Achieving Breakthroughs in Global Hydrologic Science by Unlocking the Power of Multisensor, Multidisciplinary Earth Observations

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Key Points:

- Retrievals from satellite remote sensing have transformed hydrology by providing global information about state variables and fluxes.
- Benefits of remote sensing to hydrologic science will benefit from integrating information from multiple sensors and disciplines.

Abstract

Over the last half century, remote sensing has transformed hydrologic science. Whereas early efforts were devoted to observation of discrete variables, we now consider spaceborne missions dedicated to interlinked global hydrologic processes. Furthermore, cloud computing and computational techniques are accelerating analyses of these data. How will the hydrologic community use these new resources to better understand the world's water and related challenges facing society? In this Commentary, we suggest that optimizing the benefits of remote sensing for advancing hydrologic research will happen by integrating multidisciplinary and multisensor data, leveraging commercial satellite measurements, and employing data assimilation, cloud computing, and machine learning. We provide several recommendations to these ends.

Plain Language Summary

Observations from satellites have transformed hydrologic science. Early efforts, five decades ago, mapped attributes like snow cover, rainfall, topography, and vegetation, but now we consider new missions specifically designed to study global hydrologic processes. We also take advantage of new technologies like cloud computing and artificial intelligence. We describe strategies for maximizing the benefits of remote sensing for hydrology, encouraging research across disciplines using multiple sensors, using new commercially available satellites, and combining remote sensing measurements with hydrologic models.

1 Introduction

Remote sensing measurements have led to paradigmatic advances across the geosciences. The vantage of Earth orbit allows sensors to spatially resolve surficial and subsurface properties planetwide, shedding new light on global processes (National Academies of Sciences, Engineering, & Medicine, 2018). Scientific discoveries enabled by global observations have so completely transformed atmospheric and ocean sciences that introductory textbooks had to be rewritten (Wunsch & Ferrari, 2018). For example, observations of atmospheric and oceanic eddies and motions on a wide range of scales led to rethinking of the frameworks of General Circulation and the Conveyor Belt (Fu & Cazenave, 2001). Indeed, given the immense financial and intellectual investment involved, the goal of a major satellite mission dedicated to hydrologic science should be nothing less than paradigm-altering science: the goal should be scientific discovery that generates new hypotheses and theories challenging our current understanding of the hydrologic cycle and its role in weather, climate, and the biosphere.

In this paper, we briefly summarize past progress (section 2) and describe a path forward towards these ambitious goals (section 3) along with several specific recommendations (section 4), with the focus predominantly on spaceborne remote sensing of the water balance. We do not attempt an exhaustive history of hydrologic remote sensing; several contributions have done so in depth (Lettenmaier et al., 2015; Peters-Lidard et al., 2018). While technological innovations (e.g., UAVs, smart phones for citizen science) have been transforming hydrologic science at smaller scales (McCabe et al., 2017), our focus here is on spaceborne remote sensing measurements with global capabilities, including instruments integrated with the International Space Station. Given the global focus, we discuss missions led by space agencies, as well as the private sector. We discuss missions dedicated to hydrology, as well as efforts to leverage instruments originally designed for other purposes. The objective of the paper is to describe a path forward to optimize hydrologic remote sensing in the years to come.

2 Progress in Hydrologic Remote Sensing

Remote sensing of hydrology is best understood as a set of sub-fields of varying maturity related to airborne and space-based observation of the fluxes and storages that comprise the water cycle: precipitation, evapotranspiration, river discharge, and storage in groundwater, soil moisture, snow cover and water equivalent, and surface water (Lakshmi et al., 2014). Transformative advances in measuring the water cycle should be expected when global patterns in each storage and flux term can be adequately measured. Currently, maturity varies widely among sub-fields: some sub-fields, like precipitation, count decades of history, while others still require enabling technological advances. For example, mapping snow extent is mature and done regularly (Hall et al., 2002), but accurate snow depth or snow water equivalent measurements remain unavailable from space for the mountain areas with deep snow (Dozier, Bair, & Davis, 2016). Here we consider several of these sub-fields, roughly in order of decreasing maturity: precipitation, terrestrial water storage, soil moisture, evapotranspiration, surface water (river discharge and surface water storage), and snow. For a comprehensive review of current capabilities and limitations, please see Lettenmaier et al. (2015) and Peters-Lidard et al. (2018).

Some of the first hydrologic remote sensing applications estimated precipitation from cloud images from weather satellites over fifty years ago (Lettenmaier et al., 2015). Remote sensing skill took an important step by leveraging passive microwave measurements (Levizzani & Cattani, 2019), and took a major leap forward with the launch of TRMM in 1997, the Tropical Rainfall Measuring Mission and the first dedicated precipitation mission based on radar measurements (Kummerow et al., 2000). The current Global Precipitation Measurement Mission comprises a constellation of satellites whose radar-based core launched in 2014 (Hou et al., 2014), producing fine temporal and spatial analyses of surface precipitation (Huffman et al., 2020). A key area of research remains improving accuracy of remotely sensed precipitation products where gauge corrections are not available (Su, Hong, & Lettenmaier, 2008). The availability and improvement of such analyses depend on the continuation and expansion of the constellation of passive microwave satellites, with the possible use of "SmallSat" constellations in the next decades.

Terrestrial water storage represents the sum of all hydrologic storage terms and can be measured from space via fluctuations in Earth's gravity field. The Gravity Recovery and Climate Experiment (GRACE) satellite mission was launched in 2002, and had multiple objectives, of which one targeted terrestrial hydrology. GRACE provided a new way to quantify changes in total terrestrial water storage at regional to continental scales, enabling maps of groundwater depletion, trends in freshwater availability, and loss of ice from Antarctica and Greenland (Rodell et al., 2018; Tapley et al., 2019). Continuity of this unique data record was considered so important that NASA and the German Space Agency launched GRACE Follow-On in 2018 (Landerer et al., 2020), and the National Academies recommended that a third mass change mission be launched in the coming decade (National Academies of Sciences, Engineering, & Medicine, 2018).

Measurement of the individual storage terms is vital, and concerted efforts to measure soil moisture date back decades to the Heat-Capacity Mapping Mission (Heilman & Moore, 1982). Passive and active microwave measurements were used opportunistically to create soil moisture data products that continue in operational use (de Jeu et al., 2008). The Soil Moisture and Ocean Salinity (SMOS) and Soil Moisture Active and Passive (SMAP) missions launched in 2009 and 2015, respectively, and enabled global soil moisture mapping (McColl et al., 2017) and breakthroughs in large-scale land atmosphere interactions, agricultural mapping (Lawston, Santanello Jr, & Kumar, 2017) and soil science (Dirmeyer & Norton, 2018). Measurement of deep soil moisture is a possible future advance, perhaps by measuring reflections of signals of opportunity transmitted by communications satellites (Yueh et al., 2020).

Remote sensing of evapotranspiration has leveraged geostationary and polar orbiting satellites designed primarily for other purposes, particularly sensors in the visible to shortwave infrared in combination with thermal wavebands allowing for monitoring from fields to continental scales (Anderson et al., 2011). Landsat, in particular, has been broadly demonstrated as having operational utility for water management and decision support (Anderson et al., 2012). Evapotranspiration is related to surface temperature and other quantities observable from space via surface energy balance parameterizations (Kustas et al., 2003). The development of data fusion methods combining multiple satellite sources has significantly improved the reliability of daily evapotranspiration monitoring relevant for many water resource applications, as seen in the OpenET (https://openetdata.org/, Ketchum et al., 2020) effort in the U.S. and the SEN-ET (Guzinski et al., 2020) developed by European Space Agency's Sentinel Application Platform. Accurate ET retrievals, especially in semi-arid regions, remain an important area of research (Xiao et al., 2017). New sensor systems such as the ECOSTRESS mission on the International Space Station (Fisher et al., 2020) sample thermal information at different times of day and show improvement in evapotranspiration monitoring by capturing dynamics caused by variation in environmental factors and agricultural practices (Anderson et al., 2021).

Information about surface water spans both river discharge and changes in surface storage. Remote sensing of surface water extent has leveraged instruments designed for other purposes, principally Landsat, whose 30 m resolution and nearly 50-year record has enabled global mapping of decadal-scale changes in surface water extent (Pekel et al., 2016). The Surface Water and Ocean Topography (SWOT) radar altimetry mission, the first satellite specifically dedicated to measure the levels of rivers and lakes, will launch in 2022 (Biancamaria, Lettenmaier, & Pavelsky, 2016). In combination with the latest measurements of surface water extent from NISAR (also to launch in 2022), and height measurements from modern laser and radar altimeters (e.g. ICESat-2, Sentinel 6 Michael Freilich), the availability of data for surface water studies is rapidly expanding, leading to major breakthroughs (Cooley, Ryan, & Smith, 2021). The influx of commercial imagery from companies such as Maxar and Planet is also changing this field rapidly by enabling frequent (~daily), fine spatial (≤3 m) observations of surface water extent (Cooley et al., 2017; 2019; Dadap et al., 2021), especially in smaller lakes and rivers. The combination of the first dedicated surface water mission (SWOT), widely available fine-resolution optical (SmallSats, Sentinel-2) and radar (NISAR) imagery, and additional spaceborne altimeters (Sentinel 6 Michael Freilich, ICESat-2) mean that a "golden age" of surface water remote sensing is clearly on the horizon. Only by combining all these measurements, perhaps using data assimilation methods, will we achieve optimal space-time coverage of river discharge and lake storage changes.

In contrast, a dedicated mission to measure snow water equivalent has never been launched, despite the fact that remote sensing of snow cover was one of the first hydrological applications of remote sensing. Lettenmaier et al. (2015) pointed out that remote sensing of mountain snow is a critical need to advance hydrologic science. Remote sensing of snow presence or absence is a well-established capability (Bormann et al., 2018), but relating snow to other processes requires knowledge of snow water equivalent. Active work on developing snow missions, for example the Canadian Space Agency's Terrestrial Snow Mass Mission concept (Garnaud et al., 2019), is ongoing. However, as we discuss later in more detail, due to snow's complexity, one technology is unlikely to be able to measure all types of global snow, likely requiring multiple observation types depending on the terrain and the magnitude of the snowfall (Dozier, Bair, & Davis, 2016).

There is thus a wide range of maturity in remote sensing of hydrologic variables, and reliable spaceborne observations of several quantities do not exist. The most detailed picture of the global water cycle can only be created using measurements of all hydrologic fluxes and states from remote platforms and models. Further, the increasing availability of observations from small and commercial satellites, sub-orbital platforms, and signals of opportunity will be valuable for downscaling and for filling spatial and temporal measurement gaps (McCabe et al., 2017). Therefore, while the influx of remote sensing data into the hydrologic sciences in the past several decades has been transformative, the biggest scientific discoveries are surely yet to come. Given this context, what is the path forward to ensure that remote sensing of hydrology achieves its full potential in the years to come?

3 Path Forward: Enabling Power of Multiple Sensors and Interdisciplinary Work in Hydrologic Remote Sensing

One possible solution to measuring the water cycle is an integrated mission that would simultaneously measure all storages and fluxes from a single platform. While such approaches have been explored, they have generally been abandoned as being cost-prohibitive. Given the wide range of maturity of the various sub-fields and noting the increasing availability of measurements across the electromagnetic spectrum and now including gravity, here we highlight the importance of leveraging all available datasets. The path toward unlocking global scientific discoveries includes multidisciplinary, multisensor remote sensing (3.1), leveraging commercial measurements (3.2), and improvements in the tools used to synthesize observations from disparate sensors, namely data assimilation and cloud computing (3.3).

3.1 Multidisciplinary and Multisensor: Avoiding Silos and Sharing Knowledge

Paradigm-altering hydrologic science driven by remote sensing will require optimal use of data from multiple disciplines and synthesizing data from multiple remote sensors. While it is already commonplace for many hydrologic applications to use multiple kinds of measurements, it is even more common for a research project to revolve around a particular sensor or subdiscipline (e.g., atmospheric science or surface hydrology), revealing a "silo mentality." All too often, perspectives, approaches, literature, or observations in one field go unused in another. Breaking out of this silo mentality can open the availability of rich new datasets.

Perhaps the simplest way of stepping away from silo thinking is to leverage measurements from other disciplines, exploring old science questions with new datasets. For example, the GRACE mission was conceived to study the dynamics of the continents, suboceanic crust, and lithosphere, and to map the geoid and thereby enable better interpretation of data from ocean altimetry (Keating et al., 1986). Well before the 2002 launch, however, recognition that the time-varying gravity field would track spatial changes in the water held in snow, ice, the soil, and groundwater contributed to the rationale for such a mission (National Research Council, 1997). Eventually, the hydrologic (Rodell, Velicogna, & Famiglietti, 2009) and cryospheric (Velicogna, 2009) investigations proved to be the most compelling and prolific applications of these data. As another example, some of the first algorithms for remote sensing of solar-induced fluorescence (SIF)—a proxy for photosynthesis about which hundreds of papers are now published each year—were based on re-imaging measurements intended for greenhouse gas monitoring (Joiner et al., 2013). Now there are efforts making use of satellite-based SIF observations for constraining global transpiration estimates from land surface models and other hydrologic states and fluxes (Jonard et al., 2020; Pagan et al., 2019). Similarly, GPS observations have been leveraged to measure soil moisture variations (Larson et al., 2008) and other hydrologic quantities. Other as-yet-unrealized valuable hydrologic datasets may exist in current spaceborne observations, including commercial datasets, SmallSats, and signals of opportunity.

Another way of moving beyond the silo mentality in remote sensing is to recognize that "noise" in one discipline may be "signal" in another. Studies of microwave remote sensing of soil moisture have long retrieved proxies for vegetation water content (van de Griend & Owe, 1994); the influence of vegetation water content on soil moisture retrievals was understood a decade earlier (Wang, 1985). However, only in the last decade has the community used low-frequency microwave remote sensing of vegetation water content as a valuable dataset in and of itself, rather than only a technical correction factor to improve soil moisture retrievals (Steele-Dunne, Friesen, & van de Giesen, 2012). Since then, vegetation water content estimates have significantly advanced understanding of stomatal closure responses to both atmospheric and soil moisture (Konings, Williams, & Gentine, 2017), the impact of vegetation diversity on the response of evapotranspiration to drought (Anderegg et al., 2018), as well as plant growth responses to water stress and other factors (Feldman et al., 2018; Liu et al., 2015). They also hold promise for a variety of applications in agriculture, carbon cycle science, and fire hazard assessment (Konings, Rao, & Steele-Dunne, 2019).

The final way of escaping from silos is to more regularly leverage all available measurements simultaneously to characterize hydrologic processes. The use of multiple observations can enable a fundamental step change in our ability to characterize a hydrologic quantity or to do groundbreaking new work. As described in section 2, multisensor remote sensing is central to strategies in the more mature sub-fields, including precipitation and evapotranspiration (Cammalleri et al., 2013, 2014). Even broader approaches merging a full spectrum of Earth observations are already being leveraged in other disciplines such as in agronomy for crop yield estimation (Guan et al., 2017). Fully achieving the "golden age" of surface water remote sensing described in the previous section requires the non-trivial work to bring together the water surface extent and water surface elevation measurements from a large range of platforms. It also requires two approaches to high-quality validation data (Lundquist et al., 2019): (1) Long-term observational networks from a wide variety of scientific disciplines, such as the Long Term Ecological Research network (LTER, Kratz et al., 2003) or the U.S. Department of Agriculture experimental watersheds (Nayak et al., 2010; Renard et al., 2008) and Long Term Agro-ecosystem Research network (Baffaut et al., 2020), provide consistent data to assess trends and to validate remotely sensed retrievals across multiple, evolving satellite sensors. (2) Dedicated field campaigns, which use remote sensing to address cross-disciplinary science questions, collect information through intensive human activity that is beyond the realistic capability of unattended instruments. Examples include FIFE (First ISLSCP Field Experiment, Sellers et al., 1988), BOREAS (Sellers et al., 1997), multiple-year field campaigns to capture a range of environmental conditions (Kustas et al., 2018), and campaigns to integrate atmospheric and hydrologic science to better model and measure mountain precipitation, often the source of most of the water (Lundquist et al., 2019).

Some quantities in the hydrologic cycle simply cannot be measured with current technologies using a single sensor alone; the prime example is snow. It is highly unlikely that a single sensor will be able to fully reveal snow characteristics, which include snow water equivalent, density, wetness, grain size, and radiative forcing from light-absorbing impurities, thereby suggesting a multi-pronged approach, leveraging multiple types of observations, time series, and modeling. As an example, increasing availability of surface altimetry measurements from stereophotogrammetry (Dehecq et al., 2020), lidar (Painter et al., 2016), or high-frequency radar (Moller et al., 2017) show promise for snow depth retrievals, but modeling will be necessary to determine density and thereby the water equivalent. The Ku-band radar approaches being pursued most recently by the Canadian Space Agency (Garnaud et al., 2019) will likely be most successful for shallow snow away from trees, such as snow accumulating on Arctic tundra. Incorporation of snow albedo and surface temperature will help to resolve the energy balance (Kongoli et al., 2014), and in turn can provide information on snowmelt rates, which can be used to retrospectively determine what snow accumulation must have been (Bair et al., 2016; Margulis et al., 2016; Rittger et al., 2016). Understanding the repeatability of these historic snow accumulation patterns can then improve prediction and modeling of current snowpacks (Pflug & Lundquist, 2020). Bringing these pieces together will provide the best chance for success but will require modeling and assimilation as described in section 3.3.

3.2 Combining Commercial and Government Satellite Observations

Measurements from commercial platforms are rapidly expanding Earth observations (McCabe et al., 2017). The current model for most Earth observation remote sensing is that government agencies are the primary providers. Indeed, the continuity and reliability of data from ESA, EUMETSAT, NASA and NOAA, for example, are essential to produce climate data records, allowing the scientific community to plan for long-term use, such as the Copernicus Sentinel program. Moreover, several companies, notably Maxar and Planet, and now ICEYE and Capella Space, provide imagery at much finer spatial resolution than most sensors funded by space agencies. How will the availability of observations from commercial platforms change the landscape of remote sensing of hydrology?

As space agencies are publicly funded, observations from many national space agencies are available free of charge. The 1984 decision to transition Landsat to a commercial operation demonstrated that data costs substantially limit the scope of science and applications; the 1999 reduction in cost and the 2008 return to free Landsat data demonstrated that freely available data bring huge benefits to modern science and applications (National Research Council, 2013; Wulder et al., 2012). A cost model where imagery must be budgeted in the costs of grants stifles scientific research and hinders its use by resource managers. Thus, the availability of commercial satellite data to researchers, whether through space agency or national science agency agreements or individual grants, is vital towards allowing these technological and observational advances to make an impact on hydrologic research. Recent progress, such as the 2018 agreement between Maxar and the U.S. Government and the 2020 agreement between Planet and NASA, makes fine-resolution imagery available to members of the research community. Such access agreements and data availability are also vital towards ensuring the reproducibility of scientific analyses using commercial data. A note of caution is that these agreements are short-term. Studies focused more broadly on environmental data show that privatization incurs some risk (National Research Council, 2001).

Whereas recent progress in the availability of commercial data is a significant step, there remain other challenges towards the broad inclusion of commercial imagery in hydrologic research. For example, thorough documentation of dataset creation and validation is critical for efficiently entraining new users, enabling them to quickly resolve inevitable misunderstandings when working with new datasets. Space agencies nationally and internationally have set a high standard for documentation and validation at all levels of the processing and algorithm chain. For example, NASA's Algorithm Theoretical Basis Documents explain not only how raw observations are converted to data products of interest, but also enough of the underlying theory to provide insights into dataset limitations. In contrast, in the private sector, fewer resources are dedicated towards accuracy assessment and calibration and validation, so uncertainties may not be well understood. Furthermore, private sector processing algorithms may be intellectual property and are not readily available to all users. Therefore, along with any commercial data agreement should come adequate documentation and data processing transparency, which are key to scientific use of remote sensing measurements.

Finally, it is vital that raw data be made available, especially in the critical period where the community is attempting to assess the utility of a new data type. Assimilation of raw radiances rather than retrieved precipitation data products was vital in the evolution of numerical weather prediction (McCarty, Jedlovec, & Miller, 2009). Similarly, hydrologists with access to the range of data products processing levels are better able to adapt algorithms for specific contexts. For example, retrieval of surface reflectance of snow-covered landscapes in mountainous terrain can benefit from more advanced modeling and high-resolution digital surface models—but only if the raw data are made available. Such availability of raw data will be especially important given the nascent development of commercial synthetic aperture radar imagery from companies such as ICEYE and Capella Space. Overall, while commercial satellite data have made substantial inroads into hydrologic research in the past five years, further development will continue to require dialogue and interaction between scientists, federal science and space agencies and private companies.

3.3 Bringing Everything Together through Data Assimilation and Cloud Computing

To fully achieve landmark changes in hydrologic science, we must leverage multidisciplinary and multisensor remote sensing measurements, and data assimilation methods are surely one of the most important tools for this merger. Data assimilation is at its heart a simple concept that is decades old, in which observations replace or adjust modeled estimates of states or fluxes (Reichle, 2008). In principle, data assimilation could be used to merge multiple observational quantities across the entire water cycle. However, the devil is in the details in terms of obtaining optimal estimates for hydrologic systems from assimilating remote sensing measurements into models; often issues center around the quantification of uncertainty.

As a non-trivial example, consider assimilation of GRACE terrestrial water storage into a large-scale hydrologic model, and comparison of the assimilation analysis estimates with in situ groundwater levels. Uncertainty could arise from the meteorological forcing data, the in situ data, model structure error associated with the generation of runoff and evaporative fluxes, representation of soil moisture-groundwater interactions, static soil parameters such as specific yield, scale mis-match between the model grid and in situ observations, GRACE data processing errors, other invalid assumptions, or any combination of these factors (Girotto et al., 2017). Ensuring that the right model states, fluxes and/or parameters are adjusted properly and that comparisons with observations in situ are correctly interpreted requires a thorough understanding of model and observation uncertainty. These issues are compounded when multiple, imperfect observations are assimilated simultaneously (Kumar et al., 2019).

Uncertainty in hydrologic predictions results from uncertainty in model inputs, including meteorological forcing data, model parameters and model structure (Ajami, Duan, & Sorooshian, 2007). Better understanding of model uncertainty hinges on assessment of hydrologic datasets, comprehension of hydrologic processes, simplifying assumptions, parameter equifinality, and how these attributes combine within hydrologic models (Moradkhani et al., 2005). Hydrologic models used wisely have enabled countless scientific discoveries: their impact can hardly be overstated. However, comparing models with remote sensing observations, especially assimilating observations into models, tends to reveal new model limitations (Liu & Gupta, 2007). It is thus vital when assimilating data to be wary of possible model structural errors (Clark et al., 2008), and thus biases, and to consistently think back to the hydrologic processes being modeled.

Better understanding of remote sensing observation uncertainty is also vital; as with model uncertainty, awareness of potential bias is critical, especially in higher level retrieved data products. For example, snow water equivalent retrievals from passive microwave data often exhibit significant biases in mountainous areas. Assimilation of these biased estimates are more likely to degrade, rather than improve, modeled estimates (Andreadis & Lettenmaier, 2006). Assimilation of radiances instead of retrieved hydrologic quantities and lower-level data products in general can help circumvent issues of bias in retrievals from remote sensing observations, for precipitation (Ebtehaj, Bras, & Foufoula-Georgiou, 2015), soil moisture (Reichle et al., 2019), snow (Li, Durand, & Margulis, 2017), and in other contexts. Additionally, instrumental-variable techniques have been applied to correct remote-sensing-based estimates of soil moisture/evapotranspiration coupling strength for the biasing impact of random retrieval errors (Crow et al., 2015; Lei et al., 2018). Through this advancement, Crow et al. (2020) recently identified the over-coupling of soil moisture and surface evapotranspiration as an important source of systematic modeling error in numerical weather prediction of summertime near-surface air temperature. Another important effort in understanding retrieval errors is mapping error climatology and relating these to physical processes (Barros & Arulraj, 2020). Support for remote sensing theory and remote sensing phenomenology is a cornerstone for efforts to understand uncertainty in remote sensing observations, as well as assimilation of microwave radiances, in part via development of forward simulation models that relate remote sensing measurements to the hydrological quantities of interest and relevant nuisance factors. Continued progress in bringing multidisciplinary, multisensor remote sensing measurements will be achieved as further progress is made in understanding and documenting data product uncertainty.

We believe that the class of data assimilation methods that apply water balance closure as a constraint will be highly relevant to future work to bring together the various remotely sensed quantities (Pan & Wood, 2006; Pascolini-Campbell et al., 2021; Rodell et al., 2015) . Such methods compute estimates of each term in the water balance that are constrained to close the water balance, while remaining as close as possible to the measured quantities. The specified uncertainty in the retrieved quantities is critical to these estimates, as it is to all data assimilation.

Machine learning and the capacity to analyze big data are also leading to rapid innovation in remote sensing, as the community seeks to leverage major advances in related fields. Indeed, some recent work suggests that the ever-changing balance between physically based models and statistical approaches in hydrology may be tipping in the favor of statistics (Nearing et al., 2021). We must leverage these important advances, while remaining vigilant of the “black box” nature of some algorithms, so that we get the right answers for the right reasons (Kirchner, 2006). As the power of machine learning algorithms is limited by the availability of appropriate training data as well as explicitly addressing the physical processes, a critical problem is how to develop training data for approaches based on multidisciplinary, multisensor remote sensing (Elmes et al., 2020), particularly those that accurately characterize extreme events. Indeed, observational errors in training data can introduce significant bias in the resulting ML model prediction.

If data assimilation and machine learning represent algorithms to bring measurements together, cloud computing provides the means to do so in practice. The need to observe multiple hydrologic quantities with multiple types of observations simultaneously, along with the continued massive increase in data volumes, are already necessitating that much of remote sensing of hydrology move to cloud computing. The basic paradigm of data-intensive computing brings the computing to the data rather than downloading data to personal or institutional computers. Therefore, fully exploiting cloud computing requires that the data providers (NASA, NOAA, international partners, commercial satellite companies) and the vendors of cloud services (Amazon, Google, Microsoft) agree to host voluminous datasets on the clouds. Discussions are under way to do this, but as of this writing some widely used datasets are available only via download from agency repositories. The strategy is truly transformative as dataset sizes grow, but not all widely used data are available on one of the major cloud providers. Meanwhile, data volumes are continuing to expand: NISAR alone will produce up to 140 petabytes of data over its mission lifetime, comparable to the current entire data volume of NASA’s Earth Observing System Data and Information System (Blumenfeld, 2017). Renewed focus on cloud computing approaches and interoperability is needed to allow researchers to perform multisensor analyses using such new high data rate instruments or long time series of other image datasets.

Much research along with several resource management applications are moving to the cloud already. For example, the freely available cloud geospatial analytics tools of Google Earth Engine (Gorelick et al., 2017), combined with cloud access to the Landsat archive and other satellite datasets of use in hydrologic studies, has lowered the barrier of entry towards analyzing trends in surface water, combining multiple hydrologic datasets for preliminary analyses. For example, Pekel et al. (2016) and Donchyts et al. (2016) mapped global surface extent and trends, and Venancio et al. (2020) mapped evapotranspiration at field spatial scales. Bair et al. (2018) used Microsoft Azure for a machine learning application combining passive microwave data from AMSR-2 with optical imagery from MODIS to map snow water equivalent in high mountains. Zinno et al. (2020) used Amazon Web Services to process interferometric SAR imagery to create a deformation map of Italy. The power of cloud computing combined with data assimilation enable prediction of hydrologic processes between opportunities for acquisition of imagery. Therefore, demonstrating the incremental value of that new information is crucial (Bernknopf et al., 2018), as is getting feedback on data products and distribution methods (Hossain et al., 2020). We must ensure that hydrologic observations enable those who make the policies and decisions that will conserve and manage our most precious resource (Knipper et al., 2019).

4 Summary and Recommendations

Hydrologic remote sensing will achieve its true potential once measurements across relevant variables are integrated together along with hydrologic models to transform how we observe and understand the global water cycle. Success can be claimed when introductory hydrologic textbooks are rewritten. To achieve these lofty goals, the remote sensing community must escape from siloed ways of operating and improve how we work across disciplines, with multiple types and sources of observations including commercial and international imagery. We must advance understanding and treatment of observation and model uncertainty within data assimilation schemes, harness emerging machine learning capabilities, and move computing tasks to the cloud.

Accomplishing new hydrologic science will require the remote sensing community to move beyond simply learning how to estimate each state and flux of the water cycle. If our end-goal is developing useful data products, progress will be slow. Focus must shift to long-standing science questions that are now within reach, thanks to remote sensing. This change is under way: for example, Lettenmaier et al. (2015) noted that at the 25th anniversary of *Water Resources Research* in 1990, 33 years after the launch of Sputnik, only seven of the journal's published papers used remotely sensed data. At the 50th anniversary, that picture had changed, with remote sensing now widely used in hydrology. The reason given for this lag was simple: it was the time required for hydrologists to learn to work with new remote sensing measurement data types. We suggest that avoiding disciplinary silos, working with multiple types of measurements, and bringing these pieces together using data assimilation, machine learning, and cloud computing are among new important skillsets that need to be learned by the community.

In the context of the path forward we have described, what can be done to best prepare the hydrologic community now for the measurements to come from new satellites in the coming years? We offer the following three specific recommendations as examples of activities that will move the community towards the broader goals we have outlined in the previous section.

First, the trend by space agencies towards bundling multiple satellite missions within coherent observation strategies shows promise for escaping from siloed thinking. The establishment of the Sentinel program by ESA is a step towards bridging across typical disciplinary divides. Sentinel missions combine multiple sensors and are widely used by multiple scientific communities across the Earth Sciences. By bundling multiple sensors and scientific objectives into a single program, some of the inertia to interdisciplinary collaboration across hydrology remote sensing subfields is reduced. Similarly, NASA's recently announced "Earth System Observatory" (ESO) takes the Designated Observable missions from the Earth Science and Applications Decadal Survey and packages them together. Considering these missions as part of a single program elevates the big-picture vision of measuring the earth, including the water cycle, laid out in the Decadal Survey (National Academies of Science Engineering and Medicine), encouraging the community to engage across disciplines. Instead of pushing for a single water cycle observing mission, the ESO maximizes science returns by prioritizing overlap of the mission lifetimes (St. Germain, 2021). Combined with other forthcoming missions such as SWOT, the ESO enables analysis of interdisciplinary science questions. To mention just one example, atmospheric measurements of aerosols combined with measurements of snow albedo (which respond to deposition of aerosols on the snow surface (Skiles et al., 2018)) could enable the community to further probe dynamics of snowmelt responses to aeolian forcing. We recommend that as ESO missions mature, funding be made available for the community to explore interdisciplinary science questions.

Second, as remote sensing of hydrology continues to mature, more subfields will be able to take advantage of the "constellation approach" to measurement currently employed by GPM as discussed in section 2. The constellation approach can be achieved in multiple ways: the "core" satellite(s) could be complemented either with SmallSats or other datastreams from existing available remote sensing datasets. Fusing data from core sensors with SmallSat retrievals and/or ground observations is not trivial and requires supported investigations, but has the potential to substantially improve the scale and accuracy of measurement. For example, SmallSats can be used to improve temporal resolution, even if precision is less than what would be expected for a core satellite (Houborg & McCabe, 2018). The constellation approach may enable a quantity of interest to be better measured, and it may also help a particular mission provide information on parts of the water cycle outside the originally envisioned scope.

Third, the community would be well-served to move towards wide adoption of a common, flexible, science-oriented analytical software environment for data analysis and data assimilation problems. While community software for data assimilation problems has been developed such as the Land Information System (Kumar et al., 2006), most assimilation problems are still solved using ad hoc code created by individual research groups. There are tangible benefits to moving towards a more common computational framework as discovered by the OpenFOAM community (Chen et al., 2014). The OpenFOAM environment has let scientific curiosity drive innovation and creativity, resulting in significant advances in modeling capabilities (Chen et al., 2014). Widespread community adoption of a data assimilation software environment broadly modeled on the strengths of OpenFOAM could be transformative. The envisioned software environment needs to include capabilities for a wide range of data assimilation problems and must be flexible enough to enable new research problems with minimal architecture changes. Regular training and abundant resources must be available to lower the bar for new users to spin up. We encourage further adoption of the "Hackweek" approach to lower the bar to users working with multiple datasets and bringing them together with data assimilation tools (Huppenkothen et al., 2018). As noted earlier, many innovations following new satellites are unexpected, resulting from ingenious applications of new datastreams. Adoption of a common assimilation framework can position the community to take advantage of new datasets when they arrive.

We believe that scientific breakthroughs in hydrology will be driven by both improved capabilities to measure the various states and fluxes, and from integrating knowledge among the various remote sensing of hydrology subfields along with models, to better understand the dynamics of the global water cycle. This commentary has described a path towards new hydrologic science from remote sensing using multiple sensors and interdisciplinary work. We have recommended possible steps along this path: programmatic changes to combine missions into coherent programs at the level of space agencies, moving towards the "constellation" approach to measurement, adoption of a common community data assimilation framework, and creation of a new organization focused on remote sensing of hydrology. We hope that these and other steps will speed the breaking down of silos, enabling new hydrologic discovery.

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