AGU ADVANCING EARTH AND SPACE SCIENCES

AGU Advances

COMMENTARY

10.1029/2023AV000894

Peer Review The peer review history for this article is available as a PDF in the Supporting Information.

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.

Correspondence to:

M. A. Crowley,
morgan.crowley@nrcan-rncan.gc.ca

Citation:

Crowley, M. A., Stuhlmacher, M., Trochim, E. D., Van Den Hoek, J., Pasquarella, V. J., Szeto, S. H., et al. (2023). Pillars of cloud-based Earth observation science education. *AGU Advances*, *4*, e2023AV000894. https://doi.org/10.1029/2023AV000894

Received 30 JAN 2023
Accepted 31 MAY 2023

Author Contributions:

Conceptualization: Morgan A. Crowley, Michelle Stuhlmacher, Erin D. Trochim, Jamon Van Den Hoek, Valerie J. Pasquarella, Samapriya Roy, T. C. Chakraborty, Amber Ignatius
Project Administration: Morgan A. Crowley

Pillars of Cloud-Based Earth Observation Science Education

Morgan A. Crowley[1], Michelle Stuhlmacher[2], Erin D. Trochim[3], Jamon Van Den Hoek[4], Valerie J. Pasquarella[5,6], Sabrina H. Szeto[7], Jeffrey T. Howarth[8], Rud Platt[9], Samapriya Roy[10], Beth Tellman[11], T. C. Chakraborty[12], Amber Ignatius[13], Emil Cherrington[14,15], Kel Markert[16], Qiusheng Wu[17], M. D. Madhusudan[18], Timothy Mayer[14,15], Jeffrey A. Cardille[19,20], Tyler Erickson[16], Rebecca Moore[16], Nicholas E. Clinton[16], and David Saah[21,22]

[1]Natural Resources Canada, Canadian Forestry Service - Great Lakes Forestry Centre, Sault Ste Marie, ON, Canada, [2]Department of Geography, DePaul University, Chicago, IL, USA, [3]Alaska Center for Energy and Power, University of Alaska Fairbanks, Fairbanks, AK, USA, [4]College of Earth, Ocean & Atmospheric Sciences, Oregon State University, Corvallis, OR, USA, [5]Harvard Forest, Harvard University, Petersham, MA, USA, [6]Department of Earth & Environment, Boston University, Boston, MA, USA, [7]Sabrina Szeto Consulting, Isen, Germany, [8]Geography Department, Middlebury College, Middlebury, VT, USA, [9]Department of Environmental Studies, Gettysburg College, Gettysburg, PA, USA, [10]University of Arizona, Tucson, AZ, USA, [11]School of Geography, Environment & Development, University of Arizona, Tucson, AZ, USA, [12]Pacific Northwest National Laboratory, Richland, WA, USA, [13]University of North Georgia, Institute for Environmental and Spatial Analysis, Gainesville, GA, USA, [14]University of Alabama in Huntsville, Huntsville, AL, USA, [15]SERVIR Science Coordination Office, NASA Marshall Space Flight Center, Huntsville, AL, USA, [16]Google LLC, Mountain View, CA, USA, [17]Department of Geography and Sustainability, University of Tennessee, Knoxville, TN, USA, [18]National Centre for Biological Sciences, Bangalore, India, [19]Department of Natural Resource Sciences, McGill University, Sainte-Anne-de-Bellevue, QC, Canada, [20]Bieler School of Environment, McGill University, Montreal, QC, Canada, [21]Department of Environmental Science, University of San Francisco, San Francisco, CA, USA, [22]Spatial Informatics Group, Pleasanton, CA, USA

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

Resources: Michelle Stuhlmacher, Erin D. Trochim, Jamon Van Den Hoek, Valerie J. Pasquarella, Sabrina H. Szeto, Jeffrey T. Howarth, Rud Platt, Beth Tellman
Supervision: Nicholas E. Clinton, David Saah
Visualization: Morgan A. Crowley, Michelle Stuhlmacher, Erin D. Trochim, Jamon Van Den Hoek, Rud Platt, Beth Tellman
Writing – original draft: Morgan A. Crowley, Michelle Stuhlmacher
Writing – review & editing: Morgan A. Crowley, Michelle Stuhlmacher, Erin D. Trochim, Jamon Van Den Hoek, Valerie J. Pasquarella, Sabrina H. Szeto, Jeffrey T. Howarth, Rud Platt, Samapriya Roy, Beth Tellman, T. C. Chakraborty, Amber Ignatius, Emil Cherrington, Kel Markert, Qiusheng Wu, M. D. Madhusudan, Timothy Mayer, Jeffrey A. Cardille, Tyler Erickson, Rebecca Moore, Nicholas E. Clinton, David Saah

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.eefabook.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).

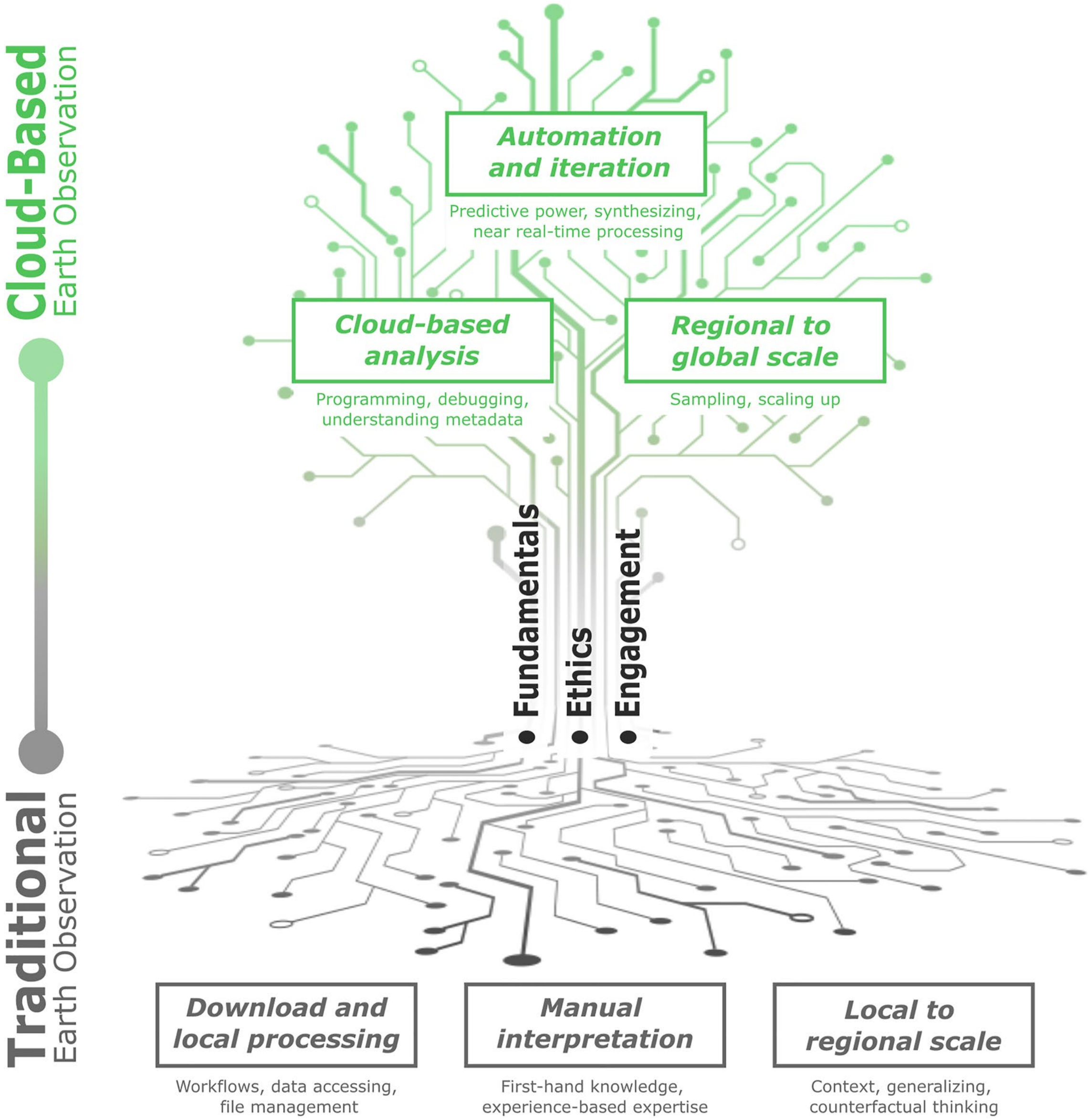

Figure 1. Cloud-based Earth observation (EO) research and teaching grows from soil rich in traditional EO concepts. This conceptual tree diagram illustrates the shift from traditional EO to cloud-based EO where the three pillars of (a) Fundamentals, (b) Ethics, and (c) Engagement form the trunk. Traditional 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 Resolutions and their tradeoffs Sources of bias and error	*We must integrate fundamental EO concepts into our lessons on cloud-based platforms to ensure valid EO contributions*	"*Cloud-based Remote Sensing with Google Earth Engine—Fundamentals and Applications*" *textbook* www.eefabook.org 55 *chapters*, 10,000 *lines of code*, 100 *authors* "*Earth Engine for Education*" *website* https://developers.google.com/earth-engine/tutorials/edu 10 *labs*, 10 *lectures*, 15 *institutions*, 6 *languages*
2	Ethics	Internal External Environmental	*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*	*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*
3	Engagement	Research engagement Local knowledge Open-access and transparent Communication strategy Knowledge exchange	*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*	*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*

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.

Acknowledgments
Authorship order was determined using the CLEAR Lab's Equity in Author Order protocol (Liboiron et al., 2017). PNNL is operated for the Department of Energy by Battelle Memorial Institute under Contract DE-AC05-76RL01830. We would also like to thank those who have contributed and been involved in the Earth Engine Education and broader Geo for Good communities over the years.

References

Aikat, J., Carsey, T. M., Fecho, K., Jeffay, K., Krishnamurthy, A., Mucha, P. J., et al. (2017). Scientific training in the era of Big Data: A new pedagogy for graduate education. *Big Data*, *5*(1), 12–18. https://doi.org/10.1089/big.2016.0014

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2020). Big Data in education: A state of the art, limitations, and future research directions. *International Journal of Educational Technology in Higher Education*, *17*(1), 44. https://doi.org/10.1186/s41239-020-00223-0

Bennett, M. M., Chen, J. K., Alvarez León, L. F., & Gleason, C. J. (2022). The politics of pixels: A review and agenda for Critical Remote Sensing. *Progress in Human Geography*, *46*(3), 729–752. https://doi.org/10.1177/03091325221074691

Block, D. R., Hague, E., Curran, W., & Rosing, H. (2018). Measuring community and University impacts of critical civic geography: Insights from Chicago. *The Professional Geographer*, *70*(2), 284–290. https://doi.org/10.1080/00330124.2017.1366777

Botje, D., Dewan, A., & Chakraborty, T. C. (2022). Comparing coarse-resolution land surface temperature products over Western Australia. *Remote Sensing*, *14*(10), 2296. https://doi.org/10.3390/rs14102296

Brown, C. F., Brumby, S. P., Guzder-Williams, B., Birch, T., Hyde, S. B., Mazzariello, J., et al. (2022). Dynamic World, near real-time global 10 m land use land cover mapping. *Scientific Data*, *9*(1), 251. https://doi.org/10.1038/s41597-022-01307-4

Chakraborty, T., Lee, X., Ermida, S., & Zhan, W. (2021). On the land emissivity assumption and Landsat-derived surface urban heat islands: A global analysis. *Remote Sensing of Environment*, *265*, 112682. https://doi.org/10.1016/j.rse.2021.112682

Chandra, G. R., & Bhatia, S. (2020). Issues and concerns in the field of remote sensing. In *2020 8th international conference on reliability* (pp. 654–658). Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO). https://doi.org/10.1109/ICRITO48877.2020.9197901

Clinton, N. (2018). Earth Engine resources for higher education. Retrieved from https://developers.google.com/earth-engine/tutorials/edu

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing*, *25*(9), 1565–1596. https://doi.org/10.1080/0143116031000101675

Crist, E. P., & Kauth, R. J. (1986). The Tasseled Cap de-mystified. *Photogrammetric Engineering & Remote Sensing*, *52*. Retrieved from https://ntrs.nasa.gov/citations/19860037907

Crowley, M. A., & Cardille, J. A. (2020). Remote Sensing's recent and future contributions to Landscape Ecology. *Current Landscape Ecology Reports*, *5*(3), 45–57. https://doi.org/10.1007/s40823-020-00054-9

Crowley, M. A., Cardille, J. A., White, J. C., & Wulder, M. A. (2019a). Generating intra-year metrics of wildfire progression using multiple open-access satellite data streams. *Remote Sensing of Environment*, *232*, 111295. https://doi.org/10.1016/j.rse.2019.111295

Crowley, M. A., Cardille, J. A., White, J. C., & Wulder, M. A. (2019b). Multi-sensor, multi-scale, Bayesian data synthesis for mapping within-year wildfire progression. *Remote Sensing Letters*, *10*(3), 302–311. https://doi.org/10.1080/2150704X.2018.1536300

Davis, D. S., Buffa, D., Rasolondrainy, T., Creswell, E., Anyanwu, C., Ibirogba, A., et al. (2021). The aerial panopticon and the ethics of archaeological remote sensing in sacred cultural spaces. *Archaeological Prospection*, *28*(3), 305–320. https://doi.org/10.1002/arp.1819

Denis, G., Claverie, A., Pasco, X., Darnis, J.-P., de Maupeou, B., Lafaye, M., & Morel, E. (2017). Towards disruptions in Earth observation? New Earth observation systems and markets evolution: Possible scenarios and impacts. *Acta Astronautica*, *137*, 415–433. https://doi.org/10.1016/j.actaastro.2017.04.034

Djenontin, I. N. S., & Meadow, A. M. (2018). The art of co-production of knowledge in environmental sciences and management: Lessons from international practice. *Environmental Management*, *61*(6), 885–903. https://doi.org/10.1007/s00267-018-1028-3

Dordevic, M., Whitmeyer, S. J., De Paor, D. G., Karabinos, P., Burgin, S., Coba, F., et al. (2016). Leveraging Google Geo tools for interactive STEM education: Insights from the GEODE project, 2016, IN51B-1834. In *Presented at the AGU Fall Meeting*.

ESA. (N.D.). Sentinel-2. Retrieved from https://sentinel.esa.int/web/sentinel/missions/sentinel-2

Evans, M. J., & Malcom, J. W. (2021). Supporting habitat conservation with automated change detection in Google Earth Engine. *Conservation Biology*, *35*(4), 1151–1161. https://doi.org/10.1111/cobi.13680

Fields, S. (2022). Decolonizing the map: Creating the Indigenous Mapping Collective. Retrieved from www.pbs.org/education/blog/decolonizing-the-map-creating-the-indigenous-mapping-collective

Firpi, O. A. A. (2016). Satellite data for all? Review of Google Earth Engine for archaeological remote sensing. *Internet Archaeology*, (42). https://doi.org/10.11141/ia.42.10

Fisher, M., Fradley, M., Flohr, P., Rouhani, B., & Simi, F. (2021). Ethical considerations for remote sensing and open data in relation to the endangered archaeology in the Middle East and North Africa project. *Archaeological Prospection*, *28*(3), 279–292. https://doi.org/10.1002/arp.1816

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, *80*(1), 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

Forehand, M. (2005). Bloom's taxonomy: Original and revised. In *Emerging perspectives on learning, teaching, and technology*. Retrieved from http://projects.coe.uga.edu/epltt

Formosa, D. (2019). The subtle sexism of hackathons. Retrieved from www.fastcompany.com/90301054/the-subtle-sexism-of-hackathons

Frankel-Reed, J. (2018). Reflecting on a decade of collaboration between NASA and USAID: Deriving value from space for international development. In *Yearbook on space policy 2016* (pp. 163–174). Springer.

Fritz, S., Fonte, C. C., & See, L. (2017). The role of citizen science in Earth observation. *Remote Sensing*, *9*(4), 357. https://doi.org/10.3390/rs9040357

Gentemann, C., Ivey, Y., Crawford, S., Baynes, K., Murphy, K., Ward, K., et al. (2021). NASA open-source science initiative: Transform to OPen science (TOPS). *Zenodo*. https://doi.org/10.5281/zenodo.5621674

Gibson, D. C., & Ifenthaler, D. (2017). Preparing the next generation of education researchers for Big Data in higher education. In B. Kei Daniel (Ed.), *Big data and learning analytics in higher education: Current theory and practice* (pp. 29–42). Springer International Publishing. https://doi.org/10.1007/978-3-319-06520-5_4

Goldblatt, R., Stuhlmacher, M. F., Tellman, B., Clinton, N., Hanson, G., Georgescu, M., et al. (2018). Using Landsat and nighttime lights for supervised pixel-based image classification of urban land cover. *Remote Sensing of Environment*, *205*, 253–275. https://doi.org/10.1016/j.rse.2017.11.026

Gomes, V. C. F., Queiroz, G. R., & Ferreira, K. R. (2020). An overview of platforms for big Earth observation data management and analysis. *Remote Sensing*, *12*(8), 1253. https://doi.org/10.3390/rs12081253

Gómez, C., White, J. C., & Wulder, M. A. (2016). Optical remotely sensed time series data for land cover classification: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *116*, 55–72. https://doi.org/10.1016/j.isprsjprs.2016.03.008

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-*, *3*(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314

Harris, R. (2013). Reflections on the value of ethics in relation to Earth observation. *International Journal of Remote Sensing*, *34*(4), 1207–1219. https://doi.org/10.1080/01431161.2012.718466

Haywood, J. M., Osborne, S. R., & Abel, S. J. (2004). The effect of overlying absorbing aerosol layers on remote sensing retrievals of cloud effective radius and cloud optical depth. *Quarterly Journal of the Royal Meteorological Society*, *130*(598), 779–800. https://doi.org/10.1256/qj.03.100

Hey, A. J., Tansley, S., Tolle, K. M., & others (2009). *The fourth paradigm: Data-intensive scientific discovery* (Vol. 1). Microsoft Research.

Hsu, H.-P., Tsai, B.-W., & Chen, C.-M. (2018). Teaching topographic map skills and geomorphology concepts with Google Earth in a one-computer classroom. *Journal of Geography*, *117*(1), 29–39. https://doi.org/10.1080/00221341.2017.1346138

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, *83*(1), 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2

Huppenkothen, D., Arendt, A., Hogg, D. W., Ram, K., VanderPlas, J. T., & Rokem, A. (2018). Hack weeks as a model for data science education and collaboration. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(36), 8872–8877. https://doi.org/10.1073/pnas.1717196115

Kansakar, P., & Hossain, F. (2016). A review of applications of satellite Earth observation data for global societal benefit and stewardship of planet Earth. *Space Policy*, *36*, 46–54. https://doi.org/10.1016/j.spacepol.2016.05.005

Kennedy, R. E., Townsend, P. A., Gross, J. E., Cohen, W. B., Bolstad, P., Wang, Y. Q., & Adams, P. (2009). Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects. *Remote Sensing of Environment*, *113*(7), 1382–1396. https://doi.org/10.1016/j.rse.2008.07.018

Kennedy, R. E., Yang, Z., Gorelick, N., Braaten, J., Cavalcante, L., Cohen, W. B., & Healey, S. (2018). Implementation of the LandTrendr algorithm on Google Earth Engine. *Remote Sensing*, *10*(5), 691. https://doi.org/10.3390/rs10050691

Kent, A. (2017). Trust me, I'ma cartographer: Post-truth and the problem of acritical cartography. *The Cartographic Journal*, *54*(3), 193–195. https://doi.org/10.1080/00087041.2017.1376489

Kochupillai, M. (2021). Outline of a novel approach for identifying ethical issues in early stages of AI4EO research. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS* (pp. 1165–1168). https://doi.org/10.1109/IGARSS47720.2021.9553727

Kopp, S., Becker, P., Doshi, A., Wright, D. J., Zhang, K., & Xu, H. (2019). Achieving the full vision of Earth observation data cubes. *Data*, *4*(3), 94. https://doi.org/10.3390/data4030094

Kumar, L., & Mutanga, O. (2018). Google Earth Engine applications since inception: Usage, trends, and potential. *Remote Sensing*, *10*(10), 1509. https://doi.org/10.3390/rs10101509

Li, Z., Gurgel, H., Xu, L., Yang, L., & Dong, J. (2022). Improving dengue forecasts by using geospatial big data analysis in Google Earth Engine and the historical dengue information-aided Long short term memory modeling. *Biology*, *11*(2), 169. https://doi.org/10.3390/biology11020169

Liang, J., Gong, J., & Li, W. (2018). Applications and impacts of Google Earth: A decadal review (2006–2016). *ISPRS Journal of Photogrammetry and Remote Sensing*, *146*, 91–107. https://doi.org/10.1016/j.isprsjprs.2018.08.019

Liboiron, M., Ammendolia, J., Winsor, K., Zahara, A., Bradshaw, H., Melvin, J., et al. (2017). Equity in author order: A feminist laboratory's approach. *Catalyst: Feminism, Theory, Technoscience*, *3*(2), 1–17. https://doi.org/10.28968/cftt.v3i2.28850

Lisle, R. J. (2006). Google Earth: A new geological resource. *Geology Today*, *22*(1), 29–32. https://doi.org/10.1111/j.1365-2451.2006.00546.x

Liss, B., Howland, M. D., & Levy, T. E. (2017). Testing Google Earth Engine for the automatic identification and vectorization of archaeological features: A case study from Faynan, Jordan. *Journal of Archaeological Science: Reports*, *15*, 299–304. https://doi.org/10.1016/j.jasrep.2017.08.013

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J. H., Ogata, H., et al. (2020). Challenges and future directions of Big Data and artificial intelligence in education. *Frontiers in Psychology*, *11*, 580820. https://doi.org/10.3389/fpsyg.2020.580820

Mahood, A. L., Joseph, M. B., Spiers, A., Koontz, M. J., Ilangakoon, N., Solvik, K., et al. (2021). Ten simple rules for working with high resolution remote sensing data. https://doi.org/10.31219/osf.io/kehqz

Masek, J. G., Wulder, M. A., Markham, B., McCorkel, J., Crawford, C. J., Storey, J., & Jenstrom, D. T. (2020). Landsat 9: Empowering open science and applications through continuity. *Remote Sensing of Environment*, *248*, 111968. https://doi.org/10.1016/j.rse.2020.111968

Mayer, T. (2020). How the SERVIR program connects space to village. Retrieved from www.servirglobal.net/Global/Articles/Article/2735/How-the-SERVIR-program-connects-space-to-village

Mejía Ávila, D., Sánchez Agámez, C., & Soto Barrera, V. C. (2021). Developing digital lessons to integrate social science teaching in Colombia using Google Earth. *International Research in Geographical & Environmental Education*, *30*(2), 112–131. https://doi.org/10.1080/10382046.2020.1766225

Minner, J., & Micklow, A. C. (2016). Lessons from technology: From a national survey of educators to participant observations from curriculum development for a new equity app. Retrieved from www.researchgate.net/profile/Jennifer-Minner-2/publication/309591740_Lessons_from_Technology_From_a_National_Survey_of_Educators_to_Participant_Observations_from_Curriculum_Development_for_a_New_Equity_App/links/5818cd6208ae50812f5dd1ac/Lessons-from-Technology-From-a-National-Survey-of-Educators-to-Participant-Observations-from-Curriculum-Development-for-a-New-Equity-App.pdf

Monet, J., & Greene, T. (2012). Using Google Earth and satellite imagery to foster place-based teaching in an introductory physical geology course. *Journal of Geoscience Education*, *60*(1), 10–20. https://doi.org/10.5408/10-203.1

Monmonier, M. (2018). *How to lie with maps* (3rd ed.). University of Chicago Press.

NASA ARSET. (2022). About ARSET | NASA applied sciences. Retrieved from http://appliedsciences.nasa.gov/what-we-do/capacity-building/arset/about-arset

NASA DEVELOP. (2022). About DEVELOP | NASA applied sciences. Retrieved from http://appliedsciences.nasa.gov/what-we-do/capacity-building/develop

Nelson, T. A., Goodchild, M. F., & Wright, D. J. (2022). Accelerating ethics, empathy, and equity in geographic information science. *Proceedings of the National Academy of Sciences of the United States of America*, *119*(19), e2119967119. https://doi.org/10.1073/pnas.2119967119

Nussbaumer Knaflic, C. (2015). *Storytelling with data: A data visualization guide for business professionals*. John Wiley & Sons. Retrieved from www.google.ca/books/edition/Storytelling_with_Data/IheRCgAAQBAJ?hl=en&gbpv=1&dq=Nussbaumer+Knaflic+storytelling+with+data&printsec=frontcover

Owusu, M., Kuffer, M., Belgiu, M., Grippa, T., Lennert, M., Georganos, S., & Vanhuysse, S. (2021). Geo-ethics in slum mapping. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS* (pp. 5700–5703). https://doi.org/10.1109/IGARSS47720.2021.9553570

Patterson, T. C. (2007). Google Earth as a (not just) geography education tool. *Journal of Geography*, *106*(4), 145–152. https://doi.org/10.1080/00221340701678032

Prados, A. I., Carleton-Hug, A., Gupta, P., Mehta, A., Blevins, B., Schmidt, C., et al. (2019). Impact of the ARSET program on use of remote-sensing data. *ISPRS International Journal of Geo-Information*, *8*(6), 261. https://doi.org/10.3390/ijgi8060261

Ratinen, I., & Keinonen, T. (2011). Student-teachers' use of Google Earth in problem-based geology learning. *International Research in Geographical & Environmental Education*, *20*(4), 345–358. https://doi.org/10.1080/10382046.2011.619811

Rosing, H., & Hofman, N. G. (2010). Notes from the field: Service learning and the development of multidisciplinary community-based research initiatives. *Journal of Community Practice*, *18*(2–3), 213–232. https://doi.org/10.1080/10705422.2010.490101

RUS Copernicus. (2022). Training – Research and user support. Retrieved from https://rus-copernicus.eu/portal/the-rus-offer/training/

Sawaguchi, T. (2018). Geoscience education using a brand-new Google Earth. *Terrae Didatica*, *14*(4), 415–416. https://doi.org/10.20396/td.v14i4.8654165

Searby, N. D., Irwin, D., & Kim, T. (2019). SERVIR: Leveraging the expertise of a space agency and a development agency to increase impact of Earth observation in the developing world. In *International Astronautical Congress (TAC)*.

Sentinel Hub. (2022). Education. Retrieved from www.sentinel-hub.com/explore/education/

Serrat-Capdevila, A., Fonseca, C., Valdes, J. B., Durcik, M., & Mithieu, F. (2015). Characterizing decision-making for Earth observation applications in water management, 2015, PA31A-2146. In *Presented at the AGU Fall Meeting*.

Shook, E., Bowlick, F. J., Kemp, K. K., Ahlqvist, O., Carbajeles-Dale, P., DiBiase, D., et al. (2019). Cyber literacy for GIScience: Toward formalizing geospatial computing education. *The Professional Geographer*, *71*(2), 221–238. https://doi.org/10.1080/00330124.2018.1518720

SilvaCarbon. (2022). eLearning Modules. Retrieved from www.silvacarbon.org

Singeo, A., & Ferguson, C. E. (2022). Lessons from Palau to end parachute science in international conservation research. *Conservation Biology*, e13971. https://doi.org/10.1111/cobi.13971

Slonecker, E. T., Shaw, D. M., & Lillesand, T. M. (1998). Emerging legal and ethical issues in advanced remote sensing technology. *Photogrammetric Engineering & Remote Sensing*, *64*(6), 589–595.

Steger, C., Nigussie, G., Alonzo, M., Warkineh, B., Van Den Hoek, J., Fekadu, M., et al. (2020). Knowledge coproduction improves understanding of environmental change in the Ethiopian highlands. *Ecology and Society*, *25*(2), art2. https://doi.org/10.5751/ES-11325-250202

Stehman, S. V. (1997). Selecting and interpreting measures of thematic classification accuracy. *Remote Sensing of Environment*, *62*(1), 77–89. https://doi.org/10.1016/S0034-4257(97)00083-7

Stehman, S. V., & Czaplewski, R. L. (1998). Design and analysis for thematic map accuracy assessment: Fundamental principles. *Remote Sensing of Environment*, *64*(3), 331–344. https://doi.org/10.1016/S0034-4257(98)00010-8

Stuhlmacher, M., Kim, Y., & Kim, J. E. (2022). The role of green space in Chicago's gentrification. *Urban Forestry and Urban Greening*, *71*, 127569. https://doi.org/10.1016/j.ufug.2022.127569

Szeto, S. H. (2022). Fostering user-driven learning communities in-person and virtually: Examples from Earth Engine meetups. In *Poster presented at the Living Planet Symposium*.

Thapa, R. B., & Bajracharya, B. (2017). Capacity building on the use of Earth observation for bridging the gaps between science and policy, 2017, PA13E-06. In *Presented at the AGU Fall Meeting*.

Thapa, R. B., Tripathi, P., Matin, M. A., Bajracharya, B., & Sandoval, B. E. H. (2021). *Strengthening the capacity on geospatial information technology and Earth observation applications* (Vol. 269). A Decade of Experience from SERVIR.

Tomlin, C. D. (2013). *GIS and cartographic modeling*. Esri Press.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, *8*(2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0

Tulbure, M. G., Hostert, P., Kuemmerle, T., & Broich, M. (2022). Regional matters: On the usefulness of regional land-cover datasets in times of global change. *Remote Sensing in Ecology and Conservation*, *8*(3), 272–283. https://doi.org/10.1002/rse2.248

UCGIS. (2016). GIS&T body of knowledge. Retrieved from https://gistbok.ucgis.org/

USDA FSA. (N.D.). National agriculture imagery program (NAIP). https://doi.org/10.5066/F7QN651G

USGS. (2022). *Landsat 9 data users handbook*. (No. Version 1). EROS, US Geological Survey. Retrieved from www.usgs.gov/media/files/landsat-9-data-users-handbook

Van Den Hoek, J., Smith, A. C., Hurni, K., Saksena, S., & Fox, J. (2021). Shedding new light on mountainous forest growth: A cross-scale evaluation of the effects of topographic illumination correction on 25 years of forest cover change across Nepal. *Remote Sensing*, *13*(11), 2131. https://doi.org/10.3390/rs13112131

Wagemann, J., Fierli, F., Mantovani, S., Siemen, S., Seeger, B., & Bendix, J. (2022). Five guiding principles to make Jupyter notebooks fit for Earth observation data education. *Remote Sensing*, *14*(14), 3359. https://doi.org/10.3390/rs14143359

Wagemann, J., Siemen, S., Seeger, B., & Bendix, J. (2021). A user perspective on future cloud-based services for Big Earth Data. *International Journal of Digital Earth*, *14*(12), 1758–1774. https://doi.org/10.1080/17538947.2021.1982031

Wetherholt, W. A., & Rundquist, B. C. (2010). A survey of ethics content in college-level remote sensing courses in the United States. *Journal of Geography*, *109*(2), 75–86. https://doi.org/10.1080/00221341.2010.482161

Woodcock, C. E., Allen, R., Anderson, M., Belward, A., Bindschadler, R., Cohen, W., et al. (2008). Free access to Landsat imagery. *Science*, *320*(5879), 1011. https://doi.org/10.1126/science.320.5879.1011a

Wulder, M. A., Coops, N. C., Roy, D. P., White, J. C., & Hermosilla, T. (2018). Land cover 2.0. *International Journal of Remote Sensing*, *39*(12), 4254–4284. https://doi.org/10.1080/01431161.2018.1452075

Xiang, X., & Liu, Y. (2017). Understanding 'change' through spatial thinking using Google Earth in secondary geography. *Journal of Computer Assisted Learning*, *33*(1), 65–78. https://doi.org/10.1111/jcal.12166

Xie, Z., Phinn, S. R., Game, E. T., Pannell, D. J., Hobbs, R. J., Briggs, P. R., & McDonald-Madden, E. (2019). Using Landsat observations (1988–2017) and Google Earth Engine to detect vegetation cover changes in rangelands - A first step towards identifying degraded lands for conservation. *Remote Sensing of Environment*, *232*, 111317. https://doi.org/10.1016/j.rse.2019.111317

Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, *27*(14), 3025–3033. https://doi.org/10.1080/01431160600589179

Yang, C., Yu, M., Li, Y., Hu, F., Jiang, Y., Liu, Q., et al. (2019). Big Earth Data analytics: A survey. *Big Earth Data*, *3*(2), 83–107. https://doi.org/10.1080/20964471.2019.1611175

Young, N. E., Anderson, R. S., Chignell, S. M., Vorster, A. G., Lawrence, R., & Evangelista, P. H. (2017). A survival guide to Landsat preprocessing. *Ecology*, *98*(4), 920–932. https://doi.org/10.1002/ecy.1730

Zhao, B., Zhang, S., Xu, C., Sun, Y., & Deng, C. (2021). Deep fake geography? When geospatial data encounter artificial intelligence. *Cartography and Geographic Information Science*, *48*(4), 338–352. https://doi.org/10.1080/15230406.2021.1910075

Zhong, Z., Hu, J., Tan, G., & Sun, C. (2009). The application of Google Earth in education. In *2009 first international workshop on education technology and computer science* (Vol. 1, pp. 10–13). https://doi.org/10.1109/ETCS.2009.10

Zhu, Z., Wulder, M. A., Roy, D. P., Woodcock, C. E., Hansen, M. C., Radeloff, V. C., et al. (2019). Benefits of the free and open Landsat data policy. *Remote Sensing of Environment*, *224*, 382–385. https://doi.org/10.1016/j.rse.2019.02.016