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Authors
Ordway, Elsa M
Elmore, Andrew J
Kolstoe, Sonja
et al.

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SPECIAL FEATURE:
HARNESSING THE NEON DATA REVOLUTION

Leveraging the NEON Airborne Observation Platform for socio-environmental systems research

Elsa M. Ordway,[1,†] Andrew J. Elmore,[2,3] Sonja Kolstoe,[4,5] John E. Quinn,[6] Rachel Swanwick,[2] Megan Cattau,[7] Dylan Taillie,[3] Steven M. Guinn,[3] K. Dana Chadwick,[8] Jeff W. Atkins,[9] Rachael E. Blake,[2] Melissa Chapman,[10] Kelly Cobourn,[11] Tristan Goulden,[12] Matthew R. Helmus,[13] Kelly Hondula,[2,12] Carrie Hritz,[2] Jennifer Jensen,[14] Jason P. Julian,[14] Yusuke Kuwayama,[15] Vijay Lulla,[16] Donal O'Leary,[12] Donald R. Nelson,[17] Jonathan P. Ocón,[18] Stephanie Pau,[19] Guillermo E. Ponce-Campos,[20] Carlos Portillo-Quintero,[21] Narcisa G. Pricope,[22] Rosanna G. Rivero,[23] Laura Schneider,[24] Meredith Steele,[25] Mirela G. Tulbure,[26] Matthew A. Williamson,[7] and Cyril Wilson[27]

[1]*Department of Organismic and Evolutionary Biology, Harvard University, 26 Oxford Street, Cambridge, Massachusetts 02138 USA*
[2]*National Socio-Environmental Synthesis Center, University of Maryland, 1 Park Place Suite 300, Annapolis, Maryland 21401 USA*
[3]*Appalachian Laboratory, University of Maryland Center for Environmental Science, 301 Braddock Road, Frostburg, Maryland 21532 USA*
[4]*Department of Economics and Finance, Department of Environmental Studies, Salisbury University, 1101 Camden Avenue, Salisbury, Maryland 21801 USA*
[5]*USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon 97205 USA*
[6]*Department of Biology, Furman University, 3300 Poinsett Hwy, Greenville, South Carolina 29613 USA*
[7]*Human Environment Systems, Boise State University, Boise, Idaho 83712 USA*
[8]*Department of Earth System Science, Stanford University, 367 Panama Street, Stanford, California 94305 USA*
[9]*Department of Biology, Virginia Commonwealth University, 1000 W. Cary Street, Richmond, Virginia 23284 USA*
[10]*Department of Environmental Science, Policy, and Management, University of California Berkeley, 130 Hilgard Way, Berkeley, California 94720 USA*
[11]*Department of Forest Resources and Environmental Conservation, Virginia Tech, 310 W Campus Drive, Blacksburg, Virginia 24061 USA*
[12]*Battelle, National Ecological Observatory Network (NEON), 1685 38th Street, Boulder, Colorado, USA*
[13]*Integrative Ecology Lab, Center for Biodiversity, Department of Biology, Temple University, Philadelphia, Pennsylvania 19122 USA*
[14]*Department of Geography, Texas State University, San Marcos, Texas 78666 USA*
[15]*School of Public Policy, University of Maryland, Baltimore, Maryland 21250 USA*
[16]*Department of Geography, Indiana University-Purdue University Indianapolis, Indianapolis, Indiana 46202 USA*
[17]*Department of Anthropology, University of Georgia, 250 Baldwin Hall, Athens, Georgia 30606 USA*
[18]*Department of Geography, University of California, Los Angeles, 1255 Bunche Hall, Los Angeles, California 90095 USA*
[19]*Department of Geography, Florida State University, Tallahassee, Florida 32306 USA*
[20]*School of Natural Resources and the Environment, University of Arizona, 1064 E Lowell St, Tucson, Arizona 85721 USA*
[21]*Department of Natural Resources Management, Texas Tech University, Lubbock, Texas 79409 USA*
[22]*Department of Earth and Ocean Sciences, University of North Carolina Wilmington, 601 S. College Road, Wilmington, North Carolina 28403 USA*
[23]*College of Environment and Design, University of Georgia, 285 South Jackson Street, Athens, Georgia 30602 USA*
[24]*Department of Geography, Rutgers University, LSH Livingston Campus, Piscataway, New Jersey 08854 USA*
[25]*School of Plant and Environmental Sciences, Virginia Tech, 185 Ag Quad Ln, Blacksburg, Virginia 24061 USA*
[26]*Center for Geospatial Analytics, Department of Forestry and Environmental Resources, North Carolina State University, Raleigh, North Carolina 27695 USA*
[27]*Department of Geography & Anthropology, University of Wisconsin-Eau Claire, 105 Garfield Avenue, Eau Claire, Wisconsin 54702 USA*

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Abstract. During the 21st century, human–environment interactions will increasingly expose both systems to risks, but also yield opportunities for improvement as we gain insight into these complex, coupled systems. Human–environment interactions operate over multiple spatial and temporal scales, requiring large data volumes of multi-resolution information for analysis. Climate change, land-use change, urbanization, and wildfires, for example, can affect regions differently depending on ecological and socioeconomic structures. The relative scarcity of data on both humans and natural systems at the relevant extent can be prohibitive when pursuing inquiries into these complex relationships. We explore the value of multitemporal, high-density, and high-resolution LiDAR, imaging spectroscopy, and digital camera data from the National Ecological Observatory Network's Airborne Observation Platform (NEON AOP) for Socio-Environmental Systems (SES) research. In addition to providing an overview of NEON AOP datasets and outlining specific applications for addressing SES questions, we highlight current challenges and provide recommendations for the SES research community to improve and expand its use of this platform for SES research. The coordinated, nationwide AOP remote sensing data, collected annually over the next 30 yr, offer exciting opportunities for cross-site analyses and comparison, upscaling metrics derived from LiDAR and hyperspectral datasets across larger spatial extents, and addressing questions across diverse scales. Integrating AOP data with other SES datasets will allow researchers to investigate complex systems and provide urgently needed policy recommendations for socio-environmental challenges. We urge the SES research community to further explore questions and theories in social and economic disciplines that might leverage NEON AOP data.

Key words: CHANS; imaging spectroscopy; LiDAR; NEON AOP; remote sensing; socio-ecological systems; socio-environmental systems; Special Feature: Harnessing the NEON Data Revolution.

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† **E-mail:** elsa.ordway@gmail.com

INTRODUCTION

Pressing societal challenges at the intersection of human and natural systems, such as climate change, food insecurity, and biodiversity loss, have made the need to holistically analyze socio-environmental problems more relevant than ever before. Yet, we are still only beginning to understand the complexity of socio-environmental systems (SES, also referred to as socio-ecological systems and coupled human–natural systems). Although the National Ecological Observatory Network's Airborne Observation Platform (NEON AOP) was designed for ecological analysis, an in-depth exploration of how AOP datasets can serve a similar function for SES research will benefit the broader research community, advance future data collection initiatives, and potentially inform policy and decision-making efforts. The unique pairing of high-density and high-resolution LiDAR and imaging spectroscopy data collected concurrently for the next three decades across a large-scale network of over 81 sites likely has large, untapped potential to contribute to addressing SES research questions. Here, we briefly review the use of remote sensing data in SES research, provide an overview of the NEON AOP datasets, and outline specific data opportunities and applications for addressing SES questions. We also highlight current challenges and limitations and provide recommendations for actions that can be taken by the SES research community now to improve and expand the use of this platform for SES research in the decades to come. Given that the scoping of NEON included human-modified ecosystems, we aim to realize and expand upon that potential by highlighting existing and future SES research opportunities that could leverage the NEON AOP.

The most pressing SES questions—related to climate change impacts and feedbacks, land-use change and legacy effects, habitat loss, ecosystem services, and sustainability and development efforts—are all embedded within complex systems that are dynamic in space and time (Norberg and Cumming 2008, Kramer et al. 2017). SES research recognizes linkages and feedbacks between human and natural systems as interacting and nested across spatial, temporal, and organizational scales (Liu et al. 2007, Ostrom 2009, Turner et al. 2016, Martín-López et al. 2017). Although the appropriate scale depends on the question and study system (Levin 1992), alignment in scale across systems and identification of spatial and temporal boundaries is essential (Martín-López et al. 2017). To fully comprehend feedbacks between system components, data are required at appropriate spatial, temporal, and socioeconomic scales of interest (Cumming et al. 2006). A variety of concepts, data, and methods are necessary to effectively address the breadth of SES, with shifting boundaries across processes and scales, and numerous fields of expertise (Michener et al. 2001). Remote sensing data provide valuable information on ecosystem properties as well as socioeconomic metrics and indicators (e.g., Jean et al. 2016), with the recognition that at each level of spatiotemporal resolution (grain) and extent, and novel attributes and interactions are potentially revealed. However, owing to data limitations and mismatch, scale alignment and resolution can be a barrier to advancing lines of SES inquiry and aligning research efforts with policy interventions (Solís et al. 2017).

To date, a scale often missing in SES research is high-resolution, spatially continuous, sampled repeatedly over long periods of time. Mismatches between the socio-environmental process and data collection have historically limited analyses to snapshot characterizations of impact, rather than allowing for the evaluation of complex feedback processes between humans and the environment. In addition, rapidly advancing remote sensing technologies offer opportunities to address these data challenges and further SES research inquiry with unique datasets. Specifically, state-of-the-art remote sensing data from the NEON AOP (Kampe 2010), coupled with other efforts and datasets, can advance existing and future research efforts to help address pressing SES questions. Two technologies that represent a threshold change in how we measure ecosystem structure and function are hyperspectral imaging spectroscopy and light detection and ranging (LiDAR). LiDAR and imaging spectroscopy enable the measurement of three-dimensional structure and hyperspectral reflectance (and thus biochemical properties), respectively. Mounted on an appropriate platform (unmanned aircraft system, aircraft, satellite), LiDAR and imaging spectroscopy data can be collected at a chosen scale that is relevant for a given SES research question.

Because these technologies advanced relatively recently and are costly to employ, a rich temporal and spatial archive of data similar to that provided by other remote sensing datasets (e.g., the Landsat series of satellites, in operation since the mid-1980s) remains lacking. However, with the initiation of the NEON AOP, which integrates these sensors onto a single airborne platform and is designed to run for 30 yr, and a growing constellation of large-scale networks, new opportunities are beginning to enable researchers to overcome scaling challenges. NEON AOP data offer high spatial resolution information repeated regularly (minimum of once per year) at preselected sites that cover regional scales (~100 km^2). These data include LiDAR- and hyperspectral-derived measurements of ecosystem structure and function (e.g., vegetation height or leaf nitrogen concentrations), which have the potential to be of great value to SES researchers, despite the ecological focus of the network's design. One specific opportunity of NEON AOP data lies in the capacity to move beyond remotely sensed measures of land cover to incorporate measures of biodiversity more directly (Rissman and Gillon 2017). A particular benefit of the 30-yr time series of data will be the ability to explore feedbacks, which is central to SES studies.

As an example, remote sensing is increasingly used to improve understanding of the role of people in changing fire regimes (e.g., Dennis et al. 2005, Balch et al. 2017, Cattau et al. 2020). Both LiDAR and hyperspectral data offer particularly exciting promise for mapping and understanding fire severity, ecosystem recovery (Dennison and Roberts 2009, Veraverbeke et al. 2018), and fuel hazards—including the role of invasive species (Varga and Asner 2008, Price and Gordon 2016). NEON AOP data enable the examination of fire-related changes in vertical vegetation structure (Kane et al. 2014, McCarley et al. 2017), carbon storage (Sato et al. 2016), and species composition (Scholl et al. 2020). Still, relatively few datasets exist that allow for the evaluation of how changing fire regimes are altering human communities at continental scales. How do large, post-fire burned areas influence water quantity and quality or local land surface temperatures? How do post-fire changes in vegetation structure in mountain forests influence downslope communities or recreational activity? Critically, these human–nature interactions linked to changes in ecosystem structure and function, land-use change, watershed management, and causes and consequences of wildfire activity vary heterogeneously in space and time and operate over large spatial scales, requiring large data volumes of high-resolution information at national and regional scales. The lack of availability of these types of data has prohibited inquiries in the past.

Existing SES Research and Remote Sensing

Social–environmental scholarship has foundational theories that address how groups and societies change over time. Important analytical challenges emerge from system attributes that include social and environmental heterogeneity at multiple levels (Norberg and Cumming 2008), multi-directional networks of interactions leading to nonlinear dynamics (Liu et al. 2007), and localized, case-specific factors (Scoones 2009). Since the seminal book, *People and Pixels* (Liverman et al. 1998), the rapid growth of remote sensing technologies to explore SES questions has contributed to theoretical development in ways not previously possible. While most research has focused on land-use and land-cover mapping and change detection (Pricope et al. 2019), SES researchers continue to explore new applications, including epidemiology and environmental health sciences (Meentemeyer et al. 2012), fire regimes (Dennis et al. 2005), food security (Bakhtsiyarava et al. 2018), compliance and enforcement of environmental laws (Purdy 2010), and the continued influence of land-use legacies (Maezumi et al. 2018). Remote sensing technologies are increasingly being combined with traditional and innovative social science methods to develop and test SES hypotheses at multiple spatial and temporal scales, understand emergent system behavior, and advance theories. Importantly, remote sensing enables direct measurement or estimation of proxy measurements of variables of interest across large areas, including difficult-to-access regions where ground-based measurements and data gathering can be costly (e.g., mapping poverty indicators in sub-Saharan Africa). Novel measurement capabilities are emerging from the integration of remote sensing data with ancillary socioeconomic information.

Increasingly, social scientists are adopting new opportunities for environmental and social measurement afforded by remote sensing in combination with traditional and novel sources of SES data, though generally not at the spatial and temporal resolutions associated with AOP data. To our knowledge, although LiDAR and high-resolution RGB data have been used to examine social systems, including for flood risk mapping (Sole et al. 2008) and to develop poverty indicators (e.g., Jean et al. 2016), neither LiDAR nor imaging spectroscopy has been widely used to address integrated social–ecological systems questions (but see Niemiec et al. 2018). Existing research efforts do, however, offer the foundations for expanding SES research methods to leverage high-resolution LiDAR and hyperspectral data.

Remote sensing data have long been utilized in diverse social science disciplines, including sociology (Blumberg and Jacobson 1997), anthropology (Isager and Broge 2007), human health (Beck et al. 2000), political ecology (Zimmerer and Bassett 2003), and archeology (Forte and Campana 2016). Nighttime lights data are one example of a remotely sensed product increasingly utilized across disciplines. These data are used to estimate energy consumption, population density, fisheries, shipping and trade networks, forest fires, natural disaster impacts, and linking emissions to human and ecosystem health (Huang et al. 2014). Donaldson and Storeygard (2016) summarize economic remote sensing applications that use topographic, agricultural and urban land-use, forests, pollution monitoring, climate and weather, and nighttime lights data. They identify several benefits of satellite data for socioeconomic analysis, including the collection of cross-sectional and time-series data at low cost, higher spatial resolution than traditional economic data, and wider geographic coverage.

Additional technological innovations provide observations of human behavior that can be paired with spatial data. Examples include volunteered geographic information data sources like community science projects (e.g., Kolstoe et al. 2018), spatially explicit complaints of land-use violations (Heider et al. 2018), and social media data that can be used to gather information about when and where people visit certain locations (Teles da Mota and Pickering 2020) and the value of cultural ecosystem services (Keeler et al. 2015, Kolstoe et al. 2018). These data can also be combined with spatial data and forecasts to estimate welfare effects based on forecasted land cover and climate change (Kolstoe et al. 2018).

Although economic studies are increasingly using remotely sensed data, applications at a spatial resolution approaching AOP data remain relatively rare. Marx et al. (2019) and Vernon Henderson et al. (2016) use 0.5-m resolution satellite imagery and aerial photography to identify individual buildings and attributes, such as footprint and roof type, to understand changes in housing quality and land use in Nairobi, Kenya. Bollinger et al. (2020) use remote sensing data on landscape greenness in Phoenix, Arizona, USA, at a three-inch resolution to determine whether there are peer effects in residential water conservation. In addition, Jean et al. (2016) modeled economic livelihood with linked survey and satellite data to track and target indicators of poverty. The high-resolution, broad coverage, and unique combination of imaging spectroscopy and LiDAR sensors on the AOP offer an opportunity to build on and expand these applications and yield novel research opportunities in SES science.

AOP Data Opportunities

The NEON AOP collects remotely sensed data within designated flight boxes or footprints, referred to here as landscapes, that cover a range of land cover types. Many of the AOP landscapes incorporate human activity, including agricultural and developed areas, although landscapes vary in the proportion of these land-cover types (Fig. 1). The AOP landscapes are diverse, not only in terms of land cover and land use, but also in the people who live there and/or manage the land. Sampling the American Communities Survey (USCB 2020*a*) tract-level data reveals that nearly 1 million people live in census tracts that overlap the AOP landscapes. The planned long-term repeat acquisition of these data is critically important, with wide recognition that long-term data increase in value as the temporal archive develops. The AOP flight boxes are associated with (but spatially more extensive than) the NEON ground-based sites where ecological data are collected and were designed to achieve comprehensive representation of ecoclimatic domains in the United States, including Puerto Rico (Fig. 2).

Three features of the AOP make the associated datasets unique and a potentially valuable contribution to SES research. First are the data themselves. Sensors onboard the AOP include a high-fidelity imaging spectrometer, waveform LiDAR, and high-resolution digital camera in the visible red, green, and blue (RGB) wavelengths. The high spatial and high spectral resolution imaging spectroscopy data achieved through collection with low-altitude aircraft (~1000 A.G.L.) (Fig. 3) serve as a powerful starting point for mapping and measuring aspects of ecosystem biogeochemistry and biodiversity (Ustin et al. 2004, Chadwick et al. 2020) and providing valuable information for conservation practitioners, policymakers, and land managers (Asner et al. 2017). NEON AOP data are the only free source of repeat airborne imaging spectroscopy data, offering far greater spectral resolution than other publicly available datasets (Fig. 3b). The estimation of canopy scale leaf traits is one example of the type of products that can be derived using integrated data streams (Chadwick and Asner 2016, Martin et al. 2018, Wang et al. 2020), while an example of a product that can be derived from

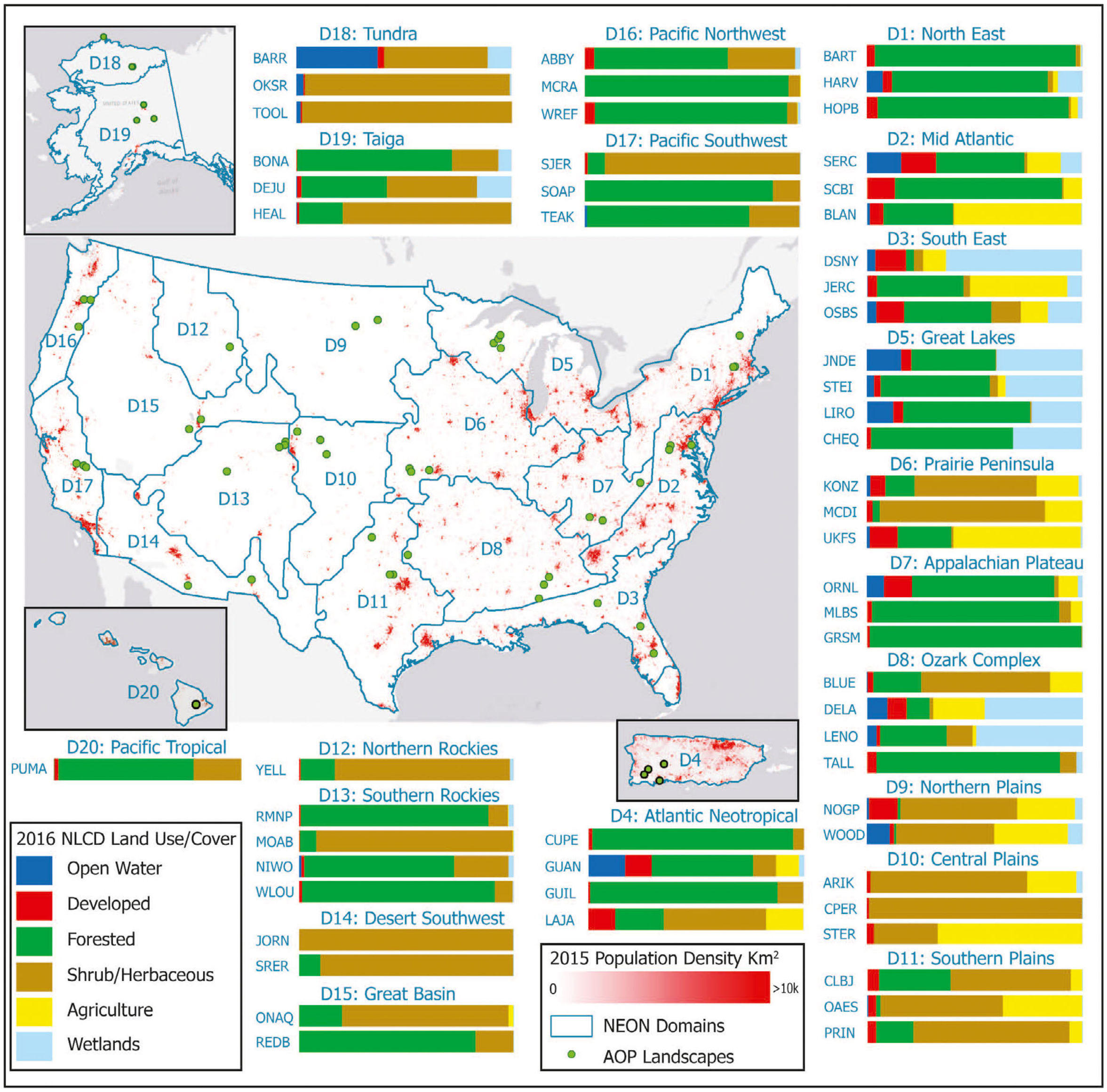

Fig. 1. Locations and fractional land cover of landscapes within AOP surveys and products available from the NEON website in mid-2020. The landscapes surveyed do not capture any of the major U.S. population centers (red areas on the map), but exhibit considerable land-use diversity. Population is from 2015 block-group level census data and land cover is from the 2016 National Land Cover Database (USGS 2016).

imaging spectroscopy data is canopy water content (Gao and Goetz 1990). The latter has provided important insights into post-drought mortality at the individual tree-scale and drivers of variation in drought sensitivity at landscape scales (Brodrick and Asner 2017, Paz-Kagan et al. 2017). An additional promising utility of NEON AOP hyperspectral data is the ability to capture and quantify otherwise difficult to measure methane and CO_2 emissions (e.g., Cusworth et al. 2021). See Table 1 for examples of products that can be generated from AOP data.

The full-waveform LiDAR data enable detailed characterization of topography and structure of

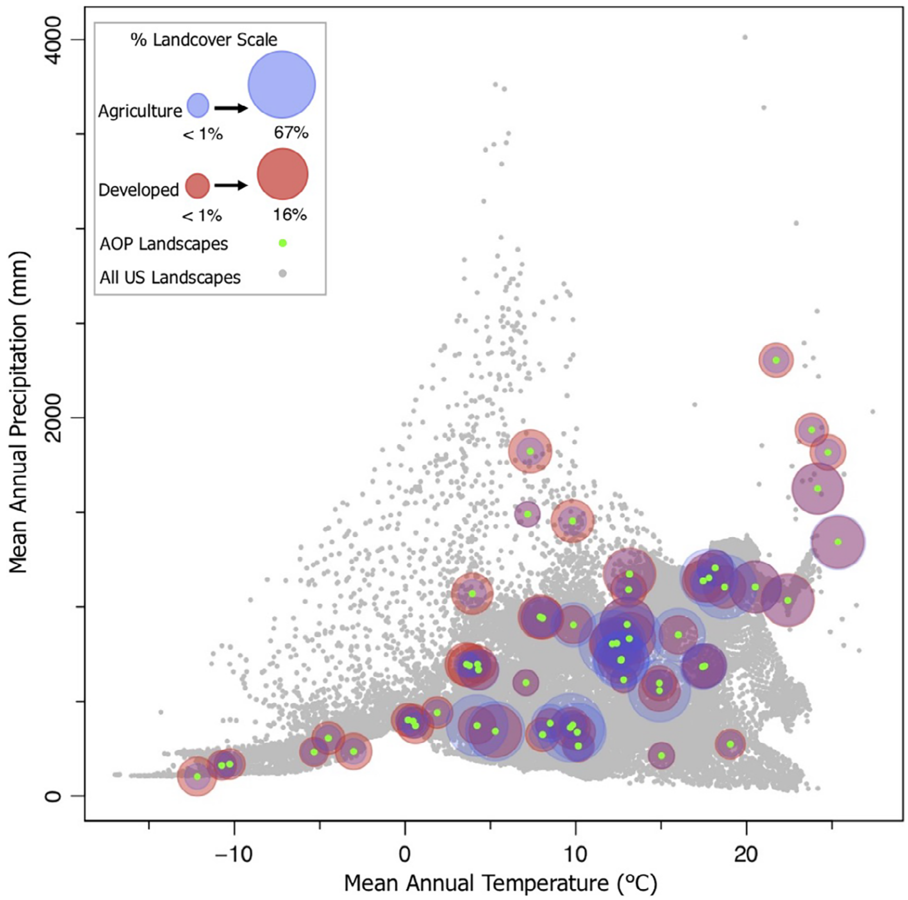

Fig. 2. Locations and fractional land-cover of landscapes within AOP surveys and products available from the NEON website in mid-2020. These NEON AOP landscapes (green dots) are distributed across the mean temperature and precipitation climate space at a 10-min resolution throughout the United States (gray dots). By design, the NEON AOP landscapes span the entire climate space to capture the diverse ecological and climatological variability throughout the United States. Different size circles indicate the proportions of land use by agriculture (blue) and developed area (red) in each unique landscape. The majority of AOP landscapes shown here consist of proportions of both land-use types (agriculture and developed) and therefore are displayed with overlapping blue and red circles.

the observed landscape. Airborne LiDAR data are primarily used for generating bare-earth digital terrain models (DTMs), modeling hillslope hydrology and geomorphology, measuring and characterizing vegetation structure (Atkins et al. 2019), and estimating aboveground biomass (Lefsky et al. 2002). However, the data can also be used for urban land-cover classification (Yan et al. 2015), measuring snow depth (Deems et al. 2013), and many other applications. Vegetation structure can reveal insights into structural diversity which is linked to terrestrial ecosystem carbon, water, and energy cycling (Schneider et al. 2020) and the legacies of management history (McMahon et al. 2015). Vegetation structure metrics derived from LiDAR data can also be analyzed in conjunction with ancillary datasets for an improved understanding of the drivers and impacts of ecosystem structure on function. For example, integrating animal movement and LiDAR data has generated new insights into how ecosystem structural heterogeneity influences how animal taxonomic groups use and move through various spatial dimensions of an

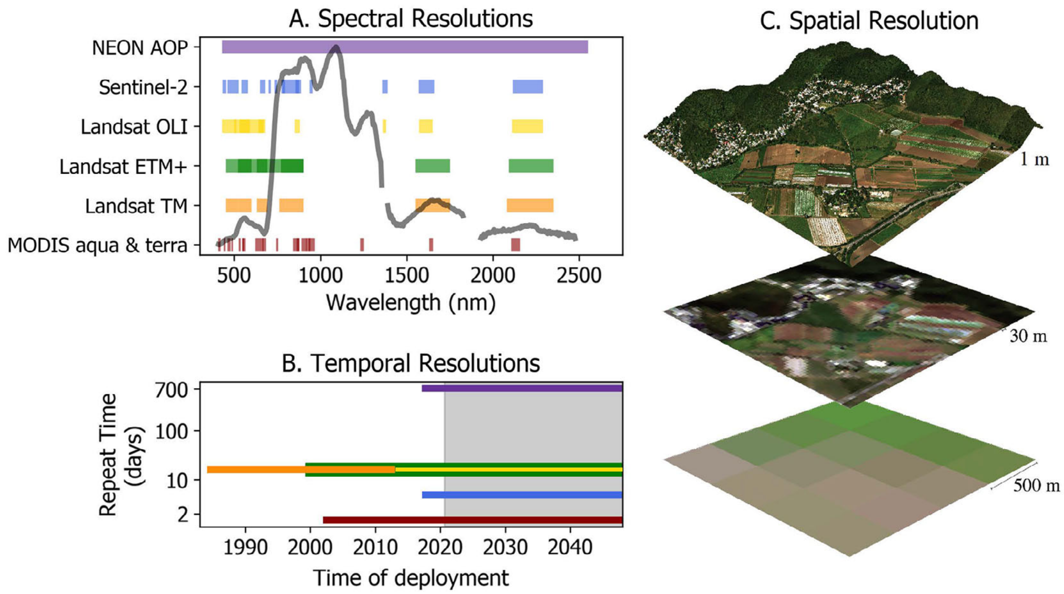

Fig. 3. Spectral (A), temporal (B), and spatial (C) resolution of NEON AOP data relative to other widely used, publicly available remote sensing datasets. (A) Spectral range for different sensors. Note that the NEON AOP is contiguous at 5 nm intervals while other sensors have much larger bandwidths. Overlapping bands are darker in color. The gray line is an example spectra for a vegetated pixel taken from an AOP acquisition to highlight the shape of the reflectance spectrum. (B) Duration of record vs. the repeat time for each sensor (colors designated in A). Future acquisitions are in gray. In (A, B), NEON AOP spectral resolution and temporal resolution are illustrated in purple, Sentinel-2 in orange, Landsat Operational Land Imager (OLI) in yellow, Landsat Enhanced Thematic Mapper Plus (ETM+) in green, Landsat Thematic Mapper (TM) in blue, and MODIS aqua and terra are in red. (C) AOP data at 1 m resolution overlain on LiDAR point cloud in Guánica, Puerto Rico, compared with 30 m Landsat OLI data and 500 m MODIS (MOD09A1) data at the same location.

ecosystem, with implication for biodiversity corridors and animal conservation strategies (Davies and Asner 2014).

The mosaics of high spatial resolution orthorectified RGB camera imagery offer additional information of the type that is increasingly used for various applications extending far beyond ecology, including mapping crop type and yield (Jain et al. 2019), flood mapping (Bonafilia et al. 2020), infrastructure and transportation (Tan 2020), and economic indicators (Jean et al. 2016). Another important aspect of AOP data is that the LiDAR, imaging spectroscopy, and high spatial resolution RGB measurements are all collocated and collected concurrently, enabling direct comparison and integration of data streams, providing a powerful opportunity to derive additional information and data products (Table 1).

Repeat measurements and the building of a long-term archive offer a second feature. AOP data are being collected at a subset of NEON sites every year, acquiring individual sites every 1–3 yr for the next thirty years. Multiple time points (also referred to as time series or panel data) are already available for several sites. The long-term nature of the NEON project enables researchers to plan for the collection of ancillary information over a concurrent time scale, laying the groundwork for decades of future work. Given the nascent stages of NEON's long-term commitment, this is an opportune time for SES researchers to engage and commence the strategic collection of complementary SES data at relevant sites.

A third feature of the NEON AOP is the broad network of 81 field sites across 20 ecoclimatic domains, which are in turn integrated (or have

Table 1. Products that can be derived from NEON AOP data.

Data type	Example SES research areas	L	IS	RGB
Topography: elevation, aspect, slope	Hydrology and watershed mapping, estimating snow water equivalent, predicting storm-related inundation and sea level rise, understanding landslide dynamics	X		
Vegetation structure: height, canopy gap fraction, vertical canopy profile	Land management and policy impacts on ecosystem health, tree mortality, and wildlife habitat	X		
Individual tree delineation†	Identification of individual trees affected by pests, pathogens, and other impact, or conservation efforts targeting specific vegetation size classes	X	X	X
Estimated biomass‡	Carbon stocks mapping for accounting and monitoring accordant with policies/targets	X		
Canopy plant traits: e.g., leaf mass per area, foliar N and P§	Plant biogeochemistry related to ecosystems' ability to buffer contaminants and/or sensitivity to nutrient runoff		X	
Plant species mapping¶	Monitoring plant species with particular relevance to people/SES (e.g., coastal redwoods)		X	
Canopy water content‖	Drought-related tree mortality early warning in important SES geographies (e.g., watersheds)		X	
Community composition: spectral beta diversity††	Relationships between plant diversity and ecosystem services (e.g., pollinator activity, yields of adjacent agricultural fields, human health)	X	X	
Classification: Land-cover type, built structures	Characterization of changing landscape mosaic in space and time, including spatial proximity of residential areas to different ecosystem types, or expansion of developed and agricultural areas	X	X	X

Notes: In some cases, fully prepared data products are provided by NEON. Other products derived from various NEON AOP datasets require additional ground data to create. Bold data types indicate products that require additional ground data. The three columns on the right indicate the sensor(s) that data are derived from. L: light detection and ranging (LiDAR), IS: imaging spectroscopy, RGB: orthorectified RGB camera imagery, N: nitrogen, P: phosphorus, AD: additional data.

† AD: High-resolution (~30 cm) GPS locations or ground-based validation of tree crown identities.

‡ Can be estimated without additional ground data if appropriate allometric equations have been developed and wood density data are available for species present at site.

§ AD: Geolocated individuals with sampled traits within roughly 2 weeks of AOP flight, depending on the phenology of the system.

¶ AD: Geolocated plants with species.

‖ Does require additional processing of raw data, although no AD is required to create products.

†† Canopy spectral diversity can be estimated without AD, although interpretability and extrapolation to vegetation communities is improved with geolocated diversity plots.

the potential to be integrated with) with other networks (e.g., Long-Term Agroecosystem Research [LTAR], Long-Term Ecological Research [LTER], Critical Zone Collaborative Network, Phenocam). The continental-scale network supports unique research opportunities for cross-site comparison, but also the exploration of aggregate effects of local dynamics at large scales, for example, climate effects of local vegetation change propagated by atmospheric circulation, that is, ecoclimate teleconnections (Swann et al. 2018). All the 81 NEON sites have been flown at least once. NEON collection efforts across these sites are coordinated with AOP flight campaigns, offering complementary and systematic atmospheric, biological, genomic, and pedological sampling resulting in over 175 data products at varying time scales that can be further integrated with existing local- or continental-scale datasets. Examples of complementary data products include near real-time measurements of atmospheric gas exchange and particulate matter, groundwater elevation and conductance, surface water nitrate concentrations, meteorological measurements at a high temporal frequency, soil carbon concentrations, and soil water content and salinity. Additionally, NEON's Assignable Assets program enables researchers to task the AOP for flight surveys at non-NEON sites or at NEON at times when AOP data are not typically collected. The NEON network makes it possible to leverage site-level data for cross-site and cross-scale analyses.

Leveraging the NEON AOP

A key contribution of NEON AOP data to the field of ecology is the improved ability to address ecological questions and test theories at a combined scale and resolution not previously possible. The AOP offers a critical resource for ecosystem science, enabling novel measurements (Table 1), ecosystem model parameterization and benchmarking, and remote sensing tutorials for using cutting-edge image processing and analysis tools. If SES variability is encompassed within the NEON landscapes and captured by these data, they will represent a highly valuable dataset for capturing spatial and temporal variability in ecosystem structure and function, while providing incredibly high spatial and spectral resolution data for SES research. The benefits of NEON AOP to SES research are, in part, a function of the heterogeneity of social variables and dimensions captured by the network.

Integrating SES datasets

The strength of the AOP lies in its potential to identify processes that underpin spatial and temporal patterns emerging from pressing environmental problems. However, identifying the complex interplay among human–nature interactions and feedback processes will require incorporating ancillary SES information across sites. Ancillary data might include spatially referenced census and parcel-level data, ranging from information on agriculture, pollutants, development, and infrastructure, to recreation data or local ecological knowledge. An increasingly valuable data source is volunteered geographic information from sources like community science projects, social media, and cell phone data, which yield insights into human behavior and people's engagement with and valuation of environmental goods and services. Non-spatial site-level contextual information can also provide rich background on land-use legacies, past disturbance events, or the timing of a relevant policy change affecting one or more NEON landscapes. A necessary first step involves establishing and collating available SES data and contextual information at these sites. While such an effort is beyond the scope of this paper, we offer an initial list of example ancillary datasets (Table 2). Far from exhaustive, Table 2 offers a starting point that could be expanded and developed by the broader SES research community and Coupled Human and Natural Systems network, perhaps as a living document. Given the 30-yr time horizon for NEON site measurements, there also remains ample time to design and implement collocated social surveys and future SES data collection moving forward.

Research areas and applications

By integrating SES data with AOP data, a number of research questions can be addressed. The NEON site management and event reporting product (NEON 2021) offers a useful starting point for identifying what SES questions and

Table 2. Categories and examples of ancillary SES datasets that can be integrated with the NEON AOP data.

Category	Example dataset(s)
Agricultural	USDA National Agricultural Statistics Service (NASS) (USDA NASS 2020*a*), CropScape - Cropland Data Layer (USDA NASS 2020*b*)
Census & survey data	American Community Survey (USCB 2020*a*), Decennial (USCB 2020*c*), Human Health Survey (IPUMS 2020*a*), Labor Force (IPUMS 2020*b*), Time Use (IPUMS 2020*c*)
Community science	Project Budburst (Budburst 2020), eBird (eBird 2020), iNaturalist (iNaturalist 2020)
Development (urban and rural)	Commuting (USCB 2020*b*), Income and Employment (BLS 2020), Human Health (CDC 2020), Poverty (USCB 2020*d*)
Infrastructure	Homeland Infrastructure Foundation-Level Data (HIFLD) (DHS 2020)
Land-use (parcel, ownership, management)	NEON Site management and event reporting (NEON 2021), LANDFIRE (USDA-USDI 2020), National Land Cover Database (USGS 2016), PLACES (Nolte 2020), Rangeland - Historical Time-Series – BIT (Rigge et al. 2019), Urban Imperviousness (Yang et al. 2003, USGS 2016)
Pollutants	EPA Geospatial Data—includes data on water quality, superfund sites, environmental justice screening metrics, toxic substances, and brownfields (EPA 2020)
Recreation	National Visitor Use Monitoring Survey (Fisher et al. 2018), permit data (hiking and backpacking permits, fishing & hunting licenses), Flickr Recreation Models (Keeler et al. 2015)
Volunteered geographic information	Twitter, cell phone data, spatially explicit complaints of land-use violations (Heider et al. 2018), trip reports shared on hiking forums (Fisher et al. 2018)

issues are most pressing at a given site or across sites. Possible questions and applications include examining the long-term consequences of prior land use on regrowth and recovery. Sites within complex land-use mosaics may offer useful locations to address questions related to, for example, the negative consequences of edge effects on forest ecosystems (Ordway and Asner 2020) or the beneficial aspects of ecosystem function and structure on nearby agricultural output or resilience to precipitation and temperature anomalies (Zhang et al. 2007). Depending on site context, there is potential for exploration of interactions between ecosystem dynamics and rural prosperity, rural and peri-urban infrastructure development (e.g., California land-use, utility companies' infrastructure, and wildfires), or for experimental land and resource management strategies to evaluate impacts. The latter might include timber harvesting, grazing, invasive species removal, or soil amendments. In the event of an extreme event or natural disaster occurring within AOP landscapes (e.g., drought, wildfire, hurricane, flooding), ecosystem responses in space and time can be evaluated, offering much needed insight into disturbance dynamics as well as, for example, the effects of these ecosystem responses on adjacent cropland productivity.

Possible applications in AOP landscapes that include urban, peri-urban, or developed areas (n = 11) include understanding of plant function, ecophysiology, and responses to disturbance (e.g., flooding, drought, high temperatures, water stress) to enhance the resilience of these ecosystems. Spatial and temporal assessments of ecosystem services provided to urban and peri-urban areas (e.g., Brown and Quinn 2018) would be improved with improved biophysical inputs to models or land-use planning. Sites with urban developed areas occur in a wide range of climatic and biophysical settings, from Utqiagvik, AK, to Yuaco, PR. Because most urban development in these sites is from smaller towns and suburbs, AOP data can enhance urban ecologists' ability to extend theory and practice gained from larger cities and make important comparisons of urban ecology across towns of differing size and socioeconomic settings. Within urban and peri-urban NEON sites and sites that incorporate areas heavily used for recreation (open spaces, state parks, US Forest Service land), SES questions could also explore relationships between human health (physical and mental) and aspects of ecosystem function, structure, diversity, and intactness.

Political ecology opportunities could arise from the convergence of SES remote sensing applications with in situ observations and local ecological knowledge (LEK) to model, map, and visualize socio-ecological change. Using spatially explicit LEK alongside fine resolution remote sensing data could serve as a particularly important opportunity for SES research within AOP landscapes, supporting the identification, and subsequent quantification of institutional structural decision-making in environmental change. LEK can also fill in undocumented sources of disturbance by offering additional ground-truth observations where sensors are absent, or where error and uncertainty in land-cover and land-change mapping are high (Heider et al. 2018). Naturally, convergent methodologies bring with them multiple stakeholders and disciplinary traditions. An important part of this process includes acknowledging (1) the actors involved in co-producing this knowledge, (2) the agency afforded or removed from each actor, and (3) the narratives at play in the decision-making process. In doing so, there is exciting potential for local ecological knowledge to help direct AOP goals and objectives and bring an even more diverse group of scientists and stakeholders to SES research. Although we have listed a variety of potential SES research areas and questions that could be explored with NEON AOP data, many more surely exist beyond what is proposed here.

Cross-site analyses and scaling

A powerful aspect of AOP data lies in the opportunities for cross-site analyses and comparison, scaling datasets, and addressing questions across spatial, temporal, and organizational scales. Examples of potential cross-site analysis opportunities include examining sites in similar ecosystems (e.g., forested or rangeland sites), sites with different land-use histories (e.g., Harvard Forest's agricultural and logging history compared to Bartlett Forest's logging history), or sites that lie within different socioeconomic or policy environments (e.g., sites that border multiple counties or jurisdictions with contrasting environmental regulation). Future efforts to build a database of site-specific SES characteristics and land-use histories will likely highlight additional possible cross-site comparisons.

Opportunities also lie in using AOP data combined with other publicly available remote sensing datasets (Fig. 3). NEON AOP data on aspects of ecosystem structure and function available across large spatial scales, repeated every one to three years, offer unprecedented access to large volumes of information at resolutions comparable to field measurements relevant to human interaction and decision-making. These data can be upscaled, downscaled, or combined with additional information to conduct analyses at the most meaningful scale at which processes emerge and address questions related to cross-scale interactions. For example, spatial upscaling and/or hindcasting has many useful applications for extending AOP data to larger spatial extents, higher temporal frequencies, or outside the temporal range of AOP data availability, at the cost of reduced spatial resolution (Hijmans et al. 2005, Kitron et al. 2010, Leitão et al. 2018). Here, hindcasting refers to retrospectively estimating a variable of interest using historical remote sensing data in combination with high-resolution satellite imagery (e.g., NEON AOP data; and see Asner et al. 2016*a*) or in situ measurements (Hicks et al. 2013) made at a single, more recent point in time.

To upscale AOP data, statistical models are used to first identify relationships between the high-resolution metrics (e.g., vegetation biomass, canopy water content) and a remotely sensed dataset that is publicly available across a larger spatial extent (i.e., nationally or globally), collected more frequently (e.g., MODIS, daily revisit frequency; Sentinel series, every 1–6 d; Landsat, every 16 d). The modeled relationship, often employing a machine learning method at present, is then used to scale up the derived metric, providing an estimate at a larger spatial extent and through previous years. Canopy water content is one example of a metric that has been spatially upscaled and hindcast (Asner et al. 2016*a*, *b*, Brodrick and Asner 2017, Brodrick et al. 2019).

Upscaling observations of ecosystem structure and function from the NEON sites to regional or national scales is a key objective of the NEON program. When it comes to SES questions, effective scaling will require identifying suitable indicators or proxies for interactions between humans and their environment within AOP landscapes that can be measured at a larger spatial grain and extent. Such scaling will be most robust if the range of response variables represented in AOP landscapes is similar to the range at the full extent of interest. In other words, it will be important that AOP landscapes capture variability inherent to the characterization of SES. Given the tremendous complexity and potential for non-stationarity in SES processes, AOP landscapes might be insufficient to inform useful generalizations for upscaling SES metrics. Nonetheless, the use of machine learning to derive estimates of SES metrics from high-resolution, high-fidelity remote sensing data is an active area of research that would benefit from AOP data.

A third advantage is the AOP's contribution to addressing questions across spatial, temporal, and organizational scales. Fig. 4 explores an example of cross-scale SES dynamics that AOP data can expose in the context of drought. Within the AOP landscapes, high-resolution information is available on species composition and vegetation structure (Fig. 4d), canopy water content (Fig. 4e), and agricultural productivity (Fig. 4f) pre-drought (Fig. 4A) and post-drought (Fig. 4B). As an example, these data can be linked to issues of environmental justice and equity in the context of water governance, pricing, and access (Fig. 4g). This cross-scale examination of relevant datasets enables a multidimensional understanding of the role of human decision-making responses, feedbacks, and impacts on SES. Over time, these data offer detailed information on shifting community composition, tree mortality, impacts on crop yields, changes in understory vegetation, wildfire risk, evaporative demand, and hydrological responses, including downstream effects on reservoir levels and stream temperatures.

Beyond the area of AOP flight coverage, medium and moderate (Fig. 4C) resolution data available at broader spatial extents and higher temporal frequencies can be integrated with AOP data to evaluate relationships between changing dynamics within the AOP landscape and the surrounding region. Metrics can be upscaled to a larger extent of interest for analysis (e.g., watershed scale). Alternatively, spatial and temporal relationships between detailed metrics

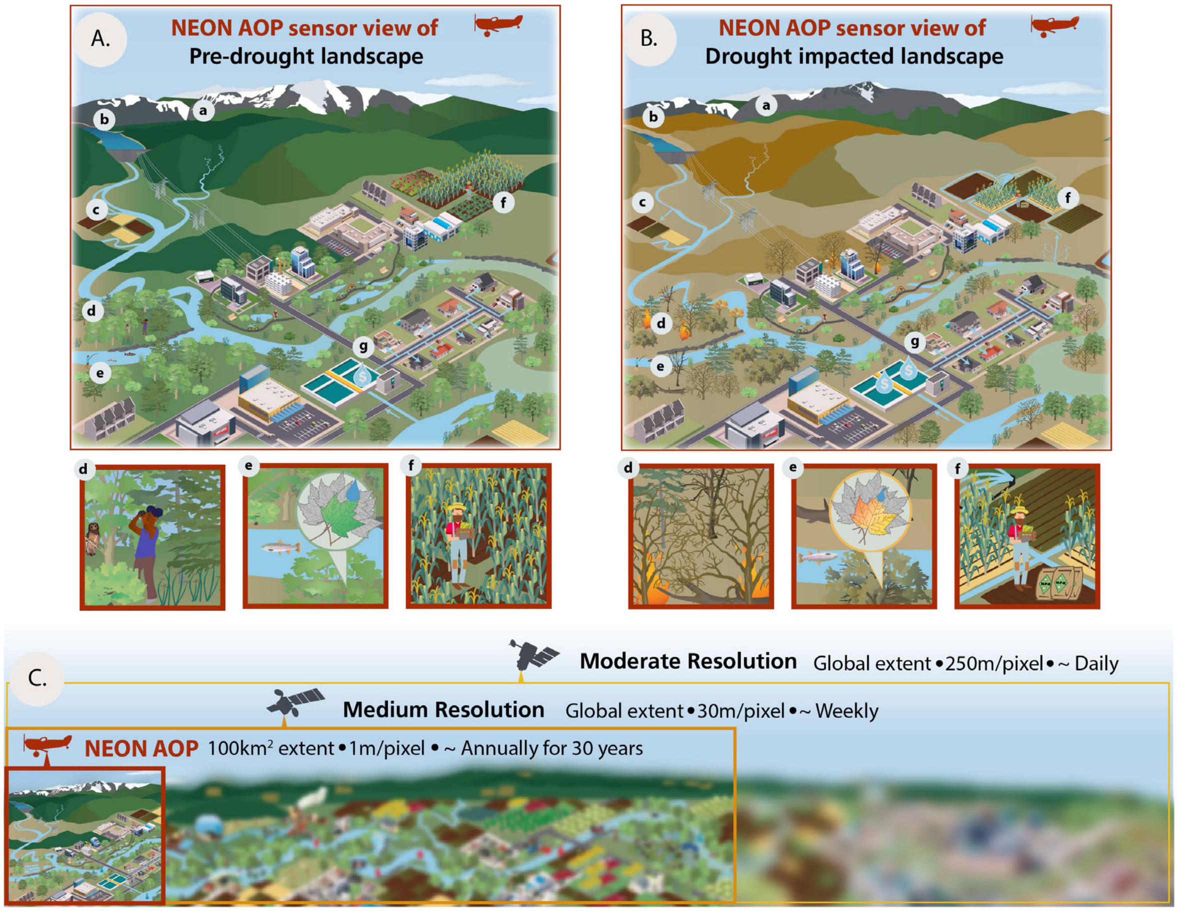

Fig. 4. Diagram highlighting aspects of the NEON AOP that can contribute to understanding SES interactions and feedback processes in space and time using drought as an example. The difference between a pre-drought (A) and drought-impacted landscape (B) was chosen to highlight processes that may occur at various scales and in different locations across the landscape (a–g) over the 30-yr planned AOP lifespan. Aspects of socio-environmental change that can be better understood within an AOP landscape are highlighted in comparisons of (d–f) in panels A and B. For example, fine-scale resolution AOP data will allow researchers to understand drought and related human behavioral impacts on plant species composition and vegetation structure (d), canopy water content (e), and crop yields (f). In addition, AOP data combined with ancillary datasets enables analysis at larger spatial scales (C). The higher temporal resolution of other sensors can also be used to understand change within years at a NEON AOP site (C) and how pressures like reduced snowpack reverberate throughout social, governance, and ecological systems (A a–g → B a–g). Symbols used with permission from UMCES IAN Symbol library (ian.umces.edu).

within AOP footprints can be analyzed in combination with related metrics beyond the footprint boundary that are retrievable from other sensors (e.g., NDVI, snow cover, reservoir, and surface water levels), for example, downstream or at a broader ecosystem scale. By leveraging AOP data in combination with additional remote sensing and SES datasets in and around AOP landscapes, SES questions can begin to address mismatches between data availability and socio-environmental processes of interest.

Challenges and Limitations

Leveraging existing AOP data for SES research offers exciting opportunities, although there are limitations given potential misalignment between the location of AOP landscapes and questions of interest and the timing of data collection. Critically, existing AOP footprints do not represent a suite of sites that were specifically chosen for SES research. For example, urban areas, urban–rural gradients, diversity of cropping systems, coastal zones, and wetlands are under-represented or completely missing from the network of core NEON sites (Kampe 2010). Fundamental human dimensions are also missing including representation of demographics, economic systems, and governance structures that would need to be captured for comprehensive and impactful SES research.

It should be noted that SES questions exist wherever humans interact with the environment, suggesting SES research could be conducted at any AOP landscape with people living and working in or near the flight area, if there is a history of past human impact within the landscape, or to understand the impact of global change on SES. We argue that there is much to be gained by proceeding with research question development after carefully vetting AOP sites and ancillary data available for addressing any given SES question. In addition, the frequency of AOP flights will influence the types of observable SES dynamics and feedbacks. For example, the plan to survey every 1–3 yr during the peak growing season supports vegetation measurement capabilities, but may limit other types of observations. Processes that operate at sub-annual timescales or are stochastic in nature (wildfire, floods, wind events, ice storms, disease outbreaks, etc.) will be particularly problematic to observe using the existing AOP data collection framework, as they will only be captured within AOP landscapes by chance, and rarely at best. However, the guarantee of high-resolution data prior to and post-disturbance events at NEON sites will provide new opportunities for quantifying change and understanding subsequent recovery processes. The availability of the NEON Assignable Assets program may also allow for responsive research of future significant events.

Privacy concerns represent an additional challenge when investigating human–environment interactions at fine resolutions (Arbuckle 2013, Rissman et al. 2017). These concerns are likely to be exacerbated with high-resolution AOP data (Zipper et al. 2019), although they are not unique to AOP data. For example, many SES questions require studying features of people's behavior and/or people's homes and yards, or they might involve tracking movement and behavior with cell phone data, or other sensitive personal information (e.g., physical and mental health indicators) through interactions on social media. Integrating SES data, either observed with AOP or from other platforms, without permission, while currently legal, could open researchers up to criticism from a public that is not prepared to be on the pages of science journals. Engaging the public in AOP research is a natural and possibly effective solution to this issue, but will require a sustained and concerted effort to identify and engage with stakeholders at each AOP landscape. If done carefully and respectfully, however, this challenge could turn into an engagement opportunity, bringing a wider group of people into SES research (e.g., community scientists) and contributing to broader impact goals.

Recommendations

NEON AOP provides tremendous potential for supporting the advancement of SES science and theory development. The sensors, the spatial and spectral resolution, revisit frequency, all embedded in a broad network of sites, increase the ability to develop new questions and hypotheses and to conduct cross-site, cross-scale, synthetic analyses. However, to fully exploit this potential, a concerted effort by researchers is needed to develop a shared foundation on which to build. In this respect, the authors provide three recommendations for promoting and facilitating cutting-edge, problem-oriented SES research.

Concepts and data

To move beyond case studies and descriptions of SES and move toward advancing theory and understanding mechanisms to support effective interventions, researchers will need to identify or develop appropriate conceptual frameworks for understanding AOP landscapes as SES. Methods (e.g., archetype analysis via Václavík et al. 2013) will also need to be explored to characterize SES and the types of phenomenon of interest within and across AOP landscapes. Existing social and ecological data will need to be assembled and organized to promote comparative and synthetic analysis, which will require the development of shared data protocols—building on what already exists for NEON—and a central repository for raw data and data products.

Next-generation science

There is a strong need for continued investment in the development and training of interdisciplinary practitioners and scholars, with proactive engagement of more diverse and inclusive groups of people in the process. These individuals will have expertise in specific fields and the conceptual tools to work across disciplines. Training a broader workforce to use AOP data and effectively incorporate it into inter-, multi-, and transdisciplinary research will be key. Existing NEON educational resources and tutorials are a natural starting point. This also includes, however, a focus on learning how to collaboratively engage the communities in which research takes place and the co-development of research projects. Linked to this is an increased focus on ethical considerations as researchers increasingly use technologies that document the world in ways that make particular people and places identifiable.

Building the network

The scope of AOP-based SES research possibilities requires a broad community of collaborating researchers. Because AOP site selection was based on ecological concerns, there is a need for expanded representation across disciplines. As part of community building, increased use of the NEON Assignable Assets program to better represent the spatial heterogeneity of SES and SES phenomenon of interest will expand analytical capabilities.

Conclusion

The richness of the spatial and temporal measurements captured by NEON AOP combined with current environmental and social data being gathered will provide new opportunities to address SES challenges. Diagnosing and analyzing pressing environmental problems are more relevant than ever before. Insights from integrating NEON AOP data with other efforts and datasets will enable the advancement of theoretical and empirical understanding of complex systems and feedback processes. Climate change impacts and questions around resilience, land-use legacies and change, and sustainable development are core SES problems that are also leading candidates for NEON AOP analysis. Further work is needed to determine the major SES challenges and questions within the NEON site footprints. Given the nascent stages of NEON's long-term commitment, this is an opportune time for SES researchers to engage stakeholders and commence the framing of research questions and collection of SES-relevant data. We urge the SES research community to further explore whether there are questions and theories in social and economic disciplines that can leverage NEON AOP data.

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