



COMMENTARY

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Key Points:

- Novel methods of teaching must be used in the cloud-based Earth observation (EO) paradigm
- The Earth Engine Education community is a valuable example of teaching and learning in the new cloud-based EO paradigm
- Cloud-based EO science must prioritize teaching fundamentals, ethics, and engagement with the broader field

Supporting Information:

Supporting Information may be found in the online version of this article.

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






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Pillars of Cloud-Based Earth Observation Science Education

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Abstract Earth observation (EO) is undergoing a paradigm shift with the development of cloud-based analytical platforms supporting EO data collection and access, parallel processing, easier communication of results, and expanded accessibility. As the global community of users and the diversity of applications grow, there is a clear need for expanded educational capacity to leverage these developments and increase the impact of EO research and teaching. Drawing upon extensive conversations between educators, practitioners, and researchers, we propose three pillars that must be prioritized to prepare students, researchers, and professionals to take full advantage of the cloud-based EO paradigm and guide future growth.

Plain Language Summary Earth observation (EO) data are used to understand the social, environmental, and climatic causes and consequences of changes to the Earth. Greater diversity in EO data sources and access points, the evolution of web-based and collaborative platforms for analysis and communication, and the growth of the global user community are each changing how EO science is undertaken and communicated. These advances are also changing how scientists and educators teach students. Over the past few years, a group of EO educators and researchers met and identified three central pillars for teaching today's EO students within this new paradigm. The pillars of cloud-based teaching EO science are: (a) fundamental concepts, (b) ethical considerations, and (c) engagement. These pillars can guide not only EO students but also researchers and practitioners to make valid, valuable, and engaging contributions to EO science.

1. Introduction

Earth observation (EO) science and remote sensing have undergone a radical transformation in the last two decades. Satellite platforms, sensors, and instruments with ever greater spatial, temporal, and radiometric resolutions have been launched into orbit, computational processing capabilities have expanded, and increased information accessibility has connected users across the globe (Denis et al., 2017). One of the largest transformations has been the shift to open-source projects (e.g., Quantum GIS, GRASS GIS, GDAL/OGR, GeoTools, Orfeo ToolBox, PostGIS) and cloud-based cyberinfrastructures (e.g., Google Earth Engine, Google Colab, Pangeo, Microsoft Planetary Computer, Open Data Cube, JupyterHub, ArcGIS Online) for storing, processing or analyzing EO data (Gomes et al., 2020; Gorelick et al., 2017; Kopp et al., 2019; Kumar & Mutanga, 2018; Liang et al., 2018; Wagemann et al., 2022). These cloud-computing environments represent high-throughput technological

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infrastructures that enable big data processing using multiple remote physical servers, databases, and computers over the internet (Wagemann et al., 2022; Yang et al., 2019). To take advantage of these, many scientists using geospatial datasets have moved their research workflows from their local computers or servers to a cloud-based platform (Crowley & Cardille, 2020; Wagemann et al., 2021). Additionally, the wide adoption of open-access data policies enables access to freely available geospatial datasets (e.g., Gentemann et al., 2021; Gorelick et al., 2017; Woodcock et al., 2008; Zhu et al., 2019). Open-access data policies are now the norm for civilian satellite programs from the National Aeronautics and Space Administration (NASA), United States Geological Survey (USGS), European Space Agency (ESA), Brazil's National Institute for Space Research (INPE), and Japan Aerospace Exploration Agency (JAXA). The now-intertwined development of open-access EO science and cloud-based infrastructures have also driven a broader shift in EO science toward automated workflows and novel machine learning and deep learning algorithms to support sustained, near-real-time monitoring of a diversity of processes such as deforestation, natural hazards, and agricultural production (Hey et al., 2009; Kennedy et al., 2018; Wulder et al., 2018). These advances have disrupted how researchers and other users undertake EO science by providing rapid access to an ever-greater diversity of interoperable EO datasets at the global scale (Aikat et al., 2017; Denis et al., 2017).

The paradigm shift of EO to cloud-based technologies is affecting how EO science is taught (e.g., Dordevic et al., 2016; Gibson & Ifenthaler, 2017; Hsu et al., 2018; Lisle, 2006; Mejía Ávila et al., 2021; Minner & Micklow, 2016; Monet & Greene, 2012; Patterson, 2007; Ratinen & Keinonen, 2011; Sawaguchi, 2018; Xiang & Liu, 2017; Zhong et al., 2009), and is prompting educators to have conversations about how to teach the next generation of scientists and professionals to use EO to address pressing socio-ecological challenges (e.g., Baig et al., 2020; Gibson & Ifenthaler, 2017; Luan et al., 2020). In this commentary article, we provide an overview of three major pillars we have identified for teaching and learning EO science in the cloud in the era of big data (Figure 1). Our thoughts initially emerged from conversations between EO science educators, researchers, and practitioners at the 2019 Geo for Good summit in Mountain View, California, USA (<https://sites.google.com/earthoutreach.org/geoforgood19/>). These ideas were then refined in the years that have followed through annual Geo for Good summits, surveys to the community of educators and students, virtual meet-ups, a virtual speaker series, and a forthcoming open-access textbook (www.efabook.org). The conversations have only become more relevant given the shift to virtual learning environments during the global COVID-19 pandemic.

2. Pillar 1: EO Science in the Cloud Is Built on Fundamentals

The fundamentals of remote sensing and geospatial science must remain central to EO science curricula so that students understand the (ever-growing) opportunities of EO technologies as well as their limitations. Following a revised Bloom's Taxonomy, fundamentals in EO can be broken up into procedural and conceptual domains of knowledge (Forehand, 2005). In EO science, procedural fundamentals include core workflows like raster analyses (e.g., Haralick et al., 1973; Tomlin, 2013), calculation of spectral indices (e.g., Crist & Kauth, 1986; Huete et al., 2002; Tucker, 1979; Xu, 2006), multi-temporal change detection (e.g., Coppin et al., 2004; Gómez et al., 2016; Kennedy et al., 2009), and image classification and validation (e.g., Foody, 2002; Goldblatt et al., 2018; Stehman, 1997; Stehman & Czaplewski, 1998). Conceptual domains include understanding how sensors capture imagery and radiometric concepts like radiance and reflectance (Masek et al., 2020; USGS, 2022).

Retaining a focus on EO fundamentals when teaching in the cloud can be challenging since the scope of applications and the diversity of data sets that we engage in our teaching have broadened considerably. Through cloud computing platforms, students can access data with fine spatial (e.g., 1-m National Agriculture Imagery Program [NAIP] imagery (USDA FSA, N.D)) and temporal (e.g., sub-weekly Sentinel-2 imagery (ESA, N.D)) resolutions at national or global scales, often within hours or days of collecting the imagery. Combining data across multiple EO sensors (i.e., multi-sensor fusion) and their derived products is increasingly the norm, as is the uptake of EO data by students and researchers in fields as diverse as fire ecology (Crowley et al., 2019a, 2019b), conservation biology (Evans & Malcom, 2021; Xie et al., 2019), archeology (Firpi, 2016; Liss et al., 2017), and epidemiology (Li et al., 2022). Additionally, a growing collection of open-access resources (e.g., Clinton, 2018; Prados et al., 2019; UCGIS, 2016) can support students in learning remote sensing fundamentals from educators and researchers from diverse backgrounds, including geographic locations, career stages, and scientific expertise (Table 1).

As an increasing number of platforms, sensors, and derived data products become available, teaching the inherent tradeoffs between data sets is increasingly essential (Botje et al., 2022; Kennedy et al., 2009; Mahood et al., 2021).

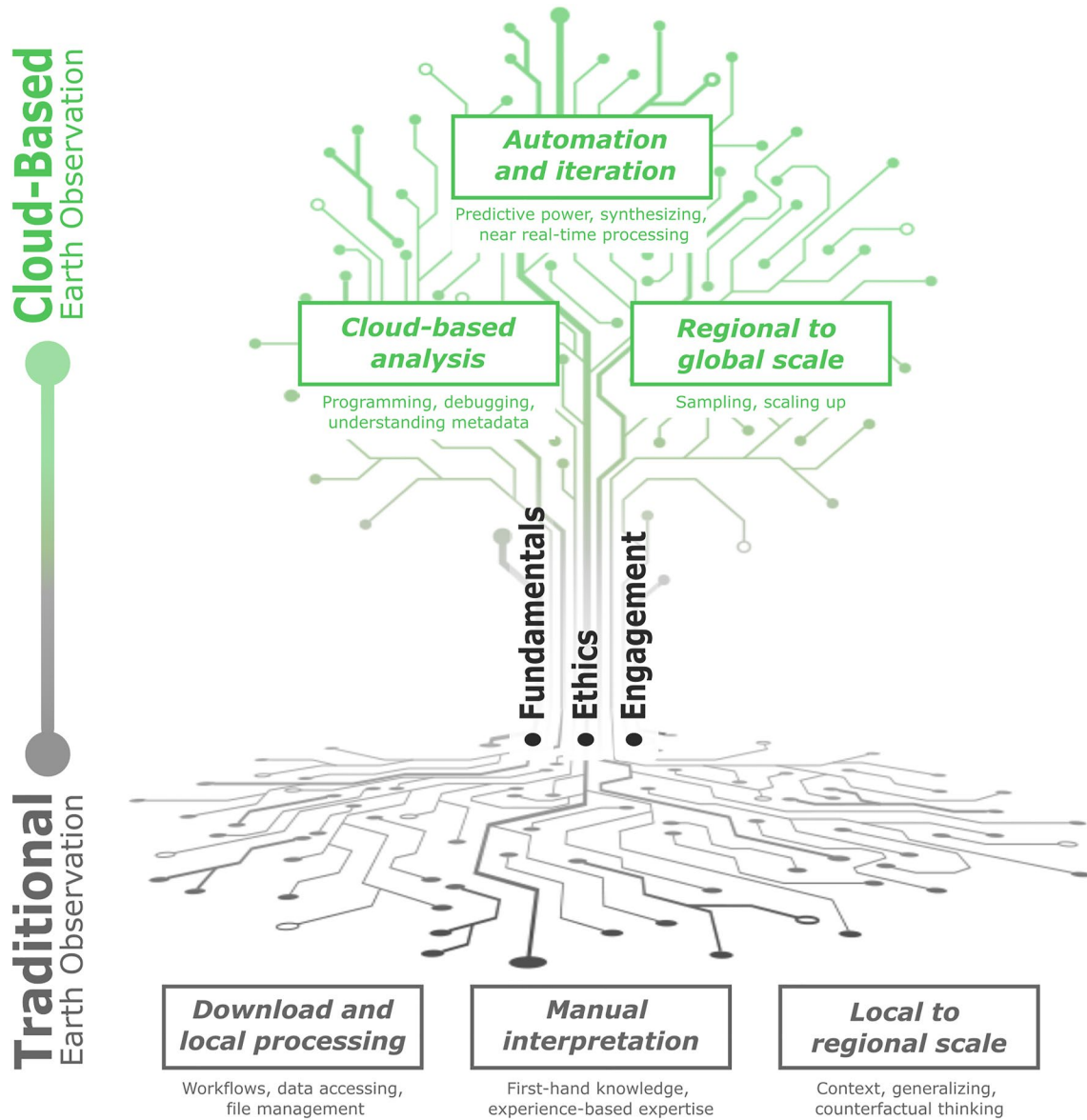


Figure 1. Cloud-based Earth observation (EO) research and teaching grows from soil rich in traditional EO concepts. This conceptual tree diagram illustrates the shift from traditional EO to cloud-based EO where the three pillars of (a) Fundamentals, (b) Ethics, and (c) Engagement form the trunk. Traditional EO is depicted as the roots of the tree, providing core processes, skills, and knowledge. Cloud-based EO is represented as the canopy where growth and development continue to occur as increased accessibility creates new opportunities. The foundational pillars provide the supporting structure to better prepare students to learn EO and emphasize the link between traditional and cloud-based paradigms.

Students must be able to leverage the concepts, theories, and principles fundamental to EO sciences to contextualize analyses performed with cloud-based computing in the big data era. For example, a product with high global accuracy may have a much lower accuracy at the local or regional level due to differences in biome, weather, land use, or the training data used to generate the product (Chakraborty et al., 2021; Haywood et al., 2004). Knowing how to determine the influence of atmospheric, topographic, and illumination conditions on image quality and assessing the necessity of potential corrections are crucial for students to understand a data set's suitability for a given application (Van Den Hoek et al., 2021; Young et al., 2017). Improved technology may not translate to greater learning potential student expertise if EO fundamentals are not already in place.

Underlying each of these fundamentals is the need for EO students to be able to identify and potentially mitigate data quality issues and communicate the uncertainty in their analyses. Training the next generation of EO scientists and industry leaders to characterize the uncertainty of an EO-based analysis (e.g., Brown et al., 2022),

Table 1

Summary of Pillars, Sub-Themes, Main Takeaways, and Examples From the Google Earth Engine Community That Demonstrate Each Pillar Through Teaching and Learning in the Cloud-Based Earth Observation Paradigm

#	Pillar	Sub-themes	Main takeaway	Example from the Google Earth Engine community and their contributions
1	Fundamentals	Core workflows	<i>We must integrate fundamental EO concepts into our lessons on cloud-based platforms to ensure valid EO contributions</i>	“Cloud-based Remote Sensing with Google Earth Engine—Fundamentals and Applications” textbook www.cefabook.org 55 chapters, 10,000 lines of code, 100 authors
		Resolutions and their tradeoffs		“Earth Engine for Education” website https://developers.google.com/earth-engine/tutorials/edu 10 labs, 10 lectures, 15 institutions, 6 languages
		Sources of bias and error		
2	Ethics	Internal	<i>We must recognize the ethical dimensions of EO science, some of which are novel due to the potential scale of EO analysis in the cloud</i>	SilvaCarbon eLearning training modules (SilvaCarbon, 2022) 6 modules, 2 languages, 25 countries Capacity building and hub-led research with SERVIR Global (Frankel-Reed, 2018; Kansakar & Hossain, 2016; Mayer, 2020; Searby et al., 2019) 5 regions, 50 countries, 600 institutions, 10,000 individuals trained
		External		
		Environmental		
3	Engagement	Research engagement	<i>As educators, we must support our students to engage with local knowledge and existing resources, as well as teach them to communicate their contributions broadly</i>	Service-learning GIS and EO classes at DePaul University (Rosing & Hofman, 2010) Annually: 3–4 classes, 40–55 students, 8–10 community partner projects “Awesome GEE Community Catalog” https://gee-community-catalog.org/ 7 contributors, 212 TB of data sets, 485 stars, 1,150 data sets “Awesome GEE” GitHub repository: https://github.com/giswqs/Awesome-GEE 9 contributors, 255 linked resources, 732 stars Earth Engine User Meetups (Szeto, 2022): www.youtube.com/EarthEngineUserMeetup 16 recorded sessions, 817 subscribers, 8,924 views
		Local knowledge		
		Open-access and transparent		
		Communication strategy		
		Knowledge exchange		

whether through qualitative or quantitative approaches, can lead to more informed use of analytical outputs and less potential for miscommunication between data creators and data users. Last, as future generations of EO scientists are educated using largely cloud-based platforms, there is also a need for teaching the limitations of cloud-based approaches and local computing alternatives. Many cloud-based services are owned by corporations, are often not open-source, and may become less widely accessible with monetization. While it is beyond the scope of this article to discuss the difference between teaching cloud-based EO and their implementation beyond the university environment, it can be an important consideration for preparing students for industrial job roles. Current cloud-based EO offerings are all led by private companies, this may have implications for data and compute access down the road if their monetization structures change. These will be important topics for the EO and education community to discuss and consider going forward as cloud-based tools for EO become more and more common.

3. Pillar 2: EO Science in the Cloud Requires a Deeper Consideration of Ethics

A longstanding conversation in the field of remote sensing and geospatial sciences has been the importance of integrating ethical considerations into courses and professional organizations, given the potentially sensitive information that can be interpreted from aerial and satellite sources (Harris, 2013; Kochupillai, 2021; Nelson et al., 2022; Slonecker et al., 1998; Wetherholt & Rundquist, 2010). The emerging field of Critical Remote Sensing (Bennett et al., 2022) examines who EO data harms and helps, and encourages EO scientists to leverage satellite data to (a) expose injustice; (b) engage local knowledge; and (c) empower marginalized actors. The types of ethical considerations of the greatest importance for students and EO practitioners continue to evolve along with increasing accessibility to sensitive data and technological advances (Kent, 2017; Zhao et al., 2021). We have identified three types of ethics—individual, social, and subject—that merit renewed priority in teaching and learning as EO and global imagery continue to become more widely accessible in this new paradigm (Figure 1).

Individual ethics refers to the intrapersonal ethical principles that guide how an individual conducts oneself when working with EO data. Individual ethics can also include accountability, transparency, service, charity, integrity, and empathy (Nelson et al., 2022). Though they may not be referred to as being part of individual ethics, these principles are often discussed in the classroom when creating replicable workflows or making publicly accessible data repositories (Shook et al., 2019). In a cloud-based environment characterized by easier access to data (e.g., sensitive high-resolution data) and dissemination of EO science, teaching individual ethics requires renewed attention that can be informed by existing capacity-building training programs from interagency organizations like SilvaCarbon (2022), SERVIR Global (Frankel-Reed, 2018; Kansakar & Hossain, 2016; Mayer, 2020; Searby et al., 2019), NASA ARSET (NASA ARSET, 2022), NASA Harvest, Sentinel Hub (Sentinel Hub, 2022), and RUS Copernicus (RUS Copernicus, 2022).

Social ethics refers to the interpersonal ethical principles that shape research, teaching, and learning with others. Social ethics includes ensuring the human dignity of subjects, working toward social justice, following laws and data limitations, working to contribute to the public good, and aiming to increase inclusivity, diversity, equity, and justice (Chandra & Bhatia, 2020; Monmonier, 2018; Nelson et al., 2022; Owusu et al., 2021). Students and scientists practice social ethics by promoting increased data accessibility for underrepresented communities, actively including Indigenous scientists in research activities or raising awareness of sources and consequences of error, bias, uncertainty, and limitations of EO data, or identifying potential harms of EO data-driven applications, whether direct or indirect. The full scope of social ethics is less frequently covered by traditional EO curriculum, but there are strong examples from the Earth Engine community that can help guide future lessons. For example, social ethics are taught to EO learners in the context of community-led research using Earth Engine by the Indigenous Mapping Collective and the Google Earth Outreach team (Fields, 2022). Additionally, social ethics regarding accuracy assessments, area estimation, error, and bias are covered by the eLearning modules from SilvaCarbon (2022) and the Earth Engine textbook (www.eefabook.org) (Table 1). Critical Remote Sensing practices (Bennett et al., 2022) are now being taught as part of remote sensing education, encouraging students to ask how satellite data exposes, empowers, or engages marginalized communities in harmful or helpful ways.

Subject ethics builds off of the fundamentals identified above and encompasses principles of trust, stewardship, confidentiality, information integrity, and regional biases of an EO study (Fisher et al., 2021; Harris, 2013; Kochupillai, 2021). In the classroom, subject ethics are often discussed in terms of false precision, map seduction, responsibility for inference, different types of error, and responsible accuracy (Monmonier, 2018). Subject ethics

are especially pertinent when it comes to working with machine learning and deep learning, as these types of algorithms can impart regional biases due to sampling deficiencies, inappropriate tuning, and insufficient data (Tulbure et al., 2022). Students should be taught how to identify whether cloud-hosted EO datasets or derived products have adequate metadata and clear provenance, and be able to determine whether the spatial, temporal, and spectral resolutions of a data set or analytical result are fit for the specific purpose at hand; being able to think through the value and relevance of a data set is especially important considering new EO products with which an instructor or student may have less experience. Students should also be taught to take a critical approach to EO data and understand what local knowledge satellite information cannot capture or obscures (Bennett et al., 2022).

4. Pillar 3: EO Science in the Cloud Benefits From Engaging With the Concerns of Diverse User Communities and Stakeholders

Given the potential global reach of cloud-based EO platforms and their users, it is vital that EO students learn how to effectively develop analyses and share results that engage with the broader EO community. Incorporating opportunities for students to contribute to interdisciplinary collaborative projects can help students develop important skills like recognizing and responding to the values and concerns of potential users or stakeholders. Inclusive hackathons that target stakeholder-derived topics are especially valuable experiences for cultivating knowledge exchange and research engagement (Formosa, 2019; Huppenkothen et al., 2018) and preparing students for the broad user base and audience that typifies the cloud-based EO paradigm. Additionally, substantive engagement with collaborators outside the academic setting is especially valuable in EO education. Collaborations outside of academia are made significantly more accessible through online-based communities like the Earth Engine developers' group, the Forum@Sentinel Hub, the ESRI user community, the Women+ in Geospatial Slack community and #EOChat and #GISChat communities on Twitter and LinkedIn.

Moving beyond the classroom to the multi-disciplinary EO community, the value of collaboratively producing EO science (e.g., co-production; Djenontin & Meadow, 2018) is particularly important to teach and practice to ensure that contributions will be valuable to multiple sectors and disciplines (Davis et al., 2021; Steger et al., 2020). Students are often presented with academic use cases in the classroom, but EO is increasingly used by government agencies, NGOs, businesses, and local stakeholders. Co-production encourages students to become familiar with a broader scope of EO applications, provides partner organizations with EO insight, and keeps the educator up to date on how EO is used in a variety of sectors. Additionally, co-production with local stakeholders can help mitigate scientific colonialism and “parachute” science when scientists carry out research in culturally disparate contexts (Fritz et al., 2017; Kansakar & Hossain, 2016; Serrat-Capdevila et al., 2015; Singeo & Ferguson, 2022; Thapa & Bajracharya, 2017; Thapa et al., 2021).

Experiences like these can be practiced in our classrooms and internships, as exemplified by programs like NASA DEVELOP (NASA DEVELOP, 2022) and the community-based service-learning GIS courses at DePaul University (Table 1). In these courses, students work with Chicago-area community groups that have EO or spatial data analysis needs (Block et al., 2018; Rosing & Hofman, 2010). For example, in the winter quarter of 2022, graduate students utilized NAIP imagery to quantify green space access for a community greening project in Pilsen (Stuhlmacher et al., 2022). Practicing multi-disciplinary collaboration builds skills in cross-disciplinary, cooperative thinking that are making the most of the cloud-based EO paradigm. Moreover, students learn to document and communicate their geospatial workflows and findings, which helps the community groups understand and use the EO deliverables (Owusu et al., 2021). Cloud-based EO platforms can also enable novel ways of sharing findings, whether using interactive visualization or real-time analysis through dashboards, mobile apps, and websites (Nussbaumer Knaflic, 2015).

5. Discussion and Concluding Remarks

The role of teaching and learning in shaping EO science is often under-recognized outside of education circles. We have identified three pillars for teaching EO science with cloud-based platforms that are centered on fundamentals, ethics, and engagement and address novel challenges and considerations that come with having access to global-scale analysis of petabytes of EO data at our fingertips.

The future of EO science depends on how we educate the next generation of practitioners. To fully embrace the challenges and opportunities of cloud computing and EO, we must refine and transform our pedagogical approach.

Traditionally, EO has followed the teaching norms of other natural sciences by presenting the fundamentals in a siloed fashion. The proliferation of EO tools can lead to neglecting ethical considerations and engagement necessary for meaningful advancement. There is a need to create learning environments which model substantial and respectful EO science that works together rather than in opposition.

Collective and communal learning has enriched our commentary article, and we believe it is the way forward for cloud-based EO. Our familiarity with virtual, global collaboration through the Earth Engine Education and broader Earth Engine communities enabled us to transition and remain collaborative even when the COVID-19 pandemic began in March 2020. It will be vital for new cloud-based platforms to cultivate their own communities. In emphasizing a community-based approach from the researcher to the learner to the user, we believe these pillars and principles will emerge even more strongly in the future.

While these pillars may come from the Google Earth Engine Education community, they are equally relevant for teaching with other cloud-based platforms. Additionally, we selected three pillars based on discussions amongst coauthors and this community, but there are certainly more than three issues worth considering, including internet connectivity equity, data science literacy, standardization of geospatial data formats, etc., as we solidify best practices for teaching EO using the cloud. By identifying pillars like these as a community, we hope to instill in students that the most impactful and insightful EO science is not done in isolation but rather through meaningful connections with others interested in addressing shared questions or challenges. Consideration of the pillars above will help educators and students build on the legacy of EO science while leveraging the expanded opportunities and communities of cloud-based computing.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

This Commentary article does not make use of any models, data, or analysis software.

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