Grand Challenges in Satellite Remote Sensing

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INTRODUCTION

The past five decades have witnessed satellite remote sensing become one of most efficient tools for surveying the Earth at local, regional, and global spatial scales. These space-based observations have a non-destructive character that allows for rapid monitoring of the ambient atmosphere, its underlying surface, and the ocean mixed layer. Moreover, satellite instruments can observe toxic or hazardous environments without putting people or equipment at risk. Large-scale continuous satellite observations complement detailed (but sparse) field observations and provide measurements of unsurpassed volume and content for theoretical modeling and data assimilation.

There are a large number of highly important applications that currently rely upon data from satellites. Observations of the atmosphere are used for weather prediction, monitoring of environmental pollution, climatic change, etc. (Wielicki et al., 1996). Remote sensing of ocean surfaces is used for monitoring of coastline dynamics, sea surface temperature and salinity, ocean ecosystem and carbon biomass, sea level change, marine traffic and fisheries, mapping of water current and underlying topography in shallow waters, etc. (Fu et al., 2019). The remote sensing of the land from satellite greatly contributes to the exploration of mineral resources (Zhang et al., 2017), the monitoring of floods and droughts (Jeyaseelan, 2004), soil moisture (Lakshmi, 2013; Babaeian et al., 2019), vegetation (Xie et al., 2008), deforestation (Gao et al., 2020), forest fires (Lentile et al., 2006), agricultural monitoring (Atzberger, 2013), urban planning (Kadhim et al., 2016), etc. Finally, social science efforts to survey global crises (such as the COVID-19 pandemic) are benefitting from satellite remote sensing datasets that utilize diverse targeted visualization to classify human environments, and then relate these observations to various socioeconomic data sets, etc. (Diffenbaugh et al., 2020). Moreover, satellite remote sensing has provided an effective tool for gathering global information such as 1) planetary topography; 2) atmospheric profiles of the temperature, water vapor, carbon dioxide and other trace gases; 3) mineral and chemical compositions of surface and atmosphere, and 4) properties of cryosphere such as snow, sea ice, glacier, and melting ponds, and 5) particle and electromagnetic properties of the thermosphere, ionosphere and magnetosphere. Remote sensing of the Earth also advances the technological state of the art, and this assists the development of deep space remote sensing missions such as Voyager (Kohlhase and Penzo, 1977) and the Cassini-Huygens space-research mission (Matson et al., 2002).

In the early stages of observational satellite development, the design of satellite sensors was often highly target-specific. For example, a series of instruments were launched in the 1970s: Landsat and the Advanced Very High Resolution Radiometer(AVHRR) instruments targeted the monitoring of land surfaces and clouds, the Total Ozone Mapping Spectrometer (TOMS) instruments focused on observing total column ozone, and the High-resolution Infrared Radiation Sounder (HIRS) instruments supported weather forecasting and climate monitoring. The deployment of those missions provided unique data for each targeted subject, and the missions were praized by the

corresponding scientific communities. Those missions were extended for many years to obtain climatologically significant data records. The renewed missions were constantly improved (both technically and logistically) based upon the accumulated experience.

The promising results of those missions encouraged the design and launch of increasingly advanced instruments with broader observational scopes in the two decade period from ~1990 to ~2010. For example, the Measurement of Pollution in the Troposphere (MOPITT), the Orbiting Carbon Observatory (OCO), and the Greenhouse gases Observing Satellite (GOSAT) missions were deployed for advanced monitoring of greenhouse gases such as carbon dioxide (CO_2) and methane (CH_4). Several thermal enhanced infrared sounders such as AIRS, TES, IASI, IMG, and CRIS were launched to monitor the atmospheric state for weather prediction and climate change (see list of instrument acronyms at the end of this article). Other satellite imagers were deployed for observing air, land, and ocean and to support inter-disciplinary studies, such as single-viewing MODIS, MERIS, and SGLI, bi-viewing ATSR and AATSR, multi-viewing MISR radiometers and POLDER polarimeters (King et al., 1999; Thies, and Bendix, 2011; Neukermans, et al., 2018). In addition to these more traditional passive observations, active measurements like the CloudSat radar and the CALIPSO lidar were deployed for monitoring the vertical structure of clouds and aerosols that are important for diverse atmospheric applications (Stephens, et al., 2002; Winker, et al., 2009).

All of these previous efforts provided valuable insight that helped to build the understanding regarding the real value, limitations, and potential of satellite remote sensing. Indeed, the resilient development of space instrument technologies and a boom in informatics has created an unprecedented situation where the limitations in hardware, data acquisition, and processing have drastically weakened, and significantly more advanced designs of satellite sensors can be developed and deployed. Additionally, the scientific community has already obtained very sizable amounts of satellite data, accumulated substantial experience in managing and analyzing the data, has a genuinely realistic vision of possible achievements with the existing satellite dataset, as well as knowledge of the steps that are necessary for improving the usefulness of satellite data in the future.

On the other hand, the community also realizes that the fundamental challenges of remote observations never end. For instance, separating signal from noise to retrieve a particular set of geophysical variables and accurate instrument calibration are ongoing challenges. Technological advances improve the information content of the observations, but the data is never fully sufficient to uniquely characterize all of the geophysical parameters of interest; the list of desired observables grows continuously with the advancement of science. Thus, remote sensing remains a fundamentally ill-posed problem that needs to be appropriately defined and constrained by theoretical models, a priori knowledge, and ancillary observations. These are important considerations when designing new scientific objectives.

GRAND CHALLENGES

The overall grand challenge in the advancement of satellite remote sensing is discovering innovative and affordable technologies and measurement concepts to solve new problems, and dealing with issues that have come to light after the satellite remote sensing experiments of the previous half century. Specifically, several complimentary aspects are expected to be addressed:

Increased Spatial and Temporal Coverage and Resolution of Satellite Observations

One of the major advantages of the satellite remote sensing is the capability to quickly observe large regions of the Earth. At the same time, coverage limitations of currently available satellite data are also evident (an overview of satellite coverage capabilities is discussed by Kim et al., 2020). For example, polar orbiting imagers in Low Earth Orbit (LEO) generally achieve global coverage in minimum of one day (but mostly two or more days), so many natural phenomena that have higher temporal and spatial variability are not fully captured. In this regard, high-orbit geostationary observations (GEO) address this limitation by providing frequent diurnal observation of the same object. However, there is a trade-off between spatial coverage and the resolution of satellite images (usually higher coverage results in lower spatial resolution). Achieving observations with both extensive spatial-temporal coverage and high spatial resolution is desirable for many applications, but also highly challenging. Hence, the design of satellite observations may need new innovations, ancillary data, and synergies of complimentary observations to address specific objects and relevant problems. This is discussed further in the next section.

Increased Information Content and Exploring Synergy of Observations

Although the high capabilities of satellite observations have been clearly documented, the current data provided by our satellite instruments have limited information content for many applications. Therefore, the deployment of new sensors with enhanced capabilities is desirable and planned.

For example, it has been clearly recognized that Multi-Angular Polarimeters (MAPs) provide the most appropriate data for characterizing detailed columnar properties of atmospheric aerosol and cloud (Mishchenko and Travis, 1997; Hasekamp and Landgraf, 2007; Lebsock et al., 2007; Dubovik et al., 2011; Wu et al., 2015; Xu et al., 2018; Stamnes et al., 2018, etc.), so the focus on polarimetric data in aerosol and cloud characterization is expected to significantly increase in next decade (Dubovik et al., 2019). Several advanced polarimetric missions are planned to be launched in coming few years by European and US space agencies including 3MI (Multi-View Multi-Channel Multi-Polarization Imaging mission) on MetOp-SG satellite (Fougnie, et al., 2018), Multi-Angle Imager for Aerosols (MAIA) instrument (Diner et al., 2018), Spex (Spectropolarimeter for Planetary Exploration) and Hyper-Angular Rainbow Polarimeter

(HARP) as part of NASA PACE mission (Werdell et al., 2019), Multi Spectral Imaging Polarimeter (MSIP)/Aerosol-UA (Milinevsky, et al., 2019), MAP instruments as part of Copernicus CO2M Mission (European Space Agency, 2020; Janssens-Maenhout, et al., 2020; Dubovik et al., 2019), etc. Also, the China National Space Administration (CNSA) has significantly invested in polarimetric sensors. CNSA has recently launched several polarimetric remote sensing instruments including the MAI/TG-2, CAPI/TanSat, DPC/GF-5 and SMAC/GFDM and plans the launches of POSP, PCF, DPC-Lidar in coming years (Dubovik et al., 2019). The concepts of these instruments, their technical designs, and the algorithm development have been intensively discussed and tested using airborne prototypes as discussed in details by Duibovik et al. (2019).

Similarly, the number of satellite-based lidars and radars is expected to increase, since active remote sensing instruments provide detailed information about vertical variability of the atmosphere (Winker et al., 1996; Weitkamp, 2005; Chand et al., 2008). Indeed, most of the major space agencies are pursuing space-based lidar programs. For example, NASA launched the Geoscience Laser Altimeter System (GLAS) onboard the ICESat satellite in 2003 (Kwok et al., 2004), the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) onboard the CALIPSO satellite in 2006 (Winker et al., 2007), the Cloud-Aerosol Transport System (CATS) onboard the ISS in 2015 (Yorks et al., 2016), and the Advanced Topographic Laser Altimeter System (ATLAS) onboard ICESat-2 in 2018 (Neumann et al., 2019). Additionally, the ESA launched the Aladin wind lidar onboard the Aeolus satellite as part of the Living Planet Program (LPP) in 2018 (Källén, 2008), the CNSA will launch the DPC-Lidar onboard CM-1 satellite in 2021 (Dubovik et al., 2019), and the joint European/Japanese EarthCARE satellite (projected to launch in 2023) will include high-performance lidar and radar technology that has never been flown in space before (Illingsworth et al., 2015). The success and promise of these missions make lidars an essential component of future observing systems (National Academies of Sciences, Engineering, and Medicine, 2015).

At the same time, no single sensor provides comprehensive information about a targeted object in a complex environment, so there is a need to explore synergies of complementary observations. For example, even the most advanced multi-angular polarimeter cannot assure reliable 3D characterization of aerosols due to limited sensitivity to vertical variability of aerosol and clouds. The value of coordinated passive and active observations has been clearly recognized and accounted for in planning satellite missions as illustrated by **Figure 1**. For example, the A-Train satellite constellation provides polarimetric, radiometric, lidar and other complementary data (L'Ecuyer and Jiang, 2010). Similarly, the ongoing NASA Aerosol and Cloud, Convection and Precipitation (ACCP) study considers deployment of coordinated observations by passive (polarimeter, spectrometer, microwave radiometer) and active (lidar and radar) sensors (https://science.nasa.gov/earth-science/decadal-accp), National Academies of Sciences, Engineering, and Medicine, 2018.

Also, the next generation of retrievals (discussed further in the next section) intend to explore synergistic retrievals that rely upon observations from different instruments (e.g.,

Dubovik et al., 2011; Dubovik et al., 2014; Knobelspiesse, et al., 2011; Knobelspiesse and Nag, 2018). For example, the main challenge in retrieving properties of atmospheric aerosols is distinguishing light scattered by aerosol particles from light scattering by clouds, atmospheric gases, and the underlying surface. Satellite sensors such as the MODIS (radiometer) or POLDER (polarimeter) that are designed for aerosol monitoring may not have optimum capabilities for removing cloud, gas and surface contaminations (Sayer et al., 2020). Similarly, land reflectance observations usually need to remove scattering from atmospheric aerosols and gases; likewise, atmospheric gas monitoring may suffer from aerosol and cloud contamination. Thus, observations of multiple instruments with different sensitivities to clouds, aerosols and gases are always desirable. The analysis of aerosol measurements that are contaminated by clouds and trace gases over inhomogeneous surfaces may benefit from synergistic measurements from multiple instruments. IR imagery, lidar, and radar observations can be used to constrain cloud fractions, spectrometric data offers high sensitivity to gaseous concentrations, and high resolution imagery help reduce uncertainties associated with land surface heterogeneity.

For example, simultaneous multi-angular polarimetric observations by MAP/CO$_2$M and DPC deployed in the framework of CO$_2$M EU/Copernicus and GF-5 Chinese missions are expected to provide information for atmospheric correction and greenhouse gas monitoring (European Space Agency, 2020; Janssens-Maenhout, et al., 2020, Dubovik et al., 2019). Indeed, CO$_2$ and other gases obtained by such instruments as OCO and GOSAT are provided only in conditions with very minor presence of atmospheric aerosol (e.g., Crisp et al., 2012). In this regard, the addition of MAP observations in the Copernicus CO$_2$M mission is expected to improve the Greenhouse gases characterization in situations with moderate and possibly high presence of aerosols. As part of the NASA PACE mission, the SPEX and the HARP polarimetry instruments are expected to complement hyperspectral radiance data from the OCI and thereby provide more accurate aerosol information helpful for retrieving ocean surface and subsurface properties (Frouin et al., 2019; Remer et al., 2019a; Remer et al., 2019b; Werdell et al., 2019). Another example of a satellite combining polarization measurements with high-resolution spectroscopy is the high-resolution and multi-mode integrated imaging satellite (Gao Fen Duo Mo, or GFDM, Dubovik et al., 2019) successfully launched by the CNSA on July 3, 2020.

Finally, synergetic use of satellite data with surface and suborbital targeted measurements are also an important consideration. For example, the landscapes and surface properties in dense urban centers tend to be highly heterogeneous. Thus, the atmospheric processes and dynamics are affected by highly variable local activities, and observations of environmental air quality need to have high temporal frequency and high spatial resolution. Constellations of small and less expensive so called nano-
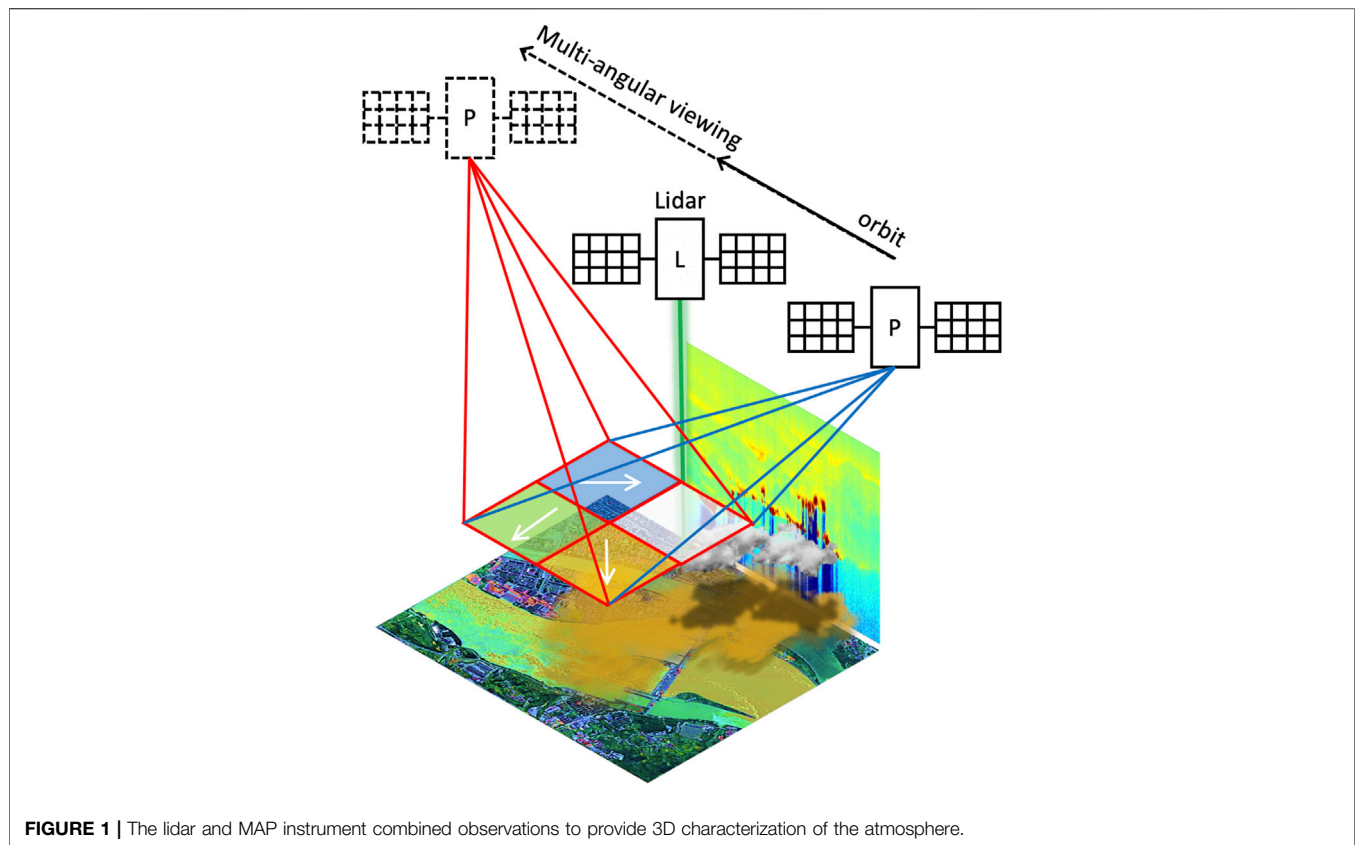
FIGURE 1 | The lidar and MAP instrument combined observations to provide 3D characterization of the atmosphere.

or cube-satellites with various equator crossing times could improve coverage with increased numbers of orbiting instruments (Knobelspiesse and Nag, 2018). Additionally, surface measurements and routine sub-orbital measurements could also enhance satellite retrievals in populated areas (Kahn et al., 2017). For example, Liu et al. (2004) and Liu et al. (2007) suggested a PM monitoring technique that uses geostatistical regression of PM concentration from ground measurements and collocated satellite observations. The regression is assisted by use of a chemical transport model to fill temporal and/or spatial gaps when the measurements are unavailable or contaminated. This approach is being employed by the MAIA project to speciate aerosol components such as sulfate, nitrate, ammonium, black carbon, organic carbon, and dust (Diner et al., 2018). The spatial PM information are then further combined with health records to better understand the relationship between aerosol pollutants and adverse public health problems (Anderson et al., 2012).

Addressing the field-of-view difference in combining observations from different instruments is another challenge. In this regard, the accumulated experience in using the data from multiple instruments with different field-of-view deployed within A-Train constellation provided valuable insights for future missions (Chahine et al., 2006; Delanoë and Hogan 2010; Kato et al., 2010,

Kato et al., 2011; Ceccaldi et al., 2013; Henderson et al., 2013; Mace and Zhang 2014).

Development of the State-of-Art Data Processing Approaches of the Next Generation

The quality of a remote-sensing retrieval algorithm is another critical aspect that affects the quality of the final product. In fact, once the instrument has been deployed, the quality of the resulting observational data cannot be radically improved, while retrieval algorithms remain under constant improvement. The final remote sensing product can be notably different not only due to ingesting data from different instruments, but also due to improvements of retrieval concepts. In this regard, the new generation of remote sensing retrieval algorithms have advanced significantly in the past decade. For example, new algorithms tend to rely upon fast and accurate atmospheric modeling (instead of using precomputed Look-Up-Tables, or LUT) and are capable of retrieving a large number of parameters. Additionally, simultaneous retrieval of aerosol properties together with land surface properties and/or cloud properties have been implemented (Hasekamp and Landgraf, 2005; Hasekamp and Landgraf, 2007; Hasekamp, 2010; Dubovik et al., 2011, 2014; Waquet et al., 2013; Xu et al., 2016; Xu et al., 2017; Li et al., 2018, etc.). Finally, within the framework of the CO2M EU/Copernicus discussed above, the joint retrieval of CO_2 and aerosol properties is a promising

approach for reducing the effect of aerosol contamination on the derived CO_2 product.

We provided several examples of synergistic instruments in Grand Challenge #2 above. The preparation of these missions includes developments of adequate algorithms that are capable of analyzing multi-instrument measurements. At the same time the fundamental logic of the retrieval algorithm evolution itself suggests a high potential of using synergy of different observations for improving the accuracy of the retrievals (e.g., Knobelspiesse, et al., 2011; Dubovik et al., 2019). Moreover the idea of the development versatile instrument independent algorithm that can be applied to different observations or their combination becomes increasingly popular. Generalized Retrieval of Aerosol and Surface Properties (GRASP) (Dubovik et al., 2011; Dubovik et al., 2014) is an example of such algorithm. This algorithm can be used for diverse satellite and ground based passive and active measurement. It has also been successfully applied for simultaneous synergetic inversion of lidar profiles and columnar radiometric observations (e.g., Lopatin et al., 2013; Lopatin et al., 2020; Román et al., 2018).

Some algorithm challenges still remain for accurate satellite remote sensing of clouds. An accurate and efficient radiative transfer model is a prerequisite. While independent column approximation is widely adopted for retrieving cloud droplet size and optical depth, 3-D radiative transfer (RT) effects caused by cloud horizontal inhomogeneity (cloud top roughness) can be a reason for retrieval biases (e.g., Davis et al., 1997; Várnai and Marshak, 2001; Zhang et al., 2012; Liang and Di Girolama, 2013). The 3-D nature of clouds becomes more of a concern for investigating the interactions between clouds and aerosols (e.g., at cloud edges), starting from coupling their retrieval into a joint framework. Within this context, development of inversion-targeted fast yet accurate 3D RT model for geometrically and optically complex media, with incorporation of spectral signature of gas absorption and proper adoption of cloud particle scattering model is a pressing need. Development of reliable 3D radiative models is also needed for accounting horizontal heterogeneity of land surface for adequate interpretation of all satellite imagery (Evans, 1998; Evans and Stephens, 1991; Lyapustin, 2002; Lyapustin and Wang, 2005). Another relevant outstanding issue is constructing 3D cloud fields to model 3D radiation fields, which could potentially be addressed using a combination of active and passive sensors (Barker et al., 2011).

Many modeling and observational studies have demonstrated the significant role of cirrus clouds in contributing to weather and climate processes (e.g., Liou, 2002). Although optically thin (Sassen and Cho, 1992), cirrus clouds have global presence and regulate the Earth's radiation and play an important role in the climate system. Cirrus particles have highly irregular shapes and their single-scattering properties such as single scattering albedo and scattering phase functions are significantly different from spherical particles (Yang et al., 2002; Yang et al., 2015). If an algorithm does not identify these irregular shapes, they can cause substantial biases in aerosol and cloud retrievals (Chew et al., 2011). Therefore, the identification of a representative cirrus particle model and including it in aerosol retrievals is a highly promising direction.

Also, the use of satellite data is strongly aligned with progress in global climate and Chemical Transport Models (CTM). For example, reliable aerosol retrievals can be assimilated into Chemical Transport Models (CTMs) to provide accurate aerosol loadings when observations are not available (e.g., Collins et al., 2001; Randles et al., 2017). At the same time, spectral and polarimetric information has substantial sensitivity to constrain aerosol type (Li et al., 2019) and satellite data may provide additional constraints for improving global emissions of the atmospheric components in chemical transport models (e.g., Chen et al., 2018; Chen et al., 2019; Elguindi et al., 2020). Therefore, synergizing satellite data processing with available modeled information is another highly promising research field for advancing satellite remote sensing.

Finally, at present, machine learning approaches are increasingly used to extract patterns and insights from the remote sensing and geospatial data (Lary et al., 2016). This branch of artificial intelligence is highly suitable and attractive for analysis and interpretation of Earth observation data because it proposes the methods that can "learn" from data, identify patterns, and make decisions with minimal human intervention. In particular, the emerging techniques of deep learning and deep neural networks have recently been used in remote sensing studies, especially for processing and analysis of huge amounts of data. Such techniques reveal the potential to extract spatio-temporal relations automatically and gain further knowledge helpful for improving forecasting and modeling of observed physical phenomena at multiple timescales. These methods are highly appealing for analysis of satellite data, especially if the versatility of data-driven machine learning is coupled with physical process models (e.g., Reichstein et al., 2019).

Achieving Continuity in Consistent Satellite Observations and Long-Term Data Record

A long-term and high-quality record of essential climate variables is critical for monitoring and studying the Earth's Climate change. A necessary condition for achieving this goal is the continuity of the observations, which can only be assured when high quality data collection continues without breach. Otherwise, gaps in a multi-instrument data record cannot be properly interpreted, and the value of the satellite record nearly vanishes.

Thus, the absolute calibration of each instrument and the intercalibration of multiple pertinent sensors remains critical for success in nearly all objectives of satellite remote sensing (Wielicki et al., 2013). Calibrating many instruments is challenging, especially for constellations of small satellites. The requirements for maintaining long-term observations were highlighted by National Academies of Sciences, Engineering, and Medicine (2015); the CLARREO (Climate Absolute Radiance and Refractivity Observatory) mission is a first attempt to define a satellite mission dedicated toward this goal (Lukashin et al., 2017). Similar to the calibration of direct observations, the traceability and consistency of the next generation of satellite products to the present-day instrument suite is critical.

CONCLUSION

Thus, after more than a half of century past the launch of first satellite, the remote sensing of the Planet Earth from space has evolved into a highly elaborate tool that fuels fundamental science and supports daily activities vital for humanity. A very large number of satellite instruments have been developed and launched, and they have supplied a huge amount of data for diverse requirements. The number of satellite instruments and the quality and scope of the information collected by satellites is constantly improving. At the same time, the accumulated experience of the satellite remote sensing community reveals the challenges that need to be addressed for future development. Although each observation of the atmosphere, land, or ocean surface (and other fields of remote sensing) may have specific and quite different issues, several conceptual challenges are common for many satellite remote sensing disciplines. Specifically, an increase in value of the data and efficiency of satellite remote sensing approaches will likely be related to successes in:

- increasing both coverage and resolution in spatial and temporal records of observations;
- increasing information content of observations by deploying the satellite instruments with enhanced capabilities and exploring synergies of complimentary observations, e.g., synergy of passive imagery with active vertical profiling of the atmosphere and hyperspectral spectrometry, combining observations of different sensitivities obtained in different spectral ranges, or at different time or spatial scales, as well as, combining satellite observations with sub-orbital observations and chemical transport model results;
- development of the next generation state-of-art data processing approaches that rely on rigorous forward modeling and numerical inversion methodologies, considers extensive sets of state parameters (e.g., joint retrieval of parameters characterizing different atmospheric components such as gases, aerosols, clouds and underlying surface), and use new solution techniques such as deep learning and neural networks;
- achieving continuity in consistent satellite observations and long-term data sets by assuring sufficient compatibility and agreement of past, present and future data sets that are required for accumulating climate records.

AUTHOR CONTRIBUTIONS

OD - concept of the paper, elaboration of strategy, contribution with overview of aerosol remote sensing and retrieval algorithms; GS - elaboration of strategy, contribution with overview of aerosol remote sensing, overall remote sensing overview, polishing of the paper style; FX - elaboration of strategy, contribution with overview of aerosol remote sensing and retrieval algorithms; YH - overall remote sensing overview, HB - elaboration of strategy, contribution with overview of transport modeling and trace gases remote sensing JL -elaboration of strategy, contribution with overview of trace gases remote sensing and trace gases retrieval algorithms; ZL - elaboration of strategy, contribution with overview of aerosol remote sensing.

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GLOSSARY

AATSR advanced along-track scanning radiometer
ACCP aerosol and cloud, convection and precipitation
AIRS atmospheric infrared sounder
ATSR along track scanning radiometer
AVHRR advanced very high resolution radiometer
CALIPSO cloud-aerosol lidar and infrared pathfinder satellite observations
CAPI cloud and aerosol polarization imager
CLARREO climate absolute radiance and refractivity observatory
CM-1 carbon monitoring satellite-1
CNSA China national space administration
CO$_2$M copernicus anthropogenic carbon dioxide monitoring
CRIS cross-track infrared sounder
CTM chemical transport models
DPC directional polarimetric camera
ESA European space agency
EarthCARE Earth clouds, aerosols and radiation explorer
GEO geosynchronous equatorial orbit
GFDM gao Fen Duo Mo satellite
GOSAT greenhouse gases observing satellite
GRASP generalized retrieval of aerosol and surface properties
HARP hyper-angular rainbow polarimeter
HIRS high-resolution infrared radiation sounder
IASI infrared atmospheric sounding interferometer
IMG interferometric monitor for greenhouse gases
LEO low earth orbit

LUT look-up-tables
LPP living planet programme
MAI multi-angle polarization imager
MAIA multi-angle imager for aerosols
MAP multiple-angle-polarimeter
MERIS medium resolution imaging spectrometer
MSIP multi spectral imaging polarimeter
MISR multi-angle imaging spectroradiometer
MODIS moderate resolution imaging spectroradiometer
MOPITT measurement of pollution in the troposphere
NASA National aeronautics and space administration
OCI ocean color instrument
OCO orbiting carbon observatory
PACE plankton aerosol-cloud-ocean ecosystems
PCF polarization CrossFire suite
PM particulate matters
POLDER polarization and directionality of the Earth's reflectances
POSP particulate observing scanning polarimeter
RT radiative transfer
SGLI second generation global imager
SMAC synchronization monitoring atmospheric corrector
SPEX spectropolarimeter for planetary exploration
TanSat carbon observing satellite
TES tropospheric emission spectrometer
TG tiangong spacecraft
TOMS total ozone mapping spectrometer