Assessing data quality in citizen science

Margaret Kosmala[1*], Andrea Wiggins[2], Alexandra Swanson[3], and Brooke Simmons[3,4]

Ecological and environmental citizen-science projects have enormous potential to advance scientific knowledge, influence policy, and guide resource management by producing datasets that would otherwise be infeasible to generate. However, this potential can only be realized if the datasets are of high quality. While scientists are often skeptical of the ability of unpaid volunteers to produce accurate datasets, a growing body of publications clearly shows that diverse types of citizen-science projects can produce data with accuracy equal to or surpassing that of professionals. Successful projects rely on a suite of methods to boost data accuracy and account for bias, including iterative project development, volunteer training and testing, expert validation, replication across volunteers, and statistical modeling of systematic error. Each citizen-science dataset should therefore be judged individually, according to project design and application, and not assumed to be substandard simply because volunteers generated it.

Front Ecol Environ 2016; 14(10): 551–560, doi:10.1002/fee.1436

Citizen science – research that engages non-professionals in the process of creating new scientific knowledge (Bonney *et al.* 2014) – has expanded greatly in the past decade (Figure 1; McKinley *et al.* 2015). Rising interest in this approach has been fueled in part by rapid technological developments (Newman *et al.* 2012), by policy and management needs for large-scale and long-term monitoring datasets (Conrad and Hilchey 2011), and by increased emphasis on science outreach and education (Silvertown 2009). While citizen-science projects vary widely in their subject matter, objectives, activities, and scale (Figures 2–4; Wiggins and Crowston 2015), one common goal is the production of reliable data that can be used for scientific purposes.

In a nutshell:

- Datasets produced by volunteer citizen scientists can have reliably high quality, on par with those produced by professionals
- Individual volunteer accuracy varies, depending on task difficulty and volunteer experience; multiple methods exist for boosting accuracy to required levels for a given project
- Most types of bias found in citizen-science datasets are also found in professionally produced datasets and can be mitigated using existing statistical tools
- Reviewers of citizen-science projects should look for iterated project design, standardization and appropriateness of volunteer protocols and data analyses, capture of metadata, and accuracy assessment

[1]*Department of Organismic and Evolutionary Biology, Harvard University, Cambridge, MA* [*]*(kosmala@fas.harvard.edu)*; [2]*College of Information Studies, University of Maryland, College Park, MD*; [3]*Department of Physics, University of Oxford, Oxford, UK*; [4]*Center for Astrophysics and Space Sciences, Department of Physics, University of California–San Diego, San Diego, CA*

The ecological and environmental sciences have been leaders in citizen science, boasting some of the longest-running projects that have contributed meaningful data to science and conservation, including the Cooperative Weather Service (first year of data collection: 1890), the National Audubon Society's Christmas Bird Count (1900; >200 publications have relied on the resulting dataset), the North American Breeding Bird Survey (1966; >670 publications), the leafing and flowering times of US lilacs and honeysuckles (1956; >50 publications; Rosemartin *et al.* 2015), and the Butterfly Monitoring Scheme (1976; >100 publications). These and other successful citizen-science projects have increased ecological and environmental knowledge at large geographic scales and at high temporal resolution (McKinley *et al.* 2015). Specific advances include improved understanding of species range shifts, phenology, macroecological diversity and community composition, life-history evolution, infectious disease systems, and invasive species dynamics (Dickinson *et al.* 2010; Bonney *et al.* 2014).

Despite the wealth of information generated and the many resulting scientific discoveries, citizen science arouses skepticism among professional scientists. The root of this skepticism may be that citizen science is still not considered a mainstream approach to science (Riesch and Potter 2014; Theobald *et al.* 2015). Alternatively, some professionals may believe that unpaid volunteers (hereafter, simply "volunteers") are not committed or skilled enough to perform at the level of paid staff. Professional scientists have questioned the ethics of partnering with volunteers (Resnik *et al.* 2015), the "motives and ambitions" of the volunteers themselves (Show 2015), and their ability to provide quality data (Alabri and Hunter 2010). The primary fear is that science and policy might be derived from unreliable data, since the quality of data produced by volunteers has long been a concern (Cohn 2008; Dickinson *et al.* 2010, 2012).

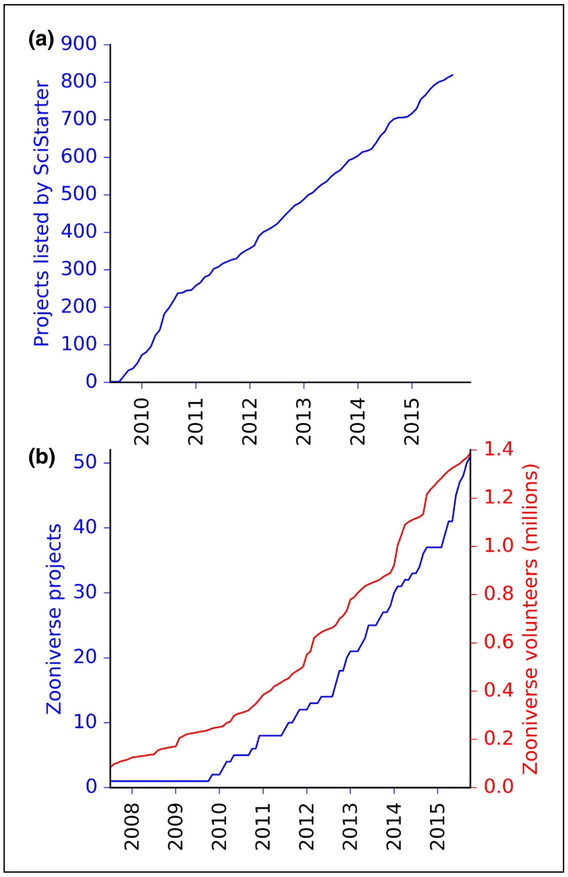


Figure 1. *The past decade has seen a rapid increase in citizen-science projects and volunteers. (a) Number of projects (a) listed on the citizen-science project directory website SciStarter and (b) created by the citizen-science portal Zooniverse (blue) and number of Zooniverse-registered volunteers (red).*

Because citizen science as a whole is often perceived as questionable science, even project results using high-quality data can be difficult to publish and are often relegated to educational or outreach portions of journals and conferences (Bonney *et al.* 2014). Many published peer-reviewed papers obscure the fact that citizen-science data are being used by mentioning a project or database by name and citation only or by consigning the methods to supplementary materials (Cooper *et al.* 2014). Further, some people believe that citizen science is worth more for its educational potential than for the science it can produce (Cohn 2008; Wiggins 2012). These views have made it challenging for scientists to obtain funding for potentially transformative citizen-science projects (Wiggins 2012), and project leaders often find it easier to obtain "experimental" startup funding than ongoing operational support for long-term projects (Wiggins and Crowston 2015).

Here we examine data quality practices across a wide range of ecological and environmental citizen-science projects and describe the most effective methods used to acquire high-quality data. We discuss current challenges and future directions in ensuring high-quality data. Our hope is that citizen-science projects will be judged on their methods and data stewardship as a whole and not simply on whether volunteers participated in the process (Panel 1).

What constitutes high-quality data?

The concept of data quality is multi-dimensional, consisting of more than a dozen possible non-exclusive metrics (Pipino *et al.* 2002). Some metrics are task-dependent, such as timeliness of data for a particular question or objective. Other measures focus on data management practices, including the provision of relevant metadata. We focus on two objective task-independent measures of data quality that prompt the most skepticism among professional ecologists and environmental managers: accuracy and bias (Panel 1). Accuracy is the degree to which data are correct overall, while bias is systematic error in a dataset.

Quality of data produced by professionals

A reasonable definition of high-quality data for citizen science is data of comparable accuracy and bias to that produced by professionals and their trainees (Bonney *et al.* 2014; Cooper *et al.* 2014; Theobald *et al.* 2015). However, few projects evaluate the accuracy and bias of professionally produced data within the same contexts as volunteer-produced data. Furthermore, much ecological data has a degree of subjective interpretation so that observations of the same sample or site vary when performed by multiple professionals or the same professional at different times.

Comparisons of data between two or more professionals can demonstrate substantial variation. For instance, percentage cover estimates of intertidal communities made in 0.25-m quadrats showed just 77.3% to 86.6% similarity (Bray-Curtis measure) between professionals (Cox *et al.* 2012). In Sweden's National Survey of Forest Soils and Vegetation, observer identity explained nearly 20% of variance in vegetation percentage cover estimates in 100-m^2 plots (Bergstedt *et al.* 2009). The Australian Institute of Marine Science Long-Term Monitoring Program considers newly trained professionals to be proficient once their classifications of coral reef organisms (Figure 2a) reach 90% agreement with those of established professionals (Ninio *et al.* 2003). In wildlife population surveys, multiple observers increase transect-survey quality because of imperfect detection by single observers (Cook and Jacobson 1979). For example, under ideal conditions, single experienced observers in Alaska recorded only 68% of known moose present in aerial surveys (LeResche and Rausch 1974).

Even for observations where the correct answer is more concrete, professionals sometimes make mistakes. Experts examining trees in urban Massachusetts agreed on species identifications 98% of the time and on tree condition 89% of the time (Bloniarz and Ryan 1996). In one study recording target plant species, professionals had an 88% accuracy rate (Crall *et al.* 2011). Experts identifying large

Panel 1. Questions to consider when evaluating citizen-science projects for data quality

The following questions are based on existing research and are meant to aid creators, evaluators, and users of citizen-science data. Creators of citizen-science projects may find them useful for project development and are encouraged to reference them in project methods. Evaluators and reviewers of citizen-science proposals and manuscripts may use them to better gauge the quality of data in citizen-science projects. Finally, citizen-science data consumers may find these questions valuable for ascertaining the suitability of datasets for particular scientific questions. Future research should build on current knowledge to strengthen and broaden best practices for data quality.

Does the project use iterative design? Developing tools and protocols for a project that produces high-quality data requires iteration, using one or more rounds of pilot or beta testing to ensure a procedure that volunteers can perform successfully without confusion or systematic errors.

How easy or hard are the tasks? Easy tasks usually have high accuracy with minimal bias. Difficult or complex tasks may require additional effort on the part of the project managers to promote accuracy and account for bias. Such efforts include training, pre-tests, ongoing volunteer assessment, expert validation, classification replication, and application of statistical tools.

How systematic are the task procedures and data entry? High-quality data require straightforward and systematic capture, classification, and data-entry procedures for the volunteers to follow. For online data entry, fields should enforce type (eg counts must be integers) and for categorical variables, users should select from lists rather than entering free-form text.

What equipment are volunteers using? Any equipment used for measurements should be standardized and calibrated across volunteers.

Does the project record relevant metadata? Projects should record metadata that may influence volunteer data capture or collection. Such data might include environmental conditions (temperature, precipitation, time of day, etc), equipment or device settings (such as mobile device operating system version), or characteristics of the volunteers themselves (such as level of education or training). If characteristics of volunteers are collected, project managers should seek approval from the relevant human subjects review board. Projects should also retain volunteer identifiers (anonymized if necessary). These metadata can be used to statistically model bias to increase valid inference from project data.

Is collection effort standardized or accounted for in data analysis? Standardized effort (capturing data at specified places, times, and/or durations of time) is ideal for ensuring unbiased data. However, many projects cannot standardize effort; for these projects, it is imperative that effort is reported by volunteers and is accounted for in statistical models and analysis.

Does the project assess data quality by appropriate comparison with professionals? In reporting results, citizen-science projects should compare volunteer data accuracy with that of professionals. Importantly, between-professionals accuracy should also be assessed so that variation due to individuals is not confused with variation due to volunteer–professional differences.

Are the data appropriate for the project's management objectives or research questions? In particular, data should be of sufficient quantity and should cover timescales and geographic extents commensurate with project objectives. Data may also need to be timely, depending on the application.

Are good data management practices used? Citizen-science project managers should implement best practices in data management (eg Borer *et al.* 2009; Michener and Jones 2012; Wiggins *et al.* 2013). In particular, data should be stored securely in a consistent and concise format that is easy to interpret and use and is made accessible to data users.

African animal species from images in Snapshot Serengeti were found to have an accuracy of 96.6%, with errors due largely to identification fatigue and data-entry error (Swanson *et al.* 2016).

Because data produced by professionals and other experts can contain error and bias, comparisons between volunteer and professional data must be careful to distinguish between inter-observer variability and variability due to status as a professional or volunteer. We should also not expect the accuracy of individual volunteers to be higher than that of individual professionals.

Quality of data produced by volunteers

Despite differences in background and experience from professional ecologists, volunteers can perform at the same level for particular data gathering and processing tasks, with variation depending on task difficulty and volunteer experience. Rates of 70–95% accuracy are typical for species identification across a diverse array of systems and taxa (Gardiner *et al.* 2012; Fuccillo *et al.* 2015; Swanson *et al.* 2016).

Volunteers' accuracy varies with task difficulty (Table 1). For Snapshot Serengeti, volunteers were better at identifying iconic mammals such as giraffe and zebra than at identifying less familiar mammals such as aardwolf and a set of easily confused antelope species (Swanson *et al.* 2016). In anuran call surveys (Figure 2b), volunteers' accuracy varied widely with species (Weir *et al.* 2005). The Monarch Larva Monitoring Project (Figure 2c) found reliable identification of 5th instar larvae, but not 1st and 2nd instar larvae (Prysby and

Table 1. Ecology and environmental citizen-science task types

Task type	*Description*	*Skill or training required*	*Examples*
Taxonomic classifications	Taxonomic identification or sorting of organisms	Low to High*	**Low**: Target crab species identification (Delaney *et al.* 2008) **Medium**: Antelope differentiation in Snapshot Serengeti (Swanson *et al.* 2016) **High**: Cryptic bird species differentiation in eBird (Kelling *et al.* 2015)
Percentage cover estimates	Visual assessment of the composition of sessile organisms and/or substrate in a given area	Medium	Intertidal communities (Cox *et al.* 2012) Forest vegetation (Bergstedt *et al.* 2009)
Presence–absence determinations	Binary determination of whether particular organisms are in a given area	Low	California Department of Fish and Wildlife's Invasive Species Citizen Science Program (www.wildlife.ca.gov/Conservation/Invasives)
Counts	Count of the number of individuals in a given area	Low to Medium	**Low**: Number of birds arriving at a feeder in Project FeederWatch (Bonter and Cooper 2012) **Medium**: Estimating number of birds in large flocks in eBird (Kelling *et al.* 2015)
Organism trait measurements	Measurements of one or more traits of replicate individuals	Low to Medium**	**Low**: Plant fruiting in Nature's Notebook (Fuccillo *et al.* 2015) **Medium**: Larval instar in the Monarch Larva Monitoring Project (Prysby and Oberhauser 2004)
Environmental measurements	Measurements of abiotic environmental conditions at a given location	Low	Atmospheric aerosols in iSPEX-EU (ispex-eu.org) Precipitation in CoCoRaHS (Moon *et al.* 2009)

Notes: *Depending on the level of differentiation required, the familiarity of organisms, the obviousness of identifying features, and the time allowed for identification or sorting. **Depending on the trait and the instrument (if any) used to measure the trait.

Oberhauser 2004). In identifications of plant species, volunteers had an 82% accuracy rate for identification of "easy" species, but just a 65% accuracy rate for "hard" ones (Crall *et al.* 2011). Volunteers could more reliably identify street trees (Figure 3a) to genus (94% accuracy) than to species (79%) (Bloniarz and Ryan 1996). Determining a crab's species (Figure 3b) was easier (95% accuracy for seventh graders) than determining its sex (80% accuracy for seventh graders) (Delaney *et al.* 2008). Kelling *et al.* (2015) identified differences in bird detection (Figure 3c) and identification rates by volunteers for species that are secretive, hard to distinguish visually, or best identified by sound.

Volunteers often improve in accuracy as they gain experience with a project. New Snapshot Serengeti participants had an average of 78.5% accuracy, but most individuals who had classified hundreds of images had accuracies over 90% (Swanson *et al.* 2016). In the French Breeding Bird Survey, observers counted 4.3% more birds per hour after their first year of observation (Jiguet 2009), and an analysis of the North American Breeding Bird Survey also found a first-year effect (Kendall *et al.* 1996). Models relying on species accumulation curves to assess the performance of volunteers revealed that bird species detection and identification abilities improved with cumulative experience (Kelling *et al.* 2015).

Techniques for producing high-quality ecological citizen-science data

Effective methods for acquiring high-quality citizen-science data vary based on the type of data being created and the resources available to the project. In general, they are similar to the procedures used by professionals (Panel 2; Wiggins and Crowston 2015). The following techniques are used by existing projects to increase the quality of citizen-science data. Successful projects typically use multiple techniques.

Iterative development of task and tool design

Iterative refinement of tasks and tools for volunteers is often a critical step in project development (Crall *et al.* 2010). The Great Sunflower Project progressively reduced the duration of observations of pollinator service, and expanded the range of plant target species, making the tasks more accessible without compromising data quality (Wiggins 2013). Mountain Watch saw a reduction in errors for hikers' observations of alpine plant phenology (Figure 4a) when tasks and data sheets were changed to specify plots where the species were known to be present rather than at volunteer-selected locations along a trail (Wiggins 2013). The Virginia Save-Our-Streams program shifted from a presence-only protocol to a count-based protocol when analyses showed that the original protocol resulted in poor data quality that consistently overrated stream condition (Engel and Voshell 2002).

Volunteer training and testing

Perhaps the most obvious approach for improving data quality is to train volunteers or to require prequalification via a skills test. The Monarch Larva Monitoring Project provides an intensive training program of 4- to 11-hour workshops for volunteers and focuses on long-term engagement. Field observations and analyses of volunteer data suggest that trained and engaged volunteers produce data of similar or higher quality than hired field assistants (Prysby and Oberhauser 2004). Similarly, in monitoring tropical resources, local volunteers who received training over 2–3 days in addition to shorter, annual refresher training produced data of similar quality to that of professional scientists (Danielsen *et al.* 2014). Training may occasionally be self-initiated by volunteers. The Breeding Bird Survey, for example, relies on skilled birders, who have gained their expertise over a lifetime of bird watching (Sauer *et al.* 2013).

Ongoing training can be beneficial. BeeWatch volunteers are provided with ongoing feedback on their bee species identifications, based on professional validation of their photographs, and this feedback increases both volunteer accuracy and retention (van der Wal *et al.* 2016). Just-in-time training can sometimes be undertaken in conjunction with project tasks. Snapshot Serengeti provides initially untrained volunteers with a set of guiding filters, which allows them to learn likely species identifications based on a target animal's morphological traits (Swanson *et al.* 2016). Similarly, eBird assists its volunteers with dynamically generated data-entry forms that list the most common birds for a volunteer's given location and time, increasing both volunteer awareness of the local species and data quality (Sullivan *et al.* 2014). Stardust@home uses known "seeded" images for ongoing assessment and provides feedback to volunteers on their success rate so that they may voluntarily try to improve their accuracy (Westphal *et al.* 2006).

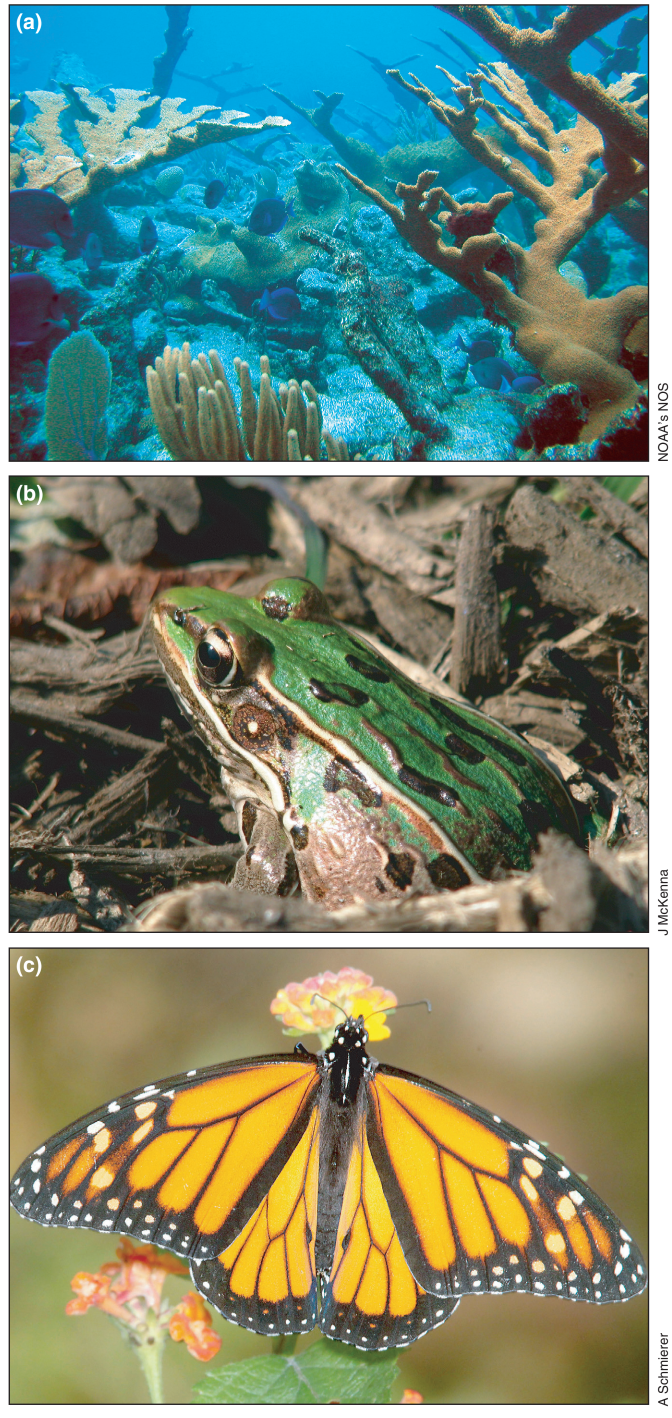


Figure 2. *Citizen-science data types are numerous. For example, (a) the Australian Institute of Marine Science Long-Term Monitoring Program collects percent cover data on coral reefs, (b) the North American Amphibian Monitoring Program identifies the vocalizations of amphibians such as the southern leopard frog (*Rana sphenocephala*), and (c) the Monarch Larva Monitoring Project counts larvae of the monarch butterfly (*Danaus plexippus*).*

Use of standardized and calibrated equipment

Standardization of measurement tools and collection of instrument calibration data are common strategies for promoting high-quality data and typically mirror established professional techniques. The CoCoRaHS precipitation monitoring network requires a standardized and reliable rain gauge (Moon *et al.* 2009). Many

Panel 2. Data capture and data classification

We distinguish between data *capture* (collection and observation) and data *classification* (the interpretation of raw data into an analyzable form). An example of data capture is the collection of insects by pitfall trap. The corresponding data classification is the determination of their taxonomic identifications. These two steps are frequently conducted concurrently by professionals (eg percentage cover estimates), but separating the process into discrete tasks allows better control over statistical analyses of data error. In citizen-science projects, volunteers may conduct data capture, data classification, or both.

Volunteer capture, professional classification: Volunteers collect samples and send them to professionals for analysis. This method is typically employed to gather data at large spatial scales and when laboratory methods are required. *Examples*: Clean Air Coalition of Western New York, Lakes of Missouri Volunteer Program, American Gut

Professional capture, volunteer classification: Professionals select subjects to evaluate, but lack capacity to classify all subjects. Projects that use large volumes of digital images produced by cameras set up by experts fall into this category. *Examples*: Snapshot Serengeti (camera traps), Floating Forests (satellite imagery), Season Spotter (automated near-Earth cameras).

Volunteer capture and classification: Volunteers collect samples, make observations, or set up automated collection devices. They also classify the observations, samples, or vouchers. *Examples*: Project FeederWatch, eBird, eMammal, Monarch Larva Monitoring Project, Nature's Notebook.

water-quality projects use standardized Secchi tubes or loan out calibrated equipment to volunteers for data capture (Sheppard and Terveen 2011), depending on the nature of the data being collected. Projects using mobile phone sensors record system data such as device model and operating system to calibrate data across devices (eg MyShake).

Expert validation

When volunteers are not highly skilled or the events they observe are ephemeral, one solution is to collect "vouchers" that will allow for expert verification. Vouchers can be physical specimens (eg Delaney *et al.* 2008; Gardiner *et al.* 2012) or photographs, video, or audio recordings (Kageyama *et al.* 2007). The eMammal project asks volunteers to set up motion-triggered cameras to monitor North American mammals (McShea *et al.* 2015). These volunteers make species identifications for "their" images, while the images themselves serve as vouchers, allowing experts to validate those identifications. Expert validation of volunteer classifications has been shown to be more cost-effective than direct expert classification for lady beetles (Figure 4b; Gardiner *et al.* 2012).

However, expert validation of every data point can be impractical, and for large projects, efficiently targeting likely wrong answers is key. Project FeederWatch uses a "smart filter" system that flags observations of unlikely species and unusually large numbers of birds. Flagged data are immediately sent to regional experts who then ask for photographic vouchers and supporting details from volunteers to validate the sightings. Over 3 years, just 1.3% of observations required expert review (Bonter and Cooper 2012). Similarly, Snapshot Serengeti uses a suite of post-hoc statistical metrics to identify "difficult" images of African animals to be sent for expert review (Swanson *et al.* 2016).

Replication and calibration across volunteers

Some projects require multiple independent volunteer measurements of each subject to improve data quality. Projects on the Zooniverse platform show each digital voucher to multiple volunteers, and all resulting classifications are combined into a "consensus" answer. For instance, each image in Snapshot Serengeti (eg Figure 4c) is shown to 5–25 volunteers and its consensus answer is the plurality of identifications from all volunteers. Consensus improved accuracy from 88.6% to 97.9% over single classifications (Swanson *et al.* 2016).

When replication for all data points is not practical, calibration across volunteers using targeted replication allows for statistical control of data quality. In Mountain Watch, volunteers collect data at fixed locations as well as at self-selected locations, with trained staff also reporting data from the fixed plots; this permits verification of observations from volunteers against those of staff naturalists. The fixed plots also allow for statistical normalization across volunteers, and additional logger data from these plots provide covariates for data analysis (Wiggins 2013). Another calibration technique involves injecting professionally classified (eg Stardust@home; Westphal *et al.* 2006) or artificially generated (eg Planet Hunters; Schwamb *et al.* 2012) vouchers into voucher sets given to volunteers for classification in order to evaluate ongoing volunteer performance.

Skill-based statistical weighting of volunteer classifications

Methods are emerging for weighting volunteer classifications based on individual characteristics, such as skill level. For projects with multiple classifications per captured datum, volunteer skill can be assessed via frequency of agreement with other volunteers. For

Snapshot Serengeti data, weighting increased consensus accuracy from 96.4% to 98.6% (Hines *et al.* 2015). In cases where there is only one classification per captured datum, skill can be assessed by testing or other means. The observation skill of eBird users was assessed using species accumulation curves, and when skill was incorporated into bird species distribution models, model accuracy increased for approximately 90% of the 120 species tested (Kelling *et al.* 2015).

Accounting for random error and systematic bias

Data produced through citizen science may contain error and bias, but existing statistical and modeling tools can mitigate these errors and biases to produce meaningful inference. A common concern is that citizen-science data is too "noisy" – ie it has too much variability. For some projects, collecting a sufficiently large amount of data may be adequate to reduce non-systematic error in volunteer-produced data through the law of large numbers (Bird *et al.* 2014). eBird data accumulate at the rate of millions of observations monthly (Sullivan *et al.* 2014), and the resulting range maps and temporal distribution patterns concur with professional knowledge (Wiggins 2012). Similarly, with more than 750,000 individual reports, the US Geological Survey's "Did You Feel It?" program yields highly accurate measures of earthquake strength when compared with readings from ground sensors (Atkinson and Wald 2007).

Many of the systematic biases in citizen-science data are the same biases that occur in professionally collected data: spatially and temporally non-random observations (biased by things such as time of day or week, weather, and human population density; eg Courter *et al.* 2013), non-standardized capture or search effort, under-detection of organisms (Elkinton *et al.* 2009; Crall *et al.* 2011), confusion between similar-looking species, and the over- or under-reporting of rare, cryptic, or elusive species as compared to more common ones (Gardiner *et al.* 2012; Kelling *et al.* 2015; Swanson *et al.* 2016). Because these biases are also found in professional ecological research, many methods have been developed for statistically controlling for and modeling them, as long as the relevant metadata are recorded (Bird *et al.* 2014).

The only known bias specific to citizen science is the potentially high variability among volunteers in terms of demographics, ability, effort, and commitment. Modeling characteristics that vary among volunteers such as age, previous experience, formal education, attitudes, and training methods may increase data reliability, although the magnitude of the effect may be project- or task-dependent (Galloway *et al.* 2006; Delaney *et al.* 2008; Crall *et al.* 2011). Bird *et al.* (2014) thoroughly described existing statistical methods – such as generalized linear

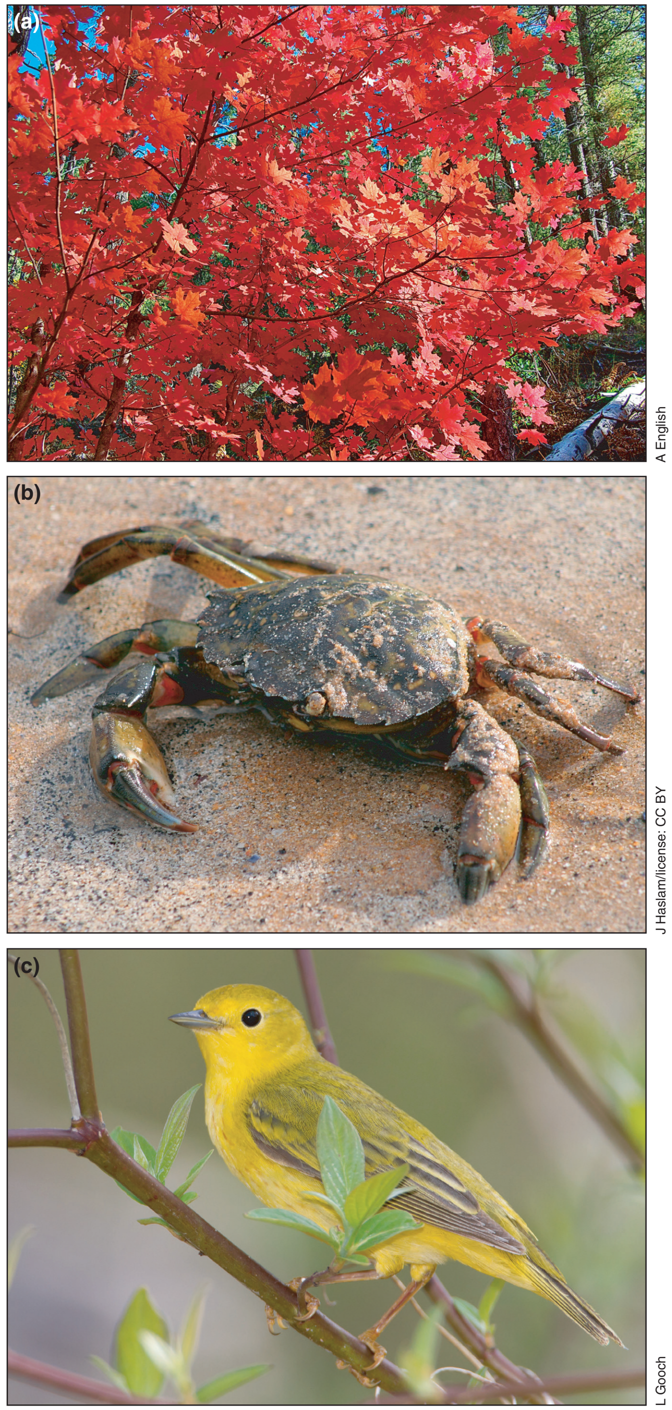
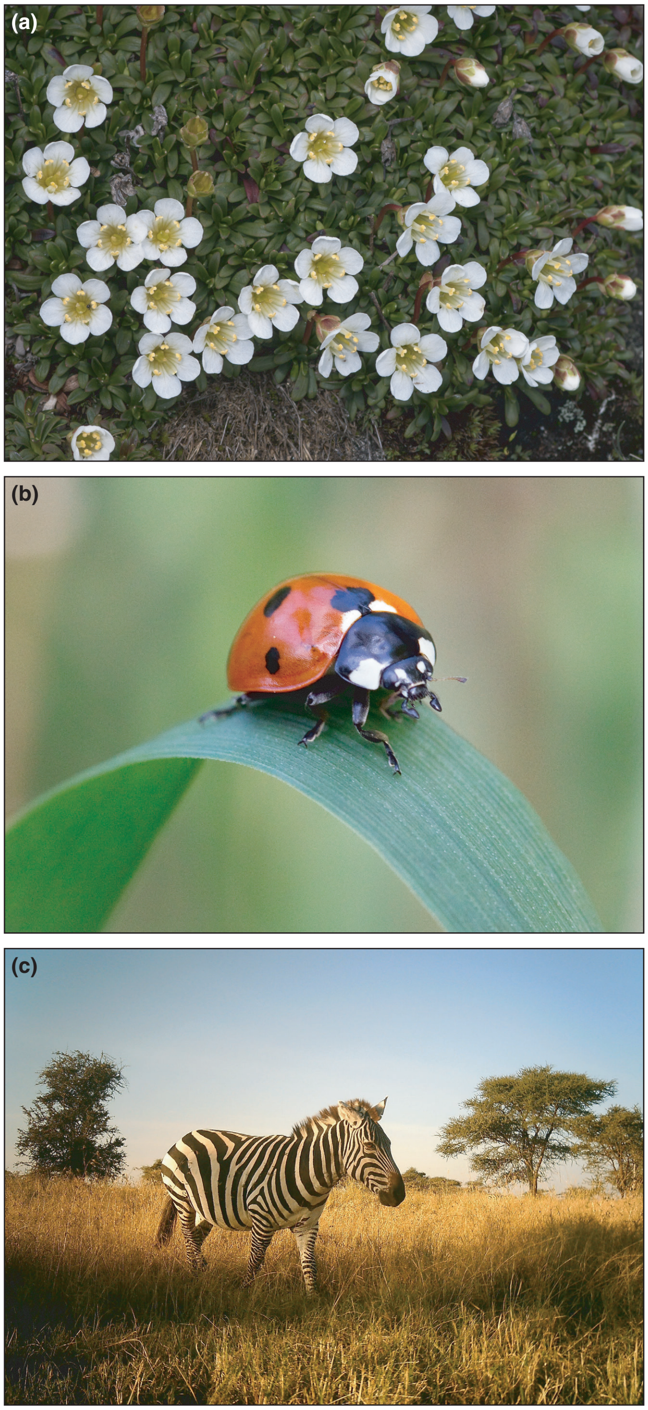


Figure 3. *Citizen-science data are collected at multiple spatial scales. For example, (a) Bloniarz and Ryan (1996) had volunteers inventory urban trees such as the red maple (*Acer rubrum*) in a single neighborhood, (b) volunteers helped Delaney* et al. *(2008) identify species of crustaceans such as this invasive shore crab (*Carcinus maenas*) along the Atlantic coast from New Jersey to Maine, and (c) volunteers all across the US participate in eBird to record birds such as the American yellow warbler (*Setophaga petechia*).*



K McFarland

S Nygaard/license: CC BY

Snapshot Serengeti

Figure 4. *Citizen-science data are collected on diverse organisms. For example, (a) Mountain Watch collects data on flowering plants such as the pincushion plant (*Diapensia lapponica*), (b) the UK Ladybird Survey and the Lost Ladybug Project record occurrences of Coccinellids, and (c) Snapshot Serengeti asks volunteers to classify mammals such as the plains zebra (*Equus quagga*).*

models, mixed-effect models, hierarchical models, and machine learning algorithms – that can be used to properly analyze large and variable datasets produced by citizen-science projects.

Challenges and the future of high-quality citizen-science data

Technology is rapidly developing that will facilitate the implementation of best practices for high-quality citizen-science data, but challenges in project technologies and data management still remain. Online resource sites (eg Cornell's Citizen Science Toolkit, US Federal Crowdsourcing and Citizen Science Toolkit), platforms for building online citizen-science projects (eg Zooniverse Project Builder, CrowdCrafting), and data-entry tools for field data (eg iNaturalist, CitSci.org, iSpot) are making it easier than ever to build citizen-science projects with online components. Yet research in the field of human–computer interaction is beginning to demonstrate direct and indirect impacts of online project and technology design on volunteer performance (Bowser *et al.* 2013; Eveleigh *et al.* 2014), and more such research is needed. The next generation of multipurpose data-entry platforms should allow for customized data constraints and real-time outlier detection to reduce data-entry error. Repositories to support terabyte-scale multimedia voucher sets are also increasingly needed (eg McShea *et al.* 2015). Other technological challenges include unreliable mobile device GPS performance, the need for offline functionality in mobile devices, issues of usability and accessibility, and user privacy protections (Bowser-Livermore and Wiggins 2015; Wiggins and He 2016).

Additional research is required on the application of existing statistical and modeling tools to citizen-science datasets, as these datasets sometimes present additional challenges (Bird *et al.* 2014). Currently, analyses of complex citizen-science data often require custom solutions developed by professional statisticians and computer scientists, using high performance or cloud computing systems (eg Yu *et al.* 2010; Hochachka *et al.* 2012) – resources that are not available to most projects. Generalizable and scalable methods to analyze variable spatiotemporal datasets will be increasingly valuable, and borrowing techniques from other fields may prove beneficial. The information science field has developed sophisticated methods for combining categorical classifications across multiple observers (eg Woźniak *et al.* 2014). Similarly, the social sciences have developed reliability and aggregation metrics that can be adapted to accommodate heterogeneous volunteer data. In the computer science field, optimal crowdsourcing has commercial applications, prompting new human computation journals and conferences (eg the journal *Human Computation*, the AAAI Human Computation conference). Task allocation algorithms, in particular, have the potential to improve both data quality and project efficiency by routing content to the best individuals (Kamar *et al.* 2012).

Conclusions

As citizen science continues to grow and mature, we expect to see a heightened awareness of data quality as a key metric of project success. Appropriate metrics of data quality compare data produced by volunteers against similar data produced by professionals, and distinguish inter-observer variability from variability due to observer experience. Evidence from across a diverse range of task types and study systems shows that volunteers can produce high-quality data, and that accuracy is particularly high for easy tasks and for experienced volunteers. High-quality data can be produced using a suite of techniques, and investment in additional research and technology has the potential to augment these techniques and make them more broadly accessible. We suggest that Panel 1 be used as a guide by citizen-science evaluators, project creators, and data users as a standard to gauge data quality. As we face grand challenges related to global environmental change, citizen science emerges as a general tool to collect otherwise unobtainable high-quality data in support of policy and resource management, conservation monitoring, and basic science.

Acknowledgements

MK was supported by a grant from the National Science Foundation, through the Macrosystems Biology Program (award EF-1065029). BS acknowledges support from Balliol College, Oxford, and the National Aeronautics and Space Administration (NASA) through Einstein Postdoctoral Fellowship Award Number PF5-160143 issued by the Chandra X-ray Observatory Center, which is operated by the Smithsonian Astrophysical Observatory for and on behalf of NASA under contract NAS8-03060.

References

Alabri A and Hunter J. 2010. Enhancing the quality and trust of citizen science data. In: IEEE Sixth International Conference on e-Science; 7–10 Dec 2010. Brisbane, Australia: IEEE.

Atkinson GM and Wald DJ. 2007. "Did You Feel It?" intensity data: a surprisingly good measure of earthquake ground motion. *Seismol Res Lett* **78**: 362–68.

Bergstedt J, Westerberg L, and Milberg P. 2009. In the eye of the beholder: bias and stochastic variation in cover estimates. *Plant Ecol* **204**: 271–83.

Bird TJ, Bates AE, Lefcheck JS, *et al.* 2014. Statistical solutions for error and bias in global citizen science datasets. *Biol Conserv* **173**: 144–54.

Bloniarz DV and Ryan HDP III. 1996. The use of volunteer initiatives in conducting urban forest resource inventories. *J Arboric* **22**: 75–82.

Bonney R, Shirk JL, Phillips TB, *et al.* 2014. Next steps for citizen science. *Science* **343**: 1436–37.

Bonter DN and Cooper CB. 2012. Data validation in citizen science: a case study from Project FeederWatch. *Front Ecol Environ* **10**: 305–07.

Borer ET, Seabloom EW, Jones MB, and Schildhauer M. 2009. Some simple guidelines for effective data management. *Bull Ecol Soc Am* **90**: 205–14.

Bowser A, Hansen D, He Y, *et al.* 2013. Using gamification to inspire new citizen science volunteers. In: Proceedings of the First International Conference on Gameful Design, Research, and Applications; 2–4 Oct 2013. Stratford, Canada: ACM.

Bowser-Livermore A and Wiggins A. 2015. Privacy in participatory research: advancing policy to support human computation. *Hum Comput* **2**: 19–44.

Cohn JP. 2008. Citizen science: can volunteers do real research? *BioScience* **58**: 192–97.

Conrad CC and Hilchey KG. 2011. A review of citizen science and community-based environmental monitoring: issues and opportunities. *Environ Monit Assess* **176**: 273–91.

Cook RD and Jacobson JO. 1979. A design for estimating visibility bias in aerial surveys. *Biometrics* **35**: 735.

Cooper CB, Shirk J, and Zuckerberg B. 2014. The invisible prevalence of citizen science in global research: migratory birds and climate change. *PLoS ONE* **9**: e106508.

Courter JR, Johnson RJ, Stuyck CM, *et al.* 2013. Weekend bias in citizen science data reporting: implications for phenology studies. *Int J Biometeorol* **57**: 715–20.

Cox TE, Philippoff J, Baumgartner E, and Smith CM. 2012. Expert variability provides perspective on the strengths and weaknesses of citizen-driven intertidal monitoring program. *Ecol Appl* **22**: 1201–12.

Crall AW, Newman GJ, Jarnevich CS, *et al.* 2010. Improving and integrating data on invasive species collected by citizen scientists. *Biol Invasions* **12**: 3419–28.

Crall AW, Newman GJ, Stohlgren TJ, *et al.* 2011. Assessing citizen science data quality: an invasive species case study. *Conserv Lett* **4**: 433–42.

Danielsen F, Jensen PM, Burgess ND, *et al.* 2014. A multicountry assessment of tropical resource monitoring by local communities. *BioScience* **64**: 236–51.

Delaney DG, Sperling CD, Adams CS, and Leung B. 2008. Marine invasive species: validation of citizen science and implications for national monitoring networks. *Biol Invasions* **10**: 117–28.

Dickinson JL, Shirk J, Bonter D, *et al.* 2012. The current state of citizen science as a tool for ecological research and public engagement. *Front Ecol Environ* **10**: 291–97.

Dickinson JL, Zuckerberg B, and Bonter DN. 2010. Citizen science as an ecological research tool: challenges and benefits. *Annu Rev Ecol Evol Syst* **41**: 149–72.

Elkinton J, Ellison A, Preisser E, and Fitzpatrick M. 2009. Observer bias and the detection of low-density populations. *Ecol Appl* **19**: 1673–79.

Engel SR and Voshell JRJ. 2002. Volunteer biological monitoring: can it accurately assess the ecological condition of streams? *Am Entomol* **48**: 164–77.

Eveleigh A, Jennett C, Blandford A, *et al.* 2014. Designing for dabblers and deterring drop-outs in citizen science. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems; 26 Apr–1 May 2014. Toronto, Canada: ACM Press.

Fuccillo KK, Crimmins TM, de Rivera CE, and Elder TS. 2015. Assessing accuracy in citizen science-based plant phenology monitoring. *Int J Biometeorol* **59**: 917–26.

Galloway AWE, Tudor MT, and Vander Haegen WM. 2006. The reliability of citizen science: a case study of Oregon white oak stand surveys. *Wildl Soc Bull* **34**: 1425–29.

Gardiner MM, Allee LL, Brown PM, *et al.* 2012. Lessons from lady beetles: accuracy of monitoring data from US and UK citizen-science programs. *Front Ecol Environ* **10**: 471–76.

Hines G, Swanson A, Kosmala M, and Lintott C. 2015. Aggregating user input in ecology citizen science projects. In: Proceedings of the Twenty-Seventh Conference on Innovative Applications of Artificial Intelligence; 25–29 Jan 2015. Austin, TX: AAAI.

Hochachka WM, Fink D, Hutchinson RA, *et al.* 2012. Data-intensive science applied to broad-scale citizen science. *Trends Ecol Evol* **27**: 130–37.

Jiguet F. 2009. Method learning caused a first-time observer effect in a newly started breeding bird survey. *Bird Study* **56**: 253–58.

Kageyama M, Monk RR, Bradley RD, *et al.* 2007. The changing significance and definition of the biological voucher. In: Williams S and Hawks C (Eds). Museum studies: perspectives and innovations. Washington, DC: Society for the Preservation of Natural History Collections.

Kamar E, Hacker S, and Horvitz E. 2012. Combining human and machine intelligence in large-scale crowdsourcing. In: Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems; 4–8 Jun 2012. Valencia, Spain: International Foundation for Autonomous Agents and Multiagent Systems.

Kelling S, Johnston A, Hochachka WM, *et al.* 2015. Can observation skills of citizen scientists be estimated using species accumulation curves? *PLoS ONE* **10**: e0139600.

Kendall WL, Peterjohn BG, and Sauer JR. 1996. First-time observer effects in the North American Breeding Bird Survey. *The Auk* **113**: 823–29.

LeResche RE and Rausch RA. 1974. Accuracy and precision of aerial moose censusing. *J Wildl Manag* **38**: 175–82.

McKinley DC, Miller-Rushing AJ, Ballard HL, *et al.* 2015. Investing in citizen science can improve natural resource management and environmental protection. *Issues in Ecology* **19**: 1–27.

McShea WJ, Forrester T, Costello R, *et al.* 2015. Volunteer-run cameras as distributed sensors for macrosystem mammal research. *Landsc Ecol* **31**: 55–66.

Michener WK and Jones MB. 2012. Ecoinformatics: supporting ecology as a data-intensive science. *Trends Ecol Evol* **27**: 85–93.

Moon JTI, Guinan PE, Snider DJ, and Lupo AR. 2009. CoCoRaHs in Missouri: four years later, the importance of observations. *Trans Missouri Acad Sci* **43**: 1–12.

Newman G, Wiggins A, Crall A, *et al.* 2012. The future of citizen science: emerging technologies and shifting paradigms. *Front Ecol Environ* **10**: 298–304.

Ninio R, Delean J, Osborne K, and Sweatman H. 2003. Estimating cover of benthic organisms from underwater video images: variability associated with multiple observers. *Mar Ecol-Prog Ser* **265**: 107–16.

Pipino LL, Lee YW, and Wang RY. 2002. Data quality assessment. *Commun ACM* **45**: 211–18.

Prysby MD and Oberhauser KS. 2004. Temporal and geographic variation in monarch densities: citizen scientists document monarch population patterns. In: Oberhauser KS and Solensky MJ (Eds). Monarch butterfly biology & conservation. Ithaca, NY: Cornell University Press.

Resnik DB, Elliott KC, and Miller AK. 2015. A framework for addressing ethical issues in citizen science. *Environ Sci Policy* **54**: 475–81.

Riesch H and Potter C. 2014. Citizen science as seen by scientists: methodological, epistemological and ethical dimensions. *Public Underst Sci* **23**: 107–20.

Rosemartin AH, Denny EG, Weltzin JF, *et al.* 2015. Lilac and honeysuckle phenology data 1956–2014. *Sci Data* **2**: 150038.

Sauer JR, Link WA, Fallon JE, *et al.* 2013. The North American Breeding Bird Survey 1966–2011: summary analysis and species accounts. *North Am Fauna* **79**: 1–32.

Schwamb ME, Lintott CJ, Fischer DA, *et al.* 2012. Planet hunters: assessing the *Kepler* inventory of short-period planets. *Astrophys J* **754**: 129.

Sheppard SA and Terveen L. 2011. Quality is a verb: the operationalization of data quality in a citizen science community. In: Proceedings of the 7th International Symposium on Wikis and Open Collaboration; 3–5 Oct 2011. Mountain View, CA: ACM.

Show H. 2015. Rise of the citizen scientist. *Nature* **524**: 265.

Silvertown J. 2009. A new dawn for citizen science. *Trends Ecol Evol* **24**: 467–71.

Sullivan BL, Aycrigg JL, Barry JH, *et al.* 2014. The eBird enterprise: an integrated approach to development and application of citizen science. *Biol Conserv* **169**: 31–40.

Swanson A, Kosmala M, Lintott C, and Packer C. 2016. A generalized approach for producing, quantifying, and validating citizen science data from wildlife images: citizen science data quality. *Conserv Biol* **30**: 520–31.

Theobald EJ, Ettinger AK, Burgess HK, *et al.* 2015. Global change and local solutions: tapping the unrealized potential of citizen science for biodiversity research. *Biol Conserv* **181**: 236–44.

van der Wal R, Sharma N, Mellish C, *et al.* 2016. The role of automated feedback in training and retaining biological recorders for citizen science: automated feedback for citizen science. *Conserv Biol* **30**: 550–61.

Weir LA, Royle JA, Nanjappa P, and Jung RE. 2005. Modeling anuran detection and site occupancy on North American Amphibian Monitoring Program (NAAMP) routes in Maryland. *J Herpetol* **39**: 627–39.

Westphal AJ, von Korff J, Anderson DP, *et al.* 2006. Stardust@home: virtual microscope validation and first results. In: 37th Annual Lunar and Planetary Science Conference; 13–17 Mar 2006; League City, TX. Abstract no 2225.

Wiggins A. 2012. Crowdsourcing scientific work: a comparative study of technologies, processes, and outcomes in citizen science (PhD dissertation). Syracuse, NY: Syracuse University.

Wiggins A. 2013. Free as in puppies: compensating for ICT constraints in citizen science. In: Proceedings of the 16th ACM Conference on Computer-Supported Cooperative Work and Social Computing; 23–27 Feb 2013. San Antonio, TX: ACM.

Wiggins A and Crowston K. 2015. Surveying the citizen science landscape. *First Monday* **20**: 1.

Wiggins A and He Y. 2016. Community-based data validation practices in citizen science. In: Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work and Social Computing; 27 Feb–2 Mar 2016. San Francisco, CA: ACM.

Wiggins A, Bonney R, Graham E, *et al.* 2013. Data management guide for public participation in scientific research. Albuquerque, NM: DataONE.

Woźniak M, Graña M, and Corchado E. 2014. A survey of multiple classifier systems as hybrid systems. *Inf Fusion* **16**: 3–17.

Yu J, Wong W-K, and Hutchinson RA. 2010. Modeling experts and novices in citizen science data for species distribution modeling. In: 2010 IEEE International Conference on Data Mining; 14–17 Dec 2010. Sydney, Australia: IEEE.

