Understanding and adapting to global environmental change is one of the major challenges of the 21st century. Among the most visible outcomes of alterations in environmental properties and processes are shifts in phenology (the seasonal activity of plants and animals). Climate-driven changes in plant phenology, for instance, can have ecosystem-wide impacts, ranging from altered carbon budgets and productivity (Ciais et al. 2013) to effects on pollinators (Bellard et al. 2012) and crop yields (Lobell et al. 2011). However, quantifying such changes over large areas at appropriate timescales is challenging, even with satellite remote-sensing products.

Repeat photography has been used to detect and document changing landscapes since the earliest days of photography. Collections of photographs acquired from fixed locations have largely framed our understanding of global change processes, including desertification, glacial retreat, and alterations in land cover and land use (Webb 2010). Until recently, ground-based collection of time-series image data over long periods was expensive and technically challenging, but advancements in imaging and communication technologies are enabling continuous, widespread monitoring of the environment.

As high-quality, low-cost digital cameras have become more widely available, interest in applying these tools to ecological studies has expanded. “Near-surface remote sensing” utilizes data from automated ground-based sensors to augment conventional remote-sensing data, and to help bridge the gap between satellite monitoring and traditional on-the-ground observations. “Phenocams” – digital cameras configured to capture time-lapses – can provide a permanent, continuous visual record of the environment over years or even decades. The term “PhenoCam” was first coined to describe a collaborative, regional-scale camera

Rapid changes to the biosphere are altering ecological processes worldwide. Developing informed policies for mitigating the impacts of environmental change requires an exponential increase in the quantity, diversity, and resolution of field-collected data, which, in turn, necessitates greater reliance on innovative technologies to monitor ecological processes across local to global scales. Automated digital time-lapse cameras – “phenocams” – can monitor vegetation status and environmental changes over long periods of time. Phenocams are ideal for documenting changes in phenology, snow cover, fire frequency, and other disturbance events. However, effective monitoring of global environmental change with phenocams requires adoption of data standards. New continental-scale ecological research networks, such as the US National Ecological Observatory Network (NEON) and the European Union’s Integrated Carbon Observation System (ICOS), can serve as templates for developing rigorous data standards and extending the utility of phenocam data through standardized ground-truthing. Open-source tools for analysis, visualization, and collaboration will make phenocam data more widely usable.
network in the northeastern US that was used to track seasonal changes in the phenology of forested ecosystems (Richardson et al. 2009; phenocam.sr.unh.edu), but “phenocam” now refers more generally to any digital camera used for time-lapse or repeat photography to study phenological and other environmental changes. Information captured by phenocams can provide essential baseline data for tracking such changes, as well as for monitoring conservation and restoration efforts. Phenocams are ideal for documenting alterations in plant phenology, animal migrations, and biotic and abiotic disturbance events. They can also be calibrated to estimate carbon, water, and nutrient fluxes, and many other processes related to global change (Richardson et al. 2007, 2013a; Ahrends et al. 2009; Morisette et al. 2009; White et al. 2009).

Phenocam use typically falls into two categories: (1) long-term monitoring (years to decades) and (2) short-term field campaigns (days to months). In the former case, the emphasis is generally on choosing robust, automated camera hardware and maintaining a continuous image record of a consistent field of view (FOV) for as long as possible. In the latter case, the research question often dictates what camera hardware is to be used (eg specialized cameras filtered for specific wavebands; WebTable 1). Here, we focus primarily on phenocams used for long-term monitoring, as this type of data is generally more suitable for cross-scale comparison and standardization.

### Phenocam science and technology

Automated image analysis techniques can be used to extract quantitative color (red, green, blue [RGB]; Figure 1), and, with some cameras, near-infrared data (Figure 1c). Information derived from these data provides metrics for vegetation status (eg green chromatic coordinate [GCC]; Figure 2; Gillespie et al. 1987; Sonnentag et al. 2012) and a modified normalized difference vegetation index (NDVI; Figure 1c; Nijland et al. 2014; Petach et al. 2014). Long-term deployment of phenocams is most useful for monitoring vegetation types that show strong color variation driven by biological response to local climate (Figure 2; Sonnentag et al. 2012) or disturbance events, such as defoliation by herbivores (Nagler et al. 2014). Tracking color changes over time enables identification of the timing and development of discrete “phenophases”, including leaf-expansion, canopy development, senescence, and flowering (Figure 2; Inoue et al. 2014). Daily imagery from upward-facing cameras has also been used to track seasonal variation in leaf area index (LAI; leaf area per unit ground area) using gap-fraction theory (Ryu et al. 2012).

Phenocam-derived data can be combined with data obtained from other co-located sensors (eg micrometeorology, surface–atmosphere fluxes) and manually recorded phenological data to characterize the relationship between environmental drivers and phenological responses (Figure 2; Toomey et al. 2015; Wingate et al. 2015). Phenocams can depict how seasonal plant cycles influence ecosystem carbon budgets,
show how these cycles scale from organisms to landscapes (Hufkens et al. 2012), and estimate gross primary productivity in some vegetation types (Toomey et al. 2015). They can also measure changes in the fractional cover of green vegetation, flowering phenology in annual or perennial plants (Crimmins and Crimmins 2008), snow cover (Julitta et al. 2014), and grassland phenology (Inoue et al. 2015). There has been less focus on the detection of phenological events in non-deciduous biomes, such as temperate or tropical evergreen forests, although seasonal changes in the apparent greenness of evergreen canopies has been related to changes in photosynthetic activity (Toomey et al. 2015). Within-canopy intra- and inter-specific variation can also be quantified from phenocams, but relatively little research has been undertaken in this area.

### Phenocam hardware

#### Hardware selection and existing standards

Given that consumer-grade cameras are not designed for scientific imaging, it is important to understand the strengths and limitations of the information they produce (Sonrentag et al. 2012). Moreover, the value
of derived data is dependent on multiple factors beyond sensor quality and resolution.

An assortment of new camera models are released each year, and novel imaging hardware and computing platforms emerge regularly; consequently, many different types of phenocams are now in use globally. A major challenge for practitioners within the phenocam community, therefore, is how to create long-term, consistent datasets when the core sensor technology (ie digital imaging hardware) is continuously changing and improving. In addition, there is a considerable amount of variability in camera reliability, cost, image quality, and technical complexity (WebTable 1). Two large-scale networks – the Phenological Eyes Network (PEN; Nasahara and Nagai 2015; pen.aghi.tsukuba.ac.jp) and the PhenoCam network (Richardson et al. 2007; phenocam.sr.unh.edu) – have developed protocols that are available for adoption by other researchers. The PhenoCam network employs above-canopy, tower-mounted, StarDot-brand, 5-megapixel “internet protocol” (IP) cameras (WebTable 1) that are angled downward toward the region of interest (Richardson et al. 2013b). These cameras also capture near-infrared imagery to measure NDVI (Petach et al. 2014). PEN uses both upward- and downward-facing, Nikon-brand cameras with 180° fish-eye lenses (Nasahara and Nagai 2015). The Terrestrial Ecosystem Research Network (TERN) in Australia is transitioning from using a mix of “game-cams” and IP cameras to using IP cameras and raspberry-Pi based systems (WebTable 1). “gamecams” (WebTable 1) and IP cameras. The US National Ecological Observatory Network (NEON) and the European Union’s Integrated Carbon Observation System (ICOS) are following the lead of PhenoCam and are installing IP cameras.

Due to the rapid advances in camera and camera-related technologies, there is no “best” hardware for a given application. New phenocam users must therefore decide between adopting more established but older technologies, relying on newer but less proven technologies, or developing custom solutions (WebTable 1; WebPanel 1). Newer cameras may cost less or provide higher-resolution data, but these data may not be congruent with data from larger research networks or published data acquired with more common cameras.

Camera and image format choice

Camera hardware and image format have considerable impacts on image quality (Macfarlane et al. 2014). Consequently, metrics that quantify a specific environmental state, such as LAI, are more affected by camera and image format than are relative phenological metrics, such as GCC-derived phenophase transition dates (Sonntag et al. 2012). For all phenocam data it is very important to maintain the same camera FOV because the unit of measurement with a phenocam is the section of landscape imaged. Changes in the FOV complicate automated processing and reduce long-term data continuity, particularly in heterogeneous environments where phenology of vegetation types may be of more interest than an averaged value from the entire FOV (see WebPanel 1 for additional technical considerations).

Building a global phenocam network

Adoption of data standards and open-access data is crucial

As the use of phenocams becomes more commonplace, formal metadata standards and best practices should be adopted to facilitate wider collaboration between data creators and to increase data usability. Although there are major hurdles for developing a global phenocam network, the success of bottom-up collaborative networks like FLUXNET (www.fluxnet.ornl.gov) provides reason for optimism. FLUXNET is a “network of networks” that uses eddy covariance techniques to measure surface–atmosphere exchanges of carbon, water, and heat. FLUXNET has promoted community standards and protocols, and encouraged data sharing and collaboration, thus enabling the aggregation of data from hundreds of individually managed FLUXNET sites globally into publicly available standardized datasets.

However, FLUXNET data are largely derived from research-grade and well-characterized standard hardware, and integrating data from the diverse range of phenocams in use globally requires resolution of issues not yet addressed by FLUXNET. In general, discrete occurrence data, such as phenophase transition dates, are interoperable between camera types because such measures are derived from relative scales (eg GCC) rather than from quantitative measures (eg LAI). Further research will need to focus on (1) what measurements relating to phenological indicators can be reliably compared among various cameras; (2) what procedures and software tools can be used (eg low-cost camera calibration panels, automated calibration software) to improve interoperability between images from different camera hardware and image datasets; and (3) what methods are best for classifying and categorizing large image datasets to facilitate discovery and use by the community.

Both PhenoCam and PEN serve as examples of the kind of bottom-up, collaborative programs that are possible with current technology. Although relying on different protocols and hardware, these networks have successfully conducted automated, multi-year phenocam programs, and are providing critical data for studying phenological patterns across wide geographic domains and biome types.

Expanding phenocam networks and reconciling scales of observation

Automated camera networks, co-located with additional instrumentation (eg micrometeorology, surface–atmosphere
Phenocams to monitor the Earth

Phenocams, data with data collected by citizen scientists, assist scaling across data products – from individual organisms to communities to landscapes. This provides opportunities for comparing phenocam datasets as well as integration with both observer-based records and satellite and airborne collected data. New continental-scale monitoring networks that have broader mandates for environmental monitoring, such as NEON (Keller et al. 2008), ICOS, and TERN, are incorporating phenocams into their instrument platforms and working to develop phenocam coordination networks within the regions being monitored. Phenocam datasets at well-developed research sites add considerable value to the extensive monitoring monitored. Phenocam datasets at well-developed research sites add considerable value to the extensive monitoring data from these networks (eg Wingate et al. 2015). The huge quantities of data being generated by these research networks necessitate the development of standards for organizing and delivering extremely large datasets from diverse sensor types demanding varied levels of post-processing. Most of these data are available through open-data frameworks that include explicit licensing terms and metadata standards to promote reuse and data sharing by stakeholders. Although this type of data standardization and public data availability has become common in some research disciplines (eg remote sensing, astronomy), such methods are largely new to the field ecology community; however, image data from PhenoCam, NEON, TERN, and ICOS are, or will soon be, made publicly available.

Installation of phenocams by continental-scale monitoring networks is also helping to formalize phenocam metadata and data standards. Many metadata standards exist for describing data (eg Ecological Markup Language, Audubon core). What specific standard is chosen is less important than ensuring that (1) the standard is well-documented and published online and (2) all camera records meet minimum metadata requirements, such as those established by existing camera networks (WebTable 2). Standardizing hardware, camera settings, and image-naming protocols among sites facilitates both the integration of existing and future phenology networks and scaling from local to regional to global coverage. New phenocam users should contact the relevant phenocam network in their area to register their camera and share data.

The long-term goal of an integrated global phenocam network would be the creation of a well-curated database listing all available phenocams and related datasets with robust metadata on image provenance, availability, data quality, and tracking of post-processing and validation steps (WebPanel 2). Such a database would enable users to register a digital object identifier (DOI) or persistent internet link to the data and analysis code used for a particular publication, and for the development of software packages that can directly access and analyze all available phenocam data.

Connecting phenocams and citizen science

Phenocam data can be expanded by integrating phenocam data with data collected by citizen scientists who volunteer for phenology projects such as USA National Phenology Network’s (USA-NPN’s) Nature’s Notebook and NEON’s Project BudBurst. Engaging citizen scientists in collection and analysis of phenological data fills an essential scientific need and provides an opportunity to engage non-scientists in the scientific process. Additional synergies arise when sampling techniques can be standardized between projects; for example, NEON’s observer-based phenological assessments will use survey protocols developed by the USA-NPN to facilitate integration between these two data sources (Denny et al. 2014).

Researchers in other scientific fields, such as astronomy (www.zooniverse.org), have successfully engaged volunteers online to process and analyze millions of images (Raddick et al. 2013). Ecological research programs are adopting similar initiatives (eg Hill et al. 2012), and should further explore this approach for user recruitment and incentivizing public participation (Newman et al. 2012). A new collaboration between PhenoCam, NEON’s Project BudBurst, and Zooniverse called Season Spotter (www.seasonspotter.org) is integrating crowdsourcing with traditional automated image analysis to maximize the amount of phenological information that can be extracted from camera images.

Expanding coverage

Major challenges must still be overcome before effective phenocam coverage at the global scale can be achieved (Figure 3). At present, PEN, PhenoCam, TERN and ICOS have web portals. PhenoCam, TERN (www.phenocam.org.au) and ICOS (http://european-webcam-network.net/) provide publicly accessible data online. Cameras are used at many research sites globally, but most images are not indexed within any central database, making data discovery and re-use difficult. Coverage also remains poor across large regions of the globe, including South America, Africa, and much of Asia (Figure 3).

To expand spatial coverage, exploration is also warranted into potential data products available from the many thousands of public web cameras (webcams) worldwide. The Archive of Many Outdoor Scenes (AMOS; www.amos.cse.wustl.edu), for example, is a global collection of long-term time-lapse imagery from nearly 30,000 public webcams (Jacobs et al. 2009). Images from thousands of traffic cameras are also available online (Morris et al. 2013). Although non-research cameras often have lower-image quality and may lack important metadata (such as location), public webcam data represent a vast but largely untapped resource for phenological monitoring (Jacobs et al. 2009; Graham et al. 2010). For analyzing such varied data types, automated classification and filtering tools are essential. One possible solution would be the development of a multi-tiered organizational struc-
ture for webcam data, based on metadata quality (WebPanel 2); such a structure would allow available camera data to be cataloged prior to analysis, and would permit users to quickly filter images and data products by automated quality metrics or available metadata.

Next-generation monitoring

An array of new technologies are becoming available that will greatly expand the quantity and utility of phenocam data. We discuss several below.

Pan–tilt–zoom and gigapixel imaging

Pan–tilt–zoom (PTZ) camera systems can move a camera to multiple preset “views” (Granados et al. 2013), thus enabling monitoring of much larger spatial areas. Some PTZ cameras can be programmed to capture overlapping images that can be stitched together with software to form multi-billion-pixel (“gigapixel”) resolution panoramas (Figure 4; Brown et al. 2012). Gigapixel imaging is an emerging technology that holds great promise because such images have sufficient resolution for monitoring thousands of individual plants over hundreds to thousands of hectares (Figure 4). For repeat photography and non-time-series panoramas, commercial hardware such as the GigaPan (www.gigapan.org) enables regular cameras to capture images at thousands of times the resolution of a normal camera image (Nourbakhsh and Sargent 2010). Automated, weatherproof systems for capturing time-lapse gigapixel images have been developed (Brown et al. 2012) but...
are not yet in wide use due to their technical complexity and the challenges of data management and analysis.

**Unmanned aerial vehicles**

Unmanned aerial vehicle (UAV) technology is developing rapidly and will play a major role in future ecological monitoring (Koh and Wich 2012; Anderson and Gaston 2013). Off-the-shelf UAVs that cost less than US$2000 can now generate high-spatial-resolution digital imagery and map layers as well as centimeter-resolution, three-dimensional (3D) “point clouds” of vegetation and topography using a phone “app” to control the UAV and desktop or internet-based software to process the images (eg www.pix4D.com, www.dronemapper.com). Restrictive regulatory frameworks in most countries and limited tools for biological analysis of UAV-derived data are primary challenges to UAV-based monitoring.

**Mesh sensor networks**

Wireless-mesh sensor networks that are used to measure soil properties, micro-meteorological parameters (temperature/relative humidity), and photosynthetically active radiation can quantify environmental drivers of phenology at considerably better spatial resolutions than traditional weather stations (Burgess et al. 2010; Rankine et al. 2014). Precision microclimate data can be coupled with phenocam-derived datasets and low-cost full-genome sequencing of thousands of individuals to allow better modeling of climate–phenology relationships and identification of traits for species adaptability to climate change (Whitham et al. 2006).

**Smart devices and social networks**

Mobile technologies and social networking are also generating huge collections of images, many of them public. Consider that while the AMOS archive has collected 7.3 million images in total (2006–2014), an estimated 1.8 billion images are now uploaded to social media daily (Meeker 2014). Images from mobile devices usually contain metadata, including location, camera compass direction, and sensor type, facilitating calculation of the specific geospatial location being sampled by each photo. Extracting biological information from such images can be challenging, but automated processing algorithms can select only images and scenes that meet specific criteria. Algorithms now exist to correct lighting variation and other artifacts across huge datasets of time-series images. For example, Martin-Brualla et al. (2015) mined 86 million public, geolocated, online photos and automatically created time-lapses from any location with more than 300 images; over 10 000 time-lapse series, were constructed in this way, including one showing the retreat of the Briksdalsbreen Glacier in Norway in 3D that was reconstructed from 9400 images over a 10-year time span. This software was largely automated and ran unsupervised. Integrating repeat photography tools into phone camera apps (eg www.projectrephoto.com) combined with, for example, onsite signage encouraging visitors to contribute images (eg www.picturepost.unh.edu) could help build these datasets (West et al. 2013).
Image processing

In addition to hardware advances, the potential of advanced computer algorithms and computational pipelines using large internet-based “cloud” computer systems has barely been tapped for phenocam data. Such “cloud” computing (ie on the internet rather than on local hardware) allows users to scale their computational requirements, on-demand, from a few to thousands of processors at relatively low cost. Cloud-based processing solutions make production of high-resolution panoramic and 3D datasets widely accessible and produce better-standardized data products. Development of long-term collaborations with researchers in the field of computer vision is recommended for such projects. Cloud computation also enables wider use of automated and semi-automated software pipelines for analyzing and mining large image datasets (eg Martin-Brualla et al. 2015). Publication of datasets and analysis code linked to persistent DOIs is becoming the norm in many scientific fields (eg Fisch et al. 2015; Filippa et al. nd), and the tools to accomplish this are being developed for NEON, TERN, and ICOS data. DOIs and persistent uniform resource locators (URLs) coupled with published interoperable data standards promote collaborative analysis and re-analysis of phenocam and related sensor data.

Summary and recommendations

A global phenocam network would facilitate wide-scale collaborative research across biomes and climate zones, with the potential to measure global change impacts on plant phenology, productivity, and function over timescales ranging from seasons to decades. For a global phenocam network to reach its full potential, we recommend the following: (1) create and adhere to metadata and image-naming standards for all camera-based data sources (WebPanel 2); (2) register all publicly available phenocams in a global database, with existing datasets made publicly available wherever possible; (3) establish new national- and continental-scale camera networks (with data-hosting infrastructure), to serve as clearinghouses for data sharing and to improve phenocam coverage in underrepresented ecosystems and regions (Figure 3); (4) co-locate new cameras at existing long-term research sites; (5) create mechanisms and standards (similar to those for satellite data products) for releasing phenocam images and derived-data products, along with co-located sensor data for ecosystem modeling efforts; (6) create mechanisms for provisioning phenocam datasets with global identifiers (DOIs, persistent URLs, etc); (7) create software and scripts to facilitate easier management and analysis of large time-series image archives (eg Filippa et al. nd) and rapid integration of new datasets into the network; (8) design new software tools for image alignment and standardization across camera types; (9) build web portals with “web-services” that allow direct access to phenocam data products via common programming tools, such as R, Matlab, and Python; (10) adopt existing data standards and robust data management practices for new phenocam deployments to enable the creation of visualization, collaboration, and analysis tools that can work with any public dataset; (11) promote strong collaborations between phenocam projects globally and with local citizen-science phenology projects; and (12) explore non-conventional camera data sources, such as AMOS (Figure 3) and online repositories of georeferenced images (eg traffic cameras, social media), as well as setting up collaborations with specialists in computer vision technologies.

Conclusions

Understanding the ecological impacts of global environmental change depends on integrating complementary monitoring approaches. High temporal and spatial resolution phenological datasets are an essential tool for understanding cross-scale ecosystem processes, and imagery from phenocams can be used to obtain information about phenological changes across a wide range of ecosystem types. Among other end-uses, these data are important for creating models to forecast shifts in phenology under different climate-change scenarios. Continued technological advances provide further opportunities for image-based, real-time monitoring of natural systems. However, critical issues related to standardization, metadata, data sharing, and re-use will need to be addressed as phenocam technology continues to grow and evolve. A coordinated global phenocam network that promotes standardization and data sharing, and facilitates the discovery and re-use of archived image data, would greatly enhance global change research capacity.

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