovers", which offer a way to increase the spatial coverage from the local to mesoscales (Desilets et al., 2010; Chrisman and Zreda, 2013), while also offering a means to merge data from fixed probes to provide a multi-scale real-time soil moisture product (Franz et al., 2015). In addition to supporting hyper-resolution land surface modelling needs, the rover approach provides opportunities not just in research, but also commercial activities: most notably in precision agriculture, e.g. mounting rovers to existing farm equipment (sprayers, tractors, etc.), autonomous farm vehicles, or to rotating infrastructure (i.e. centre-pivot irrigation systems) offers an interesting opportunistic sensing possibility. The capacity to mount probes on delivery trucks, self-driving vehicles or even national train networks, would further expand observational capacity and provide semi-repeatable local and regional mapping opportunities across both natural and urban landscapes. Mobile sensors can easily collect data from either ground vehicles (e.g. snow mobiles, dog sleds, etc.) or low flying aircraft, which offers a potentially unprecedented calibration, validation, and evaluation dataset for a range of hydrological variables. While roving probes are fairly heavy (50+ kg) and miniaturization options are somewhat limited, the use of drone swarms with several smaller probes functioning as a single unit would further increase mapping possibilities (see Sect. 3.2). With the simultaneous use of several detector energies (bare, cadmium shielded, and plastic shielded probes) recent research has illustrated the means to collect information on vegetation condition, soil organic properties, and soil moisture simultaneously, providing a valuable resource to support observation and modelling strategies (Andreasen et al., 2016). Such sensing technology also has the potential to augment on-going global digital soil mapping efforts (Sanchez et al., 2009), as well as aid in the validation of existing high resolution products (Chaney et al., 2016).

In a final example of opportunistic sensing, we examine the potential of commercial passenger and cargo aircraft as mobile airborne sensing platforms. While observations from dedicated aircraft are typically only collected during sensor testing and infrequent, targeted measurement campaigns, there is little to inhibit (at least from a scientific perspective) airborne sensors from hitching rides aboard commercial aircraft, greatly expanding their spatial and temporal data collection capabilities. Many airliners are already outfitted with Doppler radar and Aircraft Meteorological Data Relay (AMDAR) systems (Drüe et al., 2008), which provide measurements of meteorological variables that include temperature, wind vector, and dew point temperature, and are made available for assimilation into weather forecast models (Petersen, 2016) and for other scientific investigations deemed beneficial to the airlines (Sharman et al., 2014). Advanced sensors for measuring water vapour more precisely have also been tested alongside AMDAR sensors, while the benefits of including on-board infrared sensors (e.g. for volcanic ash detection) have recently been demonstrated (Prata et al., 2016). While leveraging the remote sensing potential of commercial aircraft is an approach that has been espoused for more than two decades (Fleming, 1996), it has yet to be routinely employed to enhance hydrometeorological observation. No doubt this is due in part to some of the obvious constraints on retrofitting aircraft with non-essential instrumentation, and the regulatory hurdles that would be faced in doing this. However, given that the systems described above all seek to enhance flight safety either directly (i.e. improved hazard detection) or indirectly (i.e. improved forecasting and early-warning systems), such an observing system may see more operational integration into the future.

3.7 High-definition Video from Space

One of the most exciting remote sensing opportunities that has the potential to change not just the way we observe the Earth system, but also the manner in which we can use data to inform on processes, is the emergence of high-definition (HD) digital video. This game-changing visualization approach builds on a surprisingly long history of employing airborne video in EO studies (King, 1995). Indeed, some of the earliest satellite missions such as Landsat 1-3 (Townshend, 1981) used vidicons, a type of cathode ray tube employed in capturing television images (Nagy and Nagy, 1972): although due to the temporal sampling limitations of the deployed systems, these were basically 2D image snapshots, i.e. essentially television cameras providing still photographs (Vaughan and Johnson, 1994). While the use of airborne and ground-based optical and multispectral video systems have been explored actively in vegetation and agricultural studies (Everitt et al., 1991), it is only in very recent times that the capacity to exploit full-motion HD video from space has emerged. Indeed, it is this opportunity to utilise the temporal insights that HD video allows that represents the truly revolutionary aspect of this observing system.

With full-motion video imagery comes the capacity to capture dynamic hydrology and meteorology, providing new insights that could enhance our process understanding. An ability to record the Earth system in real-time on a repeatable basis has inter-disciplinary implications. Pollution monitoring, disaster management and response, ecosystem assessment, as well as numerous and immediate hydrological applications are imaginable e.g. flow velocity, flood propagation, erosion monitoring, contaminant transport and dispersion, precipitation and cloud tracking, to name but a few. One novel application lies in the use of satellite video data to reconstruct a digital surface model (d'Angelo et al., 2016) via structure-from-motion type approaches, providing details of landscape changes in ways that static elevation datasets cannot. Being able to record debris flow down a river, or dynamic inundation in natural or urban systems could provide new insights into how we model, forecast and predict flow and related hydrological events. However, while the possibilities of video imagery from space are exciting, as a discipline we are under-prepared to utilise such data effectively. Ultra-high temporal resolution information is not something we routinely deal with, so how to exploit such data will require innovation and imagination. An obvious constraint in current modelling application is that the temporal resolution of even the most advanced hydrological schemes are usually on the order of minutes rather than seconds (Berne et al., 2004; Ochoa-Rodriguez et al., 2015). Direct ingestion is the most obvious (but least imaginative) manner in which video data could be used, but computational and model-physical constraints are apparent. So, while a range of applications can be imagined, the practicalities of integrating or ingesting high-temporal sequences into our current modelling or analysis frameworks remain largely unexplored. Indeed, video imaging and analysis is more the domain of the computational scientist than the hydrologist, so these disciplinary lines will need to be crossed to take advantage of such technological breakthroughs. Although the potential applications are many, a paradigm shift away from the use of periodic 2D snapshots will be required to exploit the feature rich temporal dimensions offered by video streams.

It is important to note that this is not blue-sky research: the technology exists, satellites are already in orbit and data streams are available, but we are not keeping pace with the rapid advance in imagery possibilities. Indeed, it is the private sector that is leading the charge in realising and utilising the technology, with Google's TerraBella (recently acquired by Planet) providing high spatial (approx. 1 m) and temporal (30 frames per second; fps) full motion video imagery (Murthy et al., 2014). UrtheCast (https://www.urthecast.com/) is another company exploring this potential, with similar spatial (1 m) but lower temporal (3 fps) specifications (see Multimedia 1): although the second generation UrtheCast system that is due for launch in late 2017 will provide imagery at 0.5 m and 30 fps, in addition to having a 1 m X- and 5 m resolution L-band synthetic aperture radar (Beckett, 2015). At the moment, both video platforms are limited to between 60-90 second captures, but expanding this technology to allow full-coverage real-time observation in low Earth orbit has been proposed on micro- and nano-type satellite configurations (Han et al., 2015). Others have presented a vision of a geostationary space surveillance system (Airbus GO-3S)

(Villien et al., 2014). Regardless of the platform, it is the combination of high-spatial and high-temporal observation that has the potential to dramatically alter the very nature of Earth observation.

Multimedia 1. On-board the International Space Station, the UrtheCast IRIS high-resolution camera (HRC) captures colour video at 3 frames per second for a duration of 60 seconds. Here we see an example of the HD Video over the Burj Khalifi in Dubai. The tracking of vehicles on roads is analogous to monitoring flow in rivers or the speed of moving clouds, while the capacity to extract 3D structure of the underlying terrain provides opportunities in dynamic monitoring of surfaces.

3.8 Cloud Computing and Data Analytics

In parallel to developments seen in other fields, novel EO satellites are acquiring data at a staggering rate, where even a single satellites collection can exceed many terabytes on a daily basis. As such, while the capacities of today's EO sensors to collect data of relevance to hydrology are truly unprecedented, the challenges faced when trying to turn the raw satellite data into useful information can be daunting. Over the regular lifetime of a satellite, more than a petabyte of raw satellite data can easily accumulate. It is by no means clear when or to what extent hydrology will fully exploit this rapidly increasing volume and diversity of EO data. However, the speed of adoption will likely be determined by the time it will take to move the vast quantities of EO data and their processing into the "cloud". This is because processing such large data volumes is impossible with standard computing resources, nor is it meaningful to distribute the data over the internet, thereby replicating many thousands of queries. Instead, the only way forward will be to "bring the users to the data". In practical terms, this means that EO data processing will increasingly take place in large virtualised data centres, allowing large numbers of users to access the data and enabling collaboration on the development and use of EO data. At a very basic level a cloud can be understood to be a large-scale computing infrastructure capable of delivering EO services over the internet. A key enabler of cloud computing was the construction and operation of extremely large-scale, commodity-computer data centres at low-cost locations to achieve economies of scale (Armbrust et al., 2010). Nowadays, with falling prices for storage and computing, thematic aspects and service quality is becoming more and more important. Some of the advantages of cloud computing include virtualized resources, parallel processing, and data service integration with scalable data storage (Hashem et al., 2015). With the existence of such infrastructure, it becomes possible to start building multi-level EO data processing chains in a collaborative manner.

The adoption of cloud computing technologies in EO and hydrology will not be without its challenges. Apart from the practical software-based considerations that allow virtualisation of large computing infrastructures with hundreds to thousands of users, a much larger obstacle is how best to organise the expert community, ensuring that joint efforts to develop code and products lead to quality controlled, well documented, and user friendly software and data. Ideally, interpretive models and subsequent data analysis would be run where the EO data reside, ensuring a seamless processing line from the raw sensor data to the final hydrologic predictions, allowing each expert along the value-adding chain to focus on his or her competencies. Considering the increasing complexity of scientific algorithms and models used in EO and hydrology, such collaboration can be expected to speed up research and development efforts, leading to a much faster data uptake in hydrological practice. Precisely where this cloud-computing might take place also raises questions (and potential concerns) related to data-archiving, distribution and intellectual property. One of the most advanced cloud platforms is Google's Earth Engine (http://earthengine.google.com), which provides a platform for petabyte-scale scientific analysis and visualization of geospatial datasets, both for public benefit (non-commercial use is for free) and for business and government users. Its data catalogue contains a wide variety of popular, curated datasets, including the world's largest online collection of Landsat scenes (Gorelick, 2013). Amazon Web Services offers a similar storage and analytics platform, which houses an expanding collection of satellite, meteorological and climate datasets available to the user community, including recent Sentinel-2 data and a number of NASA collections (aws.amazon.com/earth). Earth observation data archiving and stewardship are relatively new concepts to these more

commercially oriented services, so it is unclear how effectively they will embrace the scientific model of data retention: especially if the revenue potential of older data does not justify its storage. Whether government agencies will continue to maintain their own storage services or leverage these much larger commercial facilities also remains to be seen. Regardless of any future delivery mode, ensuring continued free-access and long-term archiving of stored Earth observations is essential to advancing the field. With the rise of artificial intelligence and deep learning approaches (discussed below), the importance of maintaining a long record of "training data" may provide a commercial incentive to archive historical records.

A number of early examples have explored the hydrology related opportunities afforded by cloud-based platforms (McGuire et al., 2014; Astsatryan et al., 2016). Donchyts et al. (2016) employed the Earth Engine for mapping surface water changes at 30 m over the past 30 years on a global scale, an effort that would not have been possible without such data analytic centralization. While the Earth Engine is popular amongst scientists, Amazon's cloud is increasingly being used by commercial companies to showcase their EO services, such as the Sentinel-2 web mapping service offered by Sinergise (www.sentinel-hub.com). Another cloud platform serving both EO and hydrological applications is currently being built by the Earth Observation Data Centre (EODC) for Water Resources Monitoring (https://www.eodc.eu/), a public-private partnership with a goal to foster the use of EO data for monitoring global water resources (Wagner et al., 2014). In addition to optical data (i.e., Landsat, Sentinel-2) EODC holds a complete global archive of Sentinel-1 Synthetic Aperture Radar (SAR) data, which can be processed with a supercomputer for continental to global scale mapping of soil moisture, water bodies and other hydrological parameters (Elefante et al., 2016). Clearly, there are many potential and diverse applications of cloud computing in hydrology, some of which are being enabled by access to the underlying Applications Program Interface (API), a common feature of many of the Silicon Valley type start-ups. Although representing rather focused examples of cloud computing opportunities, the cases noted above serve to illustrate that this revolutionary change in technology, which has the potential to completely overhaul working practices in EO and hydrology, has already started. As the spatial and temporal resolution of EO data increases, the development of efficient cloud computing, storage and on-the-fly processing solutions becomes even more relevant. This is especially pertinent for a community that seeks to embrace the concept of hyper-resolution hydrological modelling, where the scales of processing and data requirements start to push-back on available computational power and resources (Bierkens et al., 2015). Undoubtedly, any future EO strategy in the hydrological sciences will have cloud computing as a core element, so recognising and resolving the inevitable challenges and opportunities that cloud computing will bring to the community will be key to realising its potential.

A parallel consideration that will follow any increase in data volumes and the associated computing demands is the need to explore more efficient approaches to exploit and interpret the petabytes of satellite data being collected on a routine basis (Warren et al., 2015). The era of big-data and artificial intelligence is upon us: whether we are prepared for it or not. Traditional modelling and analysis techniques are ill-designed to interrogate or utilise immense EO datasets, and alternatives based on machine- and deep-learning methods that can be used for regression or classification problems involving massively multivariate systems are becoming increasingly popular. These data-analytic techniques have the potential to either completely replace process-based models, or work in combination to make them less computationally expensive (Lary et al., 2016). Commonly used machine-learning methods include artificial neural networks, support vector machines, genetic programming, decision tress or random forests, amongst many other approaches. These approaches are usually applied in a 'supervised' context, in which a database subset is used to train the algorithm to reproduce an expected response (i.e. 'learning process'), and a different subset can be used to test or validate the performance of the trained algorithm. An interesting characteristic of these methods is that little to no knowledge of the physical processes underlying the observed variables is required to implement them, which releases their potential for discovering unexpected relationships as new hydrological and climatic observations become available (Faghmous and Kumar, 2014; Lary et al., 2016).

Machine-learning methods have been applied across a range of science and engineering applications for more than two decades. A number of recent examples have targeted the (retrospective) prediction or retrieval of hydrological states and fluxes from single- and multi-satellite sources, including the estimation of typhoon rainfall over the ocean (Chen et al., 2011), the retrieval of surface soil moisture (Rodríguez-Fernández et al., 2016) and water vapor content (Aires et al., 2001), the estimation of river runoff (Rasouli et al., 2012; Deo and Şahin, 2016), the analysis of global hydro-climatic controls on vegetation (Papagiannopoulou et al., 2016), the training of high-resolution sensors for retrieval of NDVI (Houborg and McCabe, 2016), and the derivation of continental water and carbon fluxes using decision trees (Jung et al., 2009). Still, the application of these techniques to dynamically monitor hydrological events and processes using remote sensing remains an emerging field, with relatively limited existing applications. With the storage and analysis opportunities afforded by cloud computing, the capacity to streamline many of these examples into on-the-fly applications is more a reality than ever before, providing a new and on demand observation and analysis source.

Despite this remarkable confluence of data science and remote sensing, one can still resist the narrative that there is no problem that a sufficiently complex machine-learning algorithm cannot unravel given enough data (Anderson, 2008). If this were the case, there would be no need for domain expertise to understand current and future challenges in hydrology: the dilettante will have prevailed (Klemeš, 1986). Indeed, there remain several obstacles to any predicted ascension of a completely data-driven approach to hydrology. Observations of the hydrosphere often have a spatio-temporal structure that emerges in the form of correlations between variables, but this correlation may not necessarily imply causality. Therefore, being able to draw strong deterministic conclusions about the behavior of hydrologic systems based on data-driven methods often requires prior knowledge (and understanding) of the physical processes (Faghmous and Kumar, 2014). As an example, Papagiannopoulou et al. (2016) discuss how the application of random forest models to auto-correlated vegetation imagery and cross-correlated temperature and precipitation can lead to the wrong conclusion that temperature controls vegetation growth in water-limited regions. Changing sensors or satellites (e.g. as part of data continuity missions) routinely result in temporal gaps, discontinuities, and artifacts. In addition to inherent sensor degradations, these influences, without context, would impact any conclusions that data-driven models may yield on the behavior of hydrological systems. All of this is to say that without subject knowledge, such temporal record adjustments are unlikely to be diagnosed or interpreted appropriately.

On the other hand, a dogmatic approach to a purely physically based hydrological process representation has inevitable limits to advancing understanding. The concept of "letting the data speak for itself" is particularly attractive in a discipline where so much of our physical understanding is based on a relatively simplistic description of process form and function, and where its application is routinely extended beyond the scales at which it was observed to be relevant. As both hydrological and remote sensing research progress, it is prudent that we (at least initially) seek the middle-ground, where the development of machine-learning methods might be guided by theoretical constraints and understanding, and that they be used to complement or improve more traditional physically-based models, which in turn can add interpretability in regards to the underlying processes. Regardless, the opportunities being presented by these new and innovative approaches are likely to challenge our concept of hydrology as a discipline, especially as the exploration of inter-disciplinary datasets provide new insights and understanding to hydrological processes and behavior: a topic that is expanded upon in the context of a Fourth Paradigm in Hydrology, as discussed in Peters-Lidard et al. (2017) (this issue).

4 The Changing Earth Observation Landscape

We have examined some of the challenges and issues associated with satellite-based hydrological remote sensing (Sect. 2) and reviewed the innovative and exciting frontiers of emerging Earth observation technologies (Sect. 3). To conclude this synthesis, we present a brief overview on some of the important considerations that may influence how this vision for the future of EO will be realized, highlighting the roles that government space agencies and commercial enterprises may play in reshaping the field, and identifying some of the potential drawbacks, constraints and limitations that may emerge as we navigate this rapidly evolving landscape.

4.1 The Space Agency Approach

Space agencies are government entities that are tasked with undertaking and enabling the development of space based science and technology. In the United States, approximately 25% of NASA's $19B budget goes to funding the Science program, of which $2.0B is allocated to Earth Science[8]. With these resources, NASA supports 60 operating satellite missions, 35 that are in the planning stages, and over 10,000 U.S. scientists, as well as funding more than 3,000 research grants (n.b. these include awards to planetary science, astrophysics, and Earth science). Other space agencies are smaller, but still have $2-5B budgets e.g., ESA, ROSCOSMOS, CNES, DLR, and JAXA. While the budget numbers seem quite large, space agencies are still challenged to afford the suite of desired satellite missions that satisfy a diverse scientific community as well as government needs. The cost of design, launch and operation of a satellite mission has increased considerably over the last few decades. Satellite missions twenty years ago cost on the order of $100M, but today, they can reach up to (and beyond) $1B. Agency budgets, however, have not grown by a similar magnitude. Indeed, measured in 2014 dollars, NASA's budget has remained around $20B for over three decades.

To forecast the types of future missions that will be launched by space agencies, we can look to their planning process to evaluate the historical success at following such plans. The best known amongst the space agency planning efforts for Earth observation is the National Academies Earth Science and Applications from Space "Decadal Survey" (2007): an Herculean effort that energised the Earth science community to gather and prioritize NASA's future EO capacity. The endeavour identified 15 new missions for consideration as well as urging NASA to launch two additional missions already in mature planning stages, i.e. GPM and a replacement for Landsat 7. The GPM core observatory launched in February 2014, following Landsat 8 in February 2013. However, of the original 15 new missions proposed in the Decadal Survey, SMAP (Entekhabi et al., 2010) is the only one to have launched (in January 2015). Other missions were already in various stages of planning before the Decadal Survey, including the SWOT mission (Biancamaria et al., 2011), which was initiated five years prior to 2007. All of this is to illustrate that it is not unusual for government space agency missions to take on the order of two decades to go from concept to launch (see Sect. 3.1), and that the systems that move from proposal to orbit are not always identified by consensus. Indeed, sometimes an entire generation of scientists move through the community before the space-based measurement system arrives in orbit.

An important consideration, particularly in light of the "fast and nimble" approach advocated by Silicon Valley driven commercial enterprises, is that by the time any government satellite actually reaches orbit, the technology on-board may already be a decade (or more) old. The obvious implication of this is that space agencies may not be launching the most cutting edge sensing platforms. Indeed, by their nature, space agencies are risk averse, seeking out the most robust technology to survive the hazards of space and ensure delivery of mission objectives. This model stands in contrast to the technological advances being made today, especially in instrument design and function, which occur at a seemingly faster pace than in

[8] https://www.nasa.gov/sites/default/files/atoms/files/fy_2017_nasa_agency_fact_sheet.pdf

decades past. The emerging concept of "agile aerospace" combined with the opportunities being presented by commercial ventures via the rise of the CubeSat (see Sect. 3.4) and other sensing platforms, present an ideal test-bed for new technology and demonstrator systems: a theme that is explored in the following section.

4.2 The Commercialization of Space

The commercial sector presents something of a counter example to the government space agency approach. Undoubtedly, commercial enterprises build upon the successes (and sometimes direct funding) of the government sector. However, recent advances have seen an increased capacity to combine that foundation with venture capital and new technology to provide immediate EO platforms to the paying customer. Of the recent players operating in this market, perhaps the most well-known is Space Exploration Technologies (SpaceX) (www.spacex.com). Employing techniques such as 3-D printing to create strong and durable rocket parts at a fraction of the time taken for traditional casting, they have also reimagined and reengineered the reusable launch vehicle concept, representing a major innovation and cost-saving to the delivery of payloads into space. An objective of these new rocket companies is to radically improve the efficiencies of payload delivery at a fraction of current costs, which have been estimate at up to $20,000 per kg (Coopersmith, 2011). Indeed, the SpaceX approach purports to reduce costs by about half compared to traditional launch vehicles (e.g., $62M for a 22,000 kg payload on a Falcon 9 rocket)[9]. With a launch planned for late 2017, the SpaceX Falcon Heavy aims to reduce this cost further, lifting up to 54,000 kg to low Earth orbit for $90M, or $1,700/kg (n.b. finding precise figures for this is difficult, as they are "reusable rockets" and the costs decrease as function of the number of planned launches). While not a reusable launch system, Rocket Lab (www.rocketlabusa.com), a New Zealand start-up, is offering smaller launch vehicle capability, but with greater frequency and selective orbit. Aimed specifically at the small satellite market, it will launch a 150 kg payload for $5M and also provide a ride-sharing option where users can launch 1U to 12U CubeSats, opening up the prospect of investigator led space missions.

But getting to space is only one aspect of the recent rise in commercial activity. As discussed in Sect. 3.4, there are a number of companies exploiting technological advances in sensor miniaturization, reduced power consumption and improved battery life (that have been driven in large part by the mobile phone industry) to produce cheaper, smaller and more efficient satellite platforms. One of the most ambitious of these ventures may be Planet (www.planet.com), a $200M seven-year-old start-up with a stated goal of providing complete global coverage of the terrestrial surfaces of the Earth every day via a constellation of their CubeSat "Doves", representing an unprecedented high-resolution information resource (Houborg and McCabe, 2016). But Planet is just one of a number of non-agency based companies playing a role in EO: DigitalGlobe, BlackSky, Planetary Resources and Spire are just a few examples of private ventures that are operating largely independent of government space agencies.

Apart from the motivation and rationale of these companies shifting towards profit making enterprises rather than operating for the social good, a key difference between government and commercial sector approaches to space is funding for scientific use. By very approximate calculation, NASA provides about one-tenth of a satellite missions cost for scientific users. Thus, a $1B mission might provide on the order of $100M for related scientific activities. A private company, with a total budget on the order of a few hundred million dollars, would obviously place a much lower (or no) priority on directly funding the science community. However, while space agencies are certainly well motivated by science, the significant imbalance between technology and science funding indicates a strong vested interest in their supported technology engineering communities. In contrast, commercial enterprises are strongly motivated by profit i.e. venture capitalists expect a return on their investment, so optimising efficiencies in production, launch and operation are paramount.

[9] See http://www.spacex.com/about/capabilities

There are numerous examples of private-public partnerships that have shown the success of industry engagement, and many opportunities exist to exploit intersections of interest not just within industry, but also with other government departments. Of course, putting satellites into orbit is only one small part of a space agency's mission. But what is becoming clear is that there are cheaper, faster and more functional options being presented to the community from a variety of sources, both private and commercial, that present an opportunity to embrace a new era of EO beyond the traditional agency approach. In some ways, government space agencies are already adapting to leverage these changes in their own operations by sub-contracting out certain mission elements to the commercial sector e.g. resupply of the ISS using SpaceX Falcon 9 rockets, along with the many satellite components built by private companies under government contract. Still, it remains unclear how individual investigators can best leverage these new observational platforms and the data they produce within the current mode of open-access, peer-review and publication of results. Will hydrologists be able to afford this data, and once provided, will there be limitations on its use? There is a real risk that the successful commercialization of space could pose a serious threat to the function and operation of both space agency and investigator led Earth observation, as well as scientific advancement that relies on freely available and abundant data (Tollefson, 2017). How the science community and the respective national space agencies respond to these opportunities (and risks) will go some way to defining the direction of hydrologic (and related) sciences over the next decade and beyond. Given our stakeholder position and vested interest in this, it would make sense to help shape the direction of these seemingly inevitable developments.

4.3 Continuity and Stability or Disruption and Opportunity

As has become apparent, there are exciting future opportunities for hydrologic science that do not rely solely upon traditional space-borne approaches. The advent of low-cost UAVs, smartphones, and the global internet empower the individual researcher to collect their own measurements and drive and direct their own scientific goals. For instance, scientists and engineers are no longer reliant on space agency airborne campaigns that can take years to organize, cannot respond to fast-paced dynamic events (such as floods, droughts, extreme events) and are subject to the meteorological vagaries of the planned-in-advance experimental window (e.g., soil moisture campaigns that do not rain). But investigator-led approaches are often process-based and local in scale, so determining whether or how they can they be scaled-up to regional programs is an important objective. Likewise, and perhaps more importantly, ensuring that these distributed and often uncoordinated efforts can be more closely tied to existing space-based measurements or local-to-global monitoring programs is an issue requiring community attention.

Hydrologists, like all scientists, need measurements, models, and money to make discoveries. From our review, it seems inevitable that at least for the immediate (and somewhat) foreseeable future, there will be positive and negative outcomes for the EO community, with both technological changes and new players entering the space-based observation sphere. Although government agencies are unlikely to radically alter their EO programs (a positive), barring some unforeseen political event or paradigm shift, the moneys that space agencies receive have remained historically flat, while costs continue to rise (a negative). So, while the positive enables a significant sized research community, the negative is that there will likely be fewer satellites and hence a lower variety of needed measurements available to advance our understanding of the Earth system. Space agencies will surely do their best to continue funding for individual research communities e.g. working groups and airborne campaigns for each unique sector studying their particular component of the water cycle, and such approaches may well lead to scientific discoveries. But these will inevitably be at local scales and not at the global scale that satellites are designed to address. Moreover, while the traditional space agency approach of a careful and often prolonged mission planning and approval schedule may lead to the eventual launch of a satellite measuring one aspect of the water cycle, there is no guarantee that other components will be simultaneously retrieved, and hence the error envelope of models (and observations) will remain

unconstrained. One of the outstanding challenges of hydrological remote sensing remains to monitor (and close) the water cycle (McCabe et al., 2008; Sheffield et al., 2009; Zhang et al., 2016b), yet an integrated water cycle observation strategy remains very much in the conceptual phase, with no planned mission on the horizon.

Over the last few years, the commercial sector has demonstrated that space is now "open for business". A singularly positive outcome of this is that there now exists a range of global VNIR near-daily to daily measurement platforms that are available (albeit at a cost) from the commercial sector, providing ultra-high resolution detail. These commercial sensors can provide data at a higher spatial and temporal resolution than comparable space agency systems (Dash and Ogutu, 2016), although the radiometric quality of the imagery may not always be as refined (Houborg and McCabe, 2016). As already noted, there is generally no underlying scientific purpose or social good directly driving these efforts: commercial launches are ultimately driven by an economic incentive. As such, one negative resulting from this misalignment of purpose is that sensors that do not have an obvious income generating market are unlikely to be launched. For instance, active sensors have yet to make commercial inroads in the same way as optical sensors, and thus water cycle measurements that rely upon lidar or emitted radar pulses are not presently available (n.b., UrtheCast plans to equip their next generation satellite with an X- and L-band active radar, see Becket, 2015). But profit incentive is not the only difference separating these competing interests. Space agencies and the communities they serve often have an interest in data continuity: indeed, the Landsat mission has a legislated foundation to provide data "sufficiently consistent (in terms of acquisition geometry, coverage characteristics, and spectral characteristics) with previous Landsat data to allow comparisons for global and regional change detection and characterization" as part of the 1992 Land Remote Sensing Policy Act (U.S. Code Title 15, Chapter 82) (Irons et al., 2012). In light of technological advances (e.g. constellations of CubeSats) and other space agency sensors such as Sentinel-2, it could be argued that continuity of a particular mission or sensor type is no longer necessary, so long as the observations lack discontinuities caused by large spatio-temporal gaps or calibration issues. The point here is that unlike the scientific community, the commercial sector has no demand or underlying rationale for ensuring continuity beyond satisfying the needs of their particular business model. Likewise, if there is an economic incentive to pursue it, they can move quickly from one technology to the next without concern for the integrity of the long term data record: a position that may not be as easily adopted by space-agencies. Of course, a potential drawback of commercialisation lies in the quality and assessment of the delivered products. While many space agencies now allocate a proportion of the mission budget for cal/val related activities, this is not an aspect that would necessarily be considered by commercial ventures. The consequence of less stringent quality controls is that any data from new commercial platforms may contain poorly-defined accuracies and sensitivities, hampering the process of time-series and multi-satellite data merging.

Given the somewhat meandering nature of research to applications, the commercial model may not seem to have immediate relevance to advancing scientific inquiry. However, there is much to be gained in leveraging and engaging with the influx of activity in the current race to space, particularly given the range and variability of measurements that can provide new insights into process scale and response and with a density and fidelity that has never been seen before. One aspect that is not clear is whether the commercial sector will ultimately be in competition, or in cooperation, with government funded space agencies. Noting that both groups provide VNIR band imagery, it might seem that they are marketing the same product. Indeed, from an economics perspective, competition usually lowers costs. But given that space agency data are largely "free" to the scientific community (n.b., this ignores the very real cost of tax-payer funded mission launches and data collection, processing and archiving), there would not seem to be any competitive advantage or level playing field. Clearly, the value proposition will be in resolution, timeliness, or in value adding i.e. increasing imagery information content through derived or customer specific products. How government space agencies might adapt to account for this commercial rise is unclear. There are threats, but also opportunities, particularly in the demonstration of new technologies and rapid delivery of payloads to space. There are

also obvious risks in a solely commercially driven framework: uncertainties in financing, profit making incentive, imagery costs, free-use policies and freedom to publish are all potential inhibitors to unhindered scientific inquiry. The future is certainly not clear, but these are issues that require immediate consideration given what seems to be an inevitable advance towards a greater commercialisation of Earth observation.

5 Concluding Remarks

We have entered a new era of Earth observation, where the threshold for what can be sensed from small satellite, airborne platforms and even on-ground monitoring is rapidly changing and evolving. The EO technologies discussed throughout this synthesis show great potential to revolutionize and reinvigorate our understanding of hydrology and present a range of exciting platforms from which to develop new insights into hydrological process form and function. Our community has an opportunity to reshape hydrologic science across the spectrum from fundamental research to applications based objectives. Either in isolation or (ideally) in combination, researcher-led, commercial and government driven EO enterprises present new and innovative ways to envision both our own, and related disciplines. The alignment of circumstance and technology driving these advances have not happened in isolation, but reflect a convergence of innovation, breakthroughs in computational infrastructure and data storage, and opportunities for leveraging public and private assets collectively. Many of the EO advances discussed herein have arisen in just the past five years. What might the next 5-10 years have in stall? One possible scenario is contingent on the provision of global and low cost internet access (see discussion in Sect. 3.3 and efforts such as http://oneweb.world/). Given some notable failures of previous attempts, the following remains rather speculative, but presents a plausible vision of the future. With an ever-increasing availability of low cost sensors, the connectivity provided by a global internet would facilitate truly autonomous remote monitoring of the Earth system. Whether permanent, disposable or even biodegradable, thousands of cheap devices could be deployed to measure soil moisture, precipitation, snow, stage or any other imaginable variable (see van de Giesen et al., 2014), recording and broadcasting directly to the internet or through scheduled collection via targeted UAVs or sentry-systems (balloons, solar planes) in more remote regions. In such a connected world, integrating these diverse EO sources, from space-based to *in situ*, in order to optimise observing potential will be a key challenge. Technology is not the barrier to realising such a future, as much of what is needed exists already. But embracing these technologies will require a radical rethink, not just on how data is collected, but how it is used and managed in our modelling and interpretation efforts, where the focus on point-precision accuracy and error quantification can act as barriers to broader system understanding. While there are certainly challenges in realising the potential of these emerging applications, there are game-changing opportunities as well, from the novelty of new sensing platforms such as CubeSats and UAVs, to the reshaping of the computational landscape through cloud-computing and data-analytic approaches. It is our hope that this forward-looking synthesis article will help to accelerate the adoption of these (r)evolutionary techniques and technologies. What is increasingly evident is that humans have the capacity to traverse all corners of the globe and have the technology required to measure or infer most variables of interest. It is possible that *we* may be the remote sensing platforms of the future.

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Table 1. Hydrological variables and the current and planned satellite remote sensing missions that can be used to estimate them. We note that this list is not necessarily comprehensive and that there are possible trade-offs between resolution and accuracy that are not explicitly accounted for.

Hydrological Variable	Missions / Instruments	Standard Spatial Resolution (km)	Standard Temporal Resolution (days)	Launch Year	Dedicated Measurement
Rainfall	GPM	5	0.125	2014	Y
Snowfall	GPM	5	0.125	2014	N
Evaporation	Terra/MODIS Aqua/MODIS Suomi/VIIRS	0.5	1	1999 2002 2013	N
	Landsat 8 Landsat 9	0.03	32	2013 2023	N
Runoff	SWOT	0.1	11	2021	Y
Snow Cover	Terra/MODIS Aqua/MODIS Suomi/VIIRS	0.5	1	1999 2002 2013	Y
Snow Density, Depth, or Water Equivalent	GCOM-W/AMSR2	30	1	2012	N
Surface Soil Moisture	SMOS	36	3	2009	Y
	SMAP (radiometer)	36	3	2015	Y
	ASCAT	25	1	2006	N
	GCOM-W/AMSR2	50	1	2012	N
	Sentinel-1A Sentinel-1B	0.1 - 0.005	12	2014 2016	N N
Deep Soil Moisture	Biomass	0.2	18 days/yr	2021	N
Surface Water Elevation	Jason-3	10	10	2016	N
	SARAL	10	35	2013	N
	SWOT	0.1	11	2021	Y
	ICESat-2	1.5	90	2018	N
Depth to Groundwater	-	-	-	-	-
Total Groundwater Storage	-	-	-	-	-
Terrestrial Water Storage Change	GRACE	220	30	2002	Y
	GRACE-FO	180	30	2017	Y
Water Consumption	-	-	-	-	-
Water Quality	-	-	-	-	-
Vegetation/Land Cover/Irrigated Area	Terra/MODIS Aqua/MODIS Suomi/VIIRS	0.5	1	1999 2002 2013	Y
	Landsat 8 Landsat 9	0.03	16	2013 2023	Y
	Sentinel-2A	0.02	10	2015	Y
	Sentinel-2B	0.02	10	2017	Y
	Sentinel-3A	0.3	2	2016	Y
	Proba-V	0.35	2	2013	Y
Vegetation Stress	ISS/ECOSTRESS	0.07	4	2018	Y
Photosynthesis	FLEX	0.3	0.5	2022	Y
Water Vapour	Aqua/AIRS	13.5	1	2002	N
Integrated Water Budget	-	-	-	-	-

Figure Captions

Figure 1. The state of play in space today. Estimates are based on the Union of Concerned Scientists satellite database, updated from 1/1/2017 (see http://www.ucsusa.org/nuclear-weapons/space-weapons/satellite-database). In terms of the sectors operating Earth Observing systems (right panel), another 5% include shared systems between those listed.

Figure 2. An Earth observing "System of Systems" for revolutionizing our understanding of the hydrological cycle. This multi-scale, multi-resolution observation strategy is not really a concept, as the technology exists and is largely in place now. Supporting traditional space based satellites, there are now a range of orbital options from commercial CubeSats to demonstration sensors on-board the International Space Station. Beyond orbiting EO systems, technological advances in hardware design and communications are opening the skies to stratospheric balloons and solar planes, as well as an explosion of UAV-type platforms for enhanced sensing. At the ground level, the ubiquity of mobile devices are expanding traditional in-situ network capacity, while proximal sensing and signals of opportunity are opening up novel measurement strategies.

Figure 3. Employing a UAV to retrieve high-resolution multispectral information on the land surface for hydrology and related applications over an Australian rangeland site located near Fowler's Gap in New South Wales. Retrieved products include: a) a false-colour infrared image; b) a reconstructed digital surface model using visible imagery and structure-from-motion techniques; and c) an optimized soil adjusted vegetation index (OSAVI) derived from the 4-band multispectral image. Images were captured using a MicaSense/Parrot Sequoia sensor on-board a 3DR Solo quadcopter. The UAV was flying at a height of 40 m, providing a ground sampling distance of approximately 3 cm. Imagery provided by the University of Tasmania's TerraLuma Research Group.

Figure 4. Multi-scale capabilities of state of the art sensing optical satellites. Image illustrates the expanding resolution options available from both commercial and government satellites. A) Planet CubeSat at 3 m ground sampling distance over the Tawdeehiya Farm in Al Kharj, Saudi Arabia. Center pivot irrigated fields dot the landscape, with dimensions approaching 800 m. The inset in A) is zoomed to show the resolution advantages offered by the next generation of sensing solutions over B) Landsat-8 at 30 m, with C) Sentinel-2A at 10 m and D) Planet imagery at 3 m providing enhanced details. All images are false colour representations of NIR, Red and Blue in RGB bands. Sentinel-2A and Landsat-8 images were acquired on December 4th, 2016, while the Planet data were captured on December 5th, 2016.

Figure 5. Worldwide global system for mobile communication (GSM) coverage for the year 2013. The GSM network does not include the growth of related 3G or 4G networks. The image is derived from Figure 2 in Overeem et al. (2016).

Multimedia 1. On-board the International Space Station, the Urthecast IRIS high-resolution camera (HRC) captures colour video at 3 frames per second for a duration of 60 seconds. Here we see an example of the HD Video over the Burj Khalifi in Dubai. The tracking of vehicles on roads is analogous to monitoring flow in rivers or the speed of moving clouds, while the capacity to extract 3D structure of the underlying terrain provides opportunities in dynamic monitoring of surfaces.

4,000+

satellites orbiting the earth

1,459

active satellites

52%

global communication

11%

technology demonstration

26%

earth observation

7%

global navigation

4%

space science

OPERATION OF EO SYSTEMS

57%

government

6%

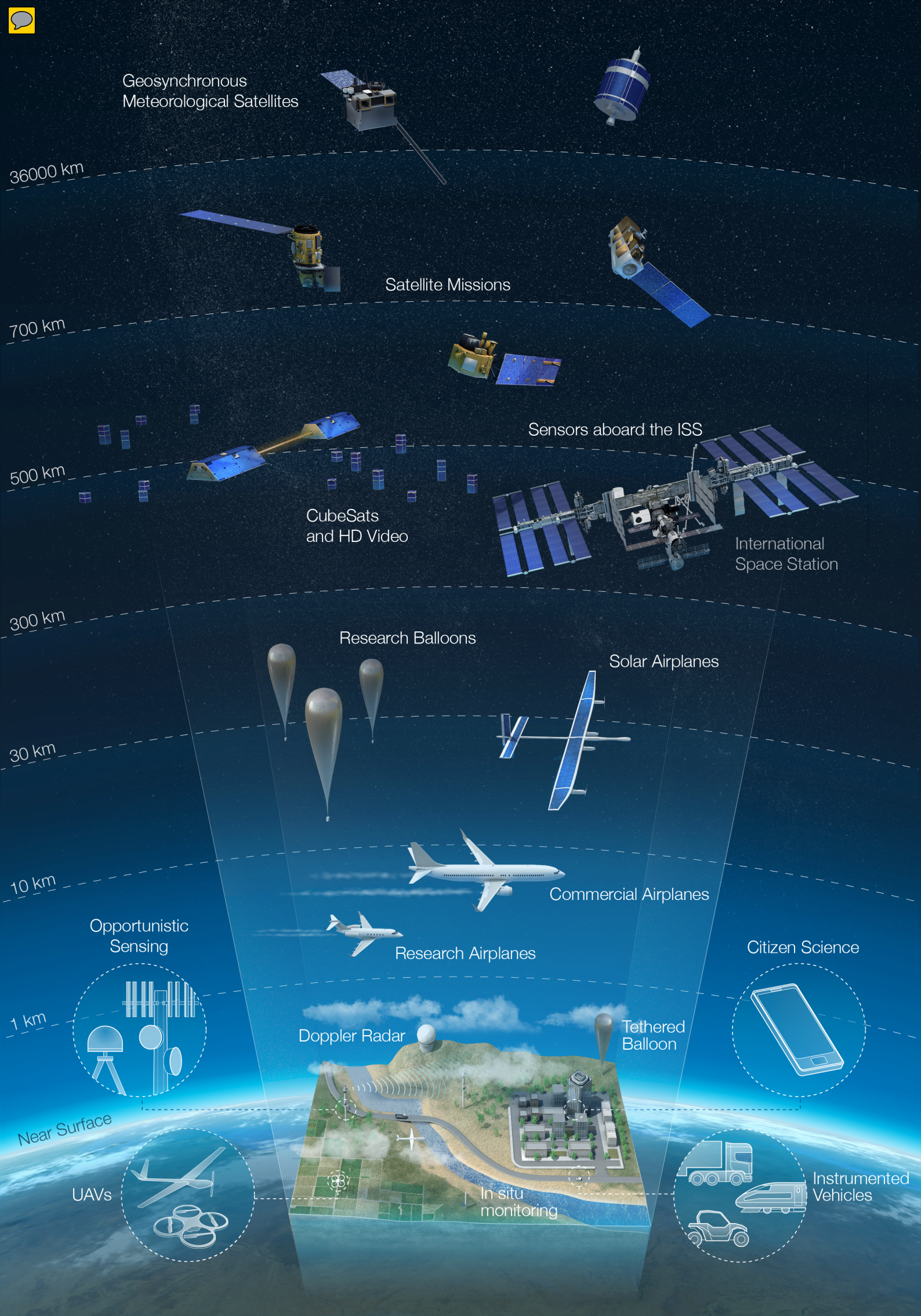
civilian

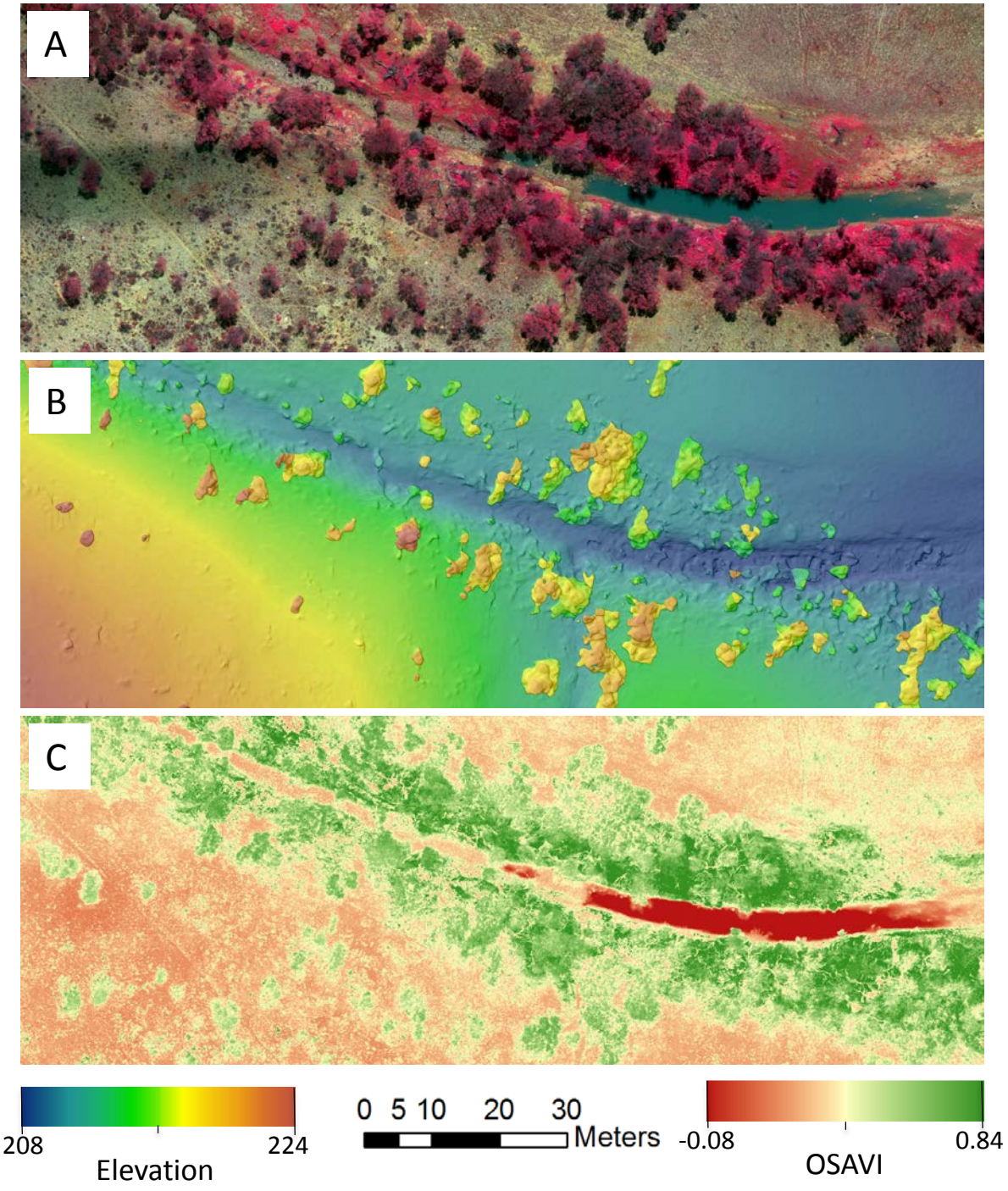
26%

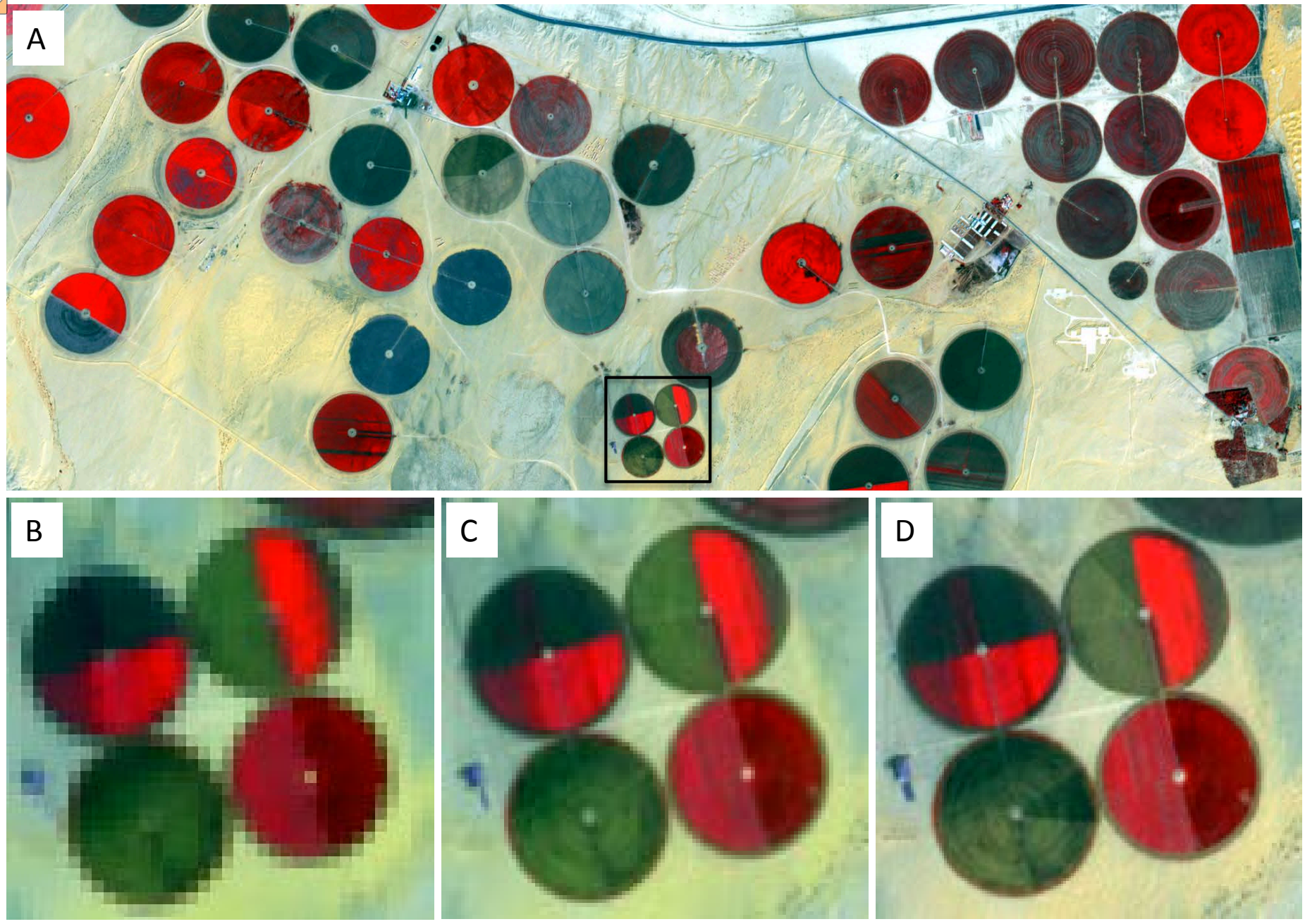
military

6%

commercial


Geosynchronous
Meteorological Satellites
36000 km
Satellite Missions
700 km
Sensors aboard the ISS
500 km
CubeSats
and HD Video
International
Space Station
300 km
Research Balloons
Solar Airplanes
30 km
Commercial Airplanes
10 km
Opportunistic
Sensing
Research Airplanes
Citizen Science
1 km
Doppler Radar
Tethered
Balloon
Near Surface
UAVs
In situ
monitoring
Instrumented
Vehicles


A
B
C
208
224
Elevation
0 5 10 20 30
Meters
-0.08
0.84
OSAVI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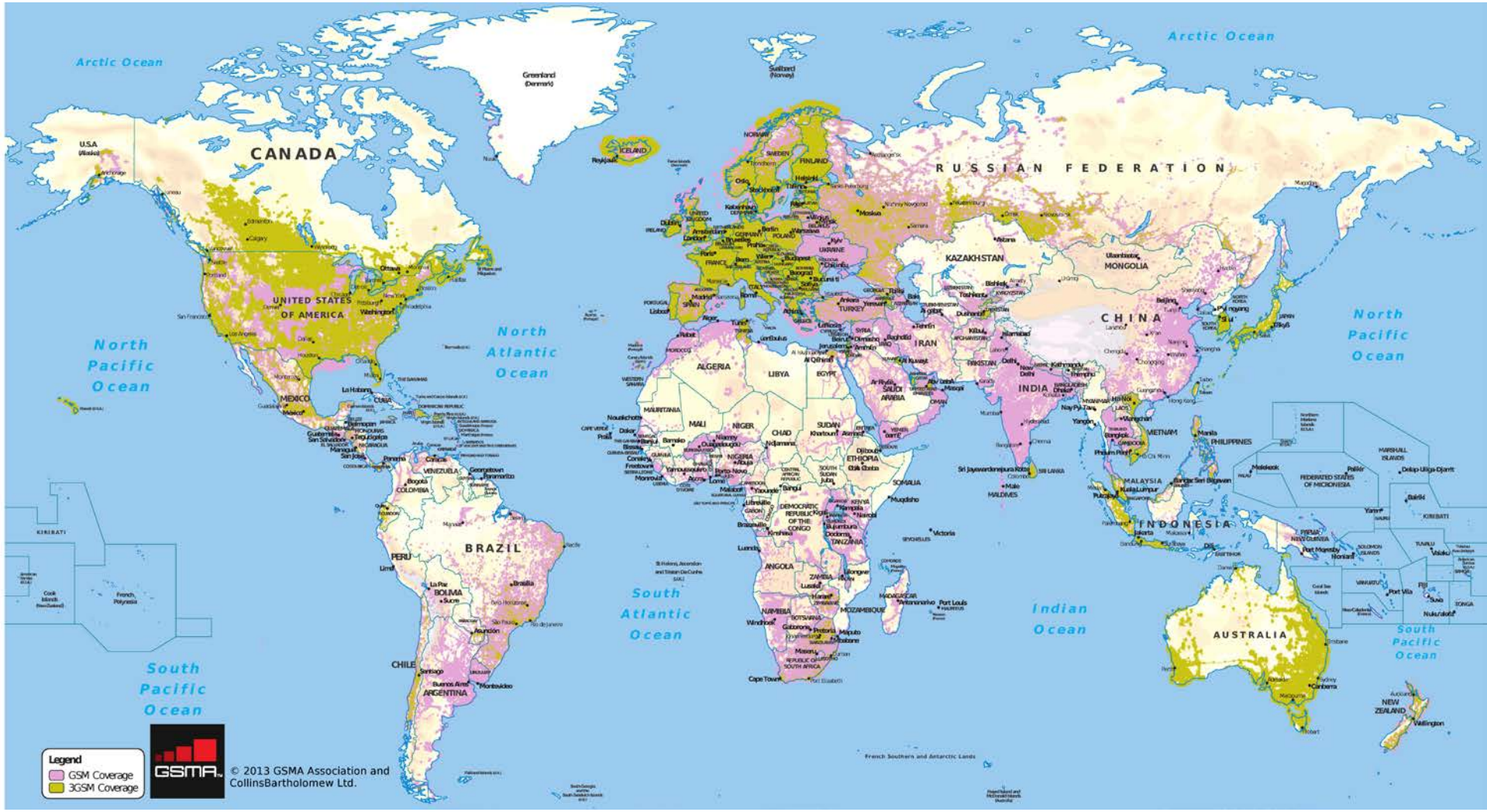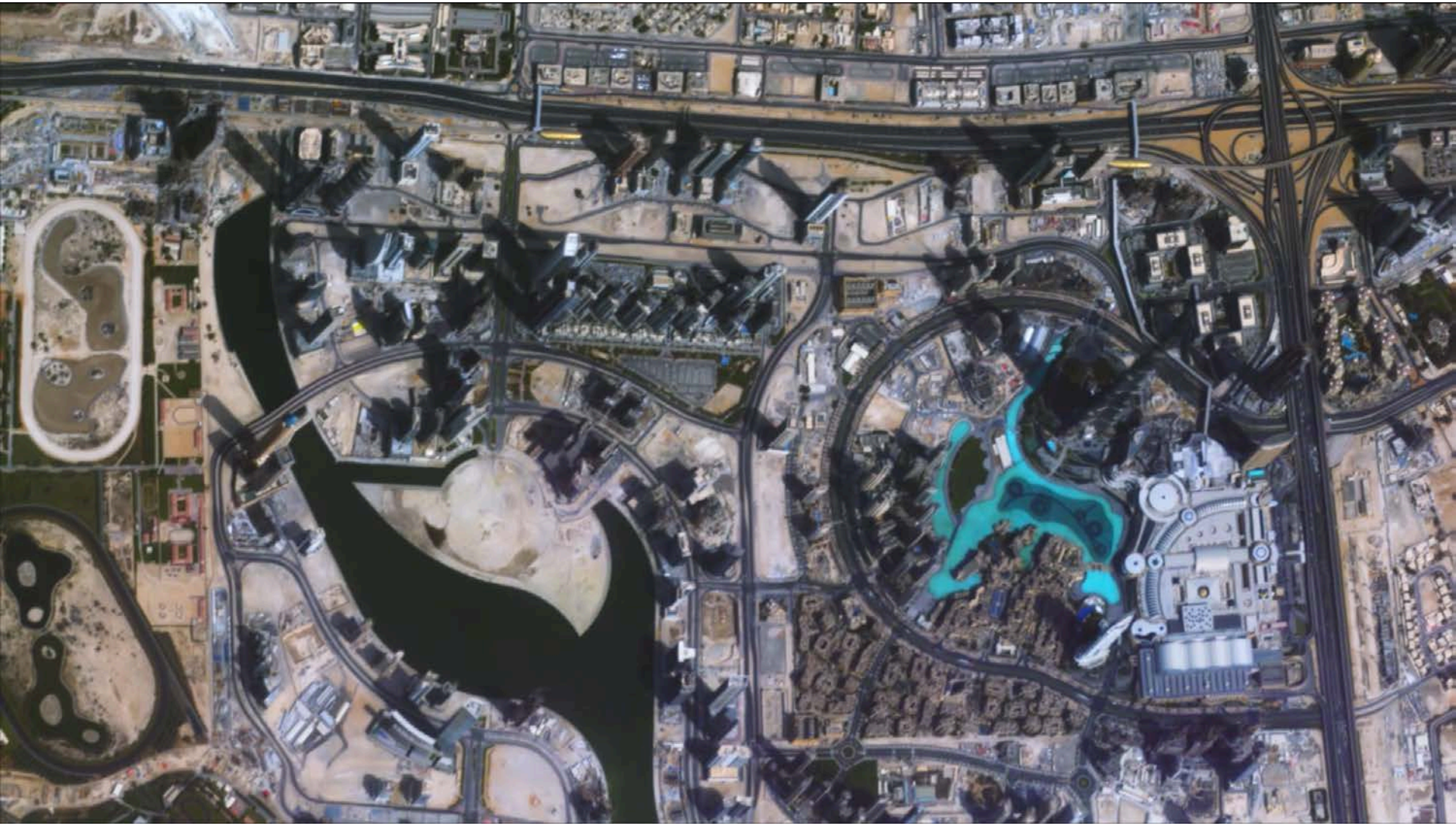
Arctic Ocean
Arctic Ocean
Greenland (Denmark)
Svalbard (Norway)
CANADA
U.S.A (Alaska)
RUSSIAN FEDERATION
ICELAND
UNITED STATES OF AMERICA
North Pacific Ocean
North Atlantic Ocean
North Pacific Ocean
KAZAKHSTAN
MONGOLIA
CHINA
IRAN
ALGERIA
LIBYA
EGYPT
INDIA
MEXICO
BRAZIL
PERU
CHILE
ARGENTINA
BOLIVIA
VENEZUELA
COLOMBIA
South Atlantic Ocean
Indian Ocean
AUSTRALIA
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