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Global use of ecosystem service models

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ABSTRACT

Spatial models of ecosystem services inform land use and development decisions. Understanding who uses these models and conditions associated with use is critical for increasing their impact. We tracked use of The Natural Capital Project's InVEST models and observed 19 different models were run 43,363 times in 104 countries over a 25-month period. Models for regulating services were most commonly used. We analyzed relationships between country-level variables and use of models and found capacity (population, GDP, Internet and computer access, and InVEST trainings), governance, biodiversity, and conservation spending are positively correlated with use. Civic involvement in conservation, carbon project funding, and forest cover are not correlated with use. Using multivariate statistical models, we analyzed which combinations of country-level variables best explain use of InVEST and found further evidence that variables related to capacity are the strongest predictors. Finally, we examined InVEST trainings in detail and found a significant effect of trainings on subsequent use of InVEST models. Our results indicate the general capacity of a country may limit uptake and use of decision support tools such as InVEST. Model-specific trainings are only one form of capacity building likely required for models to have desired levels of use and policy impact.

1. Introduction

Ecosystem services, the benefits that people receive from nature, are degraded and projected to decline further over the first half of this century (MEA, 2005). Since many current policy and economic decisions do not account for the values of ecosystem services (ES), planners and decision-makers are increasingly focused on the management of ES as a viable way to understand and manage human interactions with ecosystems (Braat and Groot, 2012; Holzman, 2012). The concept of ES is becoming essential in many of today's largest conservation organizations and academic research about the topic has increased steadily over the past two decades (Abson et al., 2014; Fisher et al., 2009).

As the ES concept grows more popular, there is more demand for ES information that has the potential to affect policy decisions (Daily and Matson, 2008; Daily et al., 2009; Mermet et al., 2014; Ruckelshaus et al., 2015). In particular, computer models that generate spatially explicit information about ES are commonly used to inform decisions (Burkhard et al., 2013; Crossman et al., 2012). The information these tools produce often illustrates how landscapes provide different amounts and patterns of ES under different future alternative scenarios (Goldstein et al., 2012; Lawler et al., 2014).

Several spatially-based decision support tools have emerged for ES assessment (Bagstad et al., 2013). Freely available tools such as InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs), ARIES (ARtificial Intelligence for Ecosystem Services), EVT (Ecosystem Valuation Toolkit), TESSA (Toolkit for Ecosystem Service Site-based Assessment), and SolVES (Social Values for Ecosystem Services) have been developed and tested in private and public environmental decision contexts (Bagstad et al., 2014; Peh et al., 2013; Ruckelshaus et al., 2015; Sherrouse et al., 2011; Villa et al., 2014). But while there have been comparisons and evaluations of tool *performance* (for example, by Bagstad et al., 2013), there has not yet been a comprehensive, systematic appraisal of actual tool *use*. In order to improve user support and expand the reach of ES tools, it is vital to track how, where, and when they are being used.

This study examines the emerging user network of one particular tool – InVEST. We analyze where users are, which models they run, and country-level factors associated with model usage over a 25-month period. InVEST, developed by the Natural Capital Project, provides a suite of software models that can be used to map and value ES, and compare trade-offs among development

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alternatives (Kareiva et al., 2011; Nelson et al., 2009). Spatially-explicit InVEST models describe how changes to ecosystems are likely to affect the flows and values of ES, across a land- or a seascape (see www.naturalcapitalproject.org). InVEST is quantitative, well-documented, and can be independently applied, but the models depend on the availability/quality of underlying spatial data and can be time consuming to parameterize (Bagstad et al., 2013). InVEST is based on biophysical models and is amenable to widespread use, making it well-suited as a test case for more general ideas (Sharp et al., 2015).

Previous research has investigated global patterns of certain kinds of conservation activities and needs. For example, countries in which conservation activities are more likely (based on lower protected area management costs, high numbers of endangered species, and identification as important for conservation) also score poorly on measures of corruption (McCreless et al., 2013; Smith et al., 2003, 2007). Other studies have found that national characteristics such as number of threatened species, quality of governance, and deforestation rates are associated with the location of REDD demonstration sites and forest carbon projects (Cerbu et al., 2011; Lin et al., 2012, 2014). These studies suggest that country-level factors could be associated with conservation science uptake.

Extending these findings to the uptake of ES modeling tools, we hypothesize that countries with high use of ES models also tend to have more capacity, more effective governance, lower environmental quality, more conservation spending, and more civic involvement in conservation (Table 1). We also make two more specific hypotheses: first, that biodiversity-related InVEST model usage is associated with lower environmental quality; and second, that carbon-related model usage occurs in countries with more forests and more overall conservation spending. Finally, we explore in more detail the effect that formal trainings have on use of ES models. We hypothesize that the average use in countries with trainings is higher than in countries without trainings, and that usage increases for a prolonged time period following trainings.

Support of these hypotheses would indicate certain conditions that facilitate the adoption and use of science-based tools. This understanding can help to predict patterns of uptake for new tools and target capacity building efforts to increase scientific and policy impact.

2. Methods

2.1. InVEST data

When an InVEST model is run on a computer connected to the Internet, a log is created with date, IP address, InVEST version, and model type. We analyzed 25 months of these logs from June 2012 through June 2014. These data represent a network of InVEST usage. Our dataset does not include model activity done from outside the user interface (for example, through Python scripts), models runs for computers not connected to the Internet, or certain specific models that were not reporting usage information during the timeframe of this study (such as coastal protection). Nevertheless, our dataset of 43,363 model runs likely represents a large majority of InVEST model runs during the study period.

We used IP addresses and GeoIP2 Precision Services provided by MaxMind to identify the country in which each model run occurred. We used model type to identify which ES model was run and we collapsed all possible model types into a concise list of primary ES models (Appendix A).

We used information about the InVEST version of each model run to exclude model development and testing activity. For part of the analysis, we also screened out use that occurred in the U.S. because (a) much of this use was likely internal Natural Capital Project scientists, and (b) we wanted to avoid skewed results due to the fact that the bulk of use was in the U.S. We focused on terrestrial/freshwater models rather than marine because many of the marine models were not tracked over the entire study period and the available country-level environmental quality data are about forests and terrestrial biodiversity. The use of marine models at trainings in Portugal, Korea, Mexico, and Canada was not included in our data, so these are conservative estimates of the ES model use that occurred in those places.

2.2. Country-level data

We gathered 19 country-level variables from global datasets (roman numerals below) and grouped them into 5 categories that we hypothesize are associated with use of ES models.

2.2.1. Capacity

We used estimates of (i) population and (ii) GDP/capita (in current US dollars) for the year 2013 available online from World Bank Open Data (http://data.worldbank.org/). (iii) We used 2013 estimates of the number of Internet users per 100 people from World Bank Indicators available online (http://data.worldbank.org/indicator/IT.NET.USER.P2). (iv) We used the percentage of households with a computer for the most recent year within the 2008–12 range for which data are available. These data were collected from national statistical offices by the International Telecommunication Union, the UN specialized agency for information and communication technologies. More information about the Internet and Computer Technology Data and Statistics Division is available online (http://www.itu.int/en/ITU-D/Statistics). (v) We included a variable to indicate whether a country had a training prior to or during the study period. This variable was 0, 1, 2, or 3 based on the length of the training (0 if there was no training, 3 if there was a training for 3 or more days).

Table 1
The main hypothesized drivers of ecosystem service model use, predicted relationships, and justifications.

Category	Relationship with use of ES models	Justification
Capacity	+	Places with more people, trainings, and access to technology have more basic capacity to use ES models
Governance	+	Stronger systems of governance enables more use of sophisticated decision support tools
Environmental quality	−	Worse environmental quality makes it more likely that people will use tools to inform environmental decisions
Conservation spending	+	Places with higher levels of conservation spending have an established presence of environmental organizations and a higher likelihood that ES models will be used
Civic engagement in conservation	+	People in places with higher rates of involvement in conservation organizations are more likely to use ES models

2.2.2. Governance

The World Bank estimates Worldwide Governance Indicators at the country level through surveys and consultations with citizens, experts, businesses, and international organizations (Kaufmann et al., 2011). We used three governance indicators relevant to the management of ESs: (vi) government effectiveness (the quality of policy formulation and implementation), (vii) regulatory quality (the ability of governments to create policies and regulations to promote private industry), and (viii) control of corruption. We used 2013 estimates of percentile (0–100%) rank among all countries for these two indicators. Data and background information for the indicators are available online (www.govindicators.org).

2.2.3. Environmental quality

The general level of environmental quality for a country is difficult to measure and quantify. We focused on three main datasets for quantifiable, comparable information about environmental quality for countries. Using information from multiple sources allowed us to minimize the bias associated with any one dataset.

(ix) The Global Environment Facility Benefits Index for Biodiversity is "a composite index of relative biodiversity potential for each country based on the species represented in each country, their threat status, and the diversity of habitat types in each country. The index has been normalized so that values run from 0 (no biodiversity potential) to 100 (maximum biodiversity potential)" (Pandey et al., 2006). Data and background information are available online from World Bank Open Data.

(x–xii): The Environmental Performance Index (EPI), estimated by the Yale Center for Environmental Law and Policy, ranks how well countries protect ecosystems and protect human health from environmental harm (Hsu et al., 2013). We used (x) overall EPI estimates for 2014, as well as two sub-indicators related to (xi) forests (percent change in forest cover between 2000 and 2012 in areas with greater than 50% tree cover) and (xii) biodiversity and habitat (an averaged composite of indices for critical habitat protection, terrestrial protected areas with national biome weight, terrestrial protected areas with global biome weight, and marine protected areas). Data and background information for the indicators are available online (http://epi.yale.edu/).

(xiii) Threatened mammal species includes the number of mammal species (excluding whales and porpoises) classified by the International Union for Conservation of Nature (IUCN) as endangered, vulnerable, rare, indeterminate, out of danger, or insufficiently known. We used 2014 estimates for each country provided by the United Nations Environmental Program, the World Conservation Monitoring Center, and the IUCN Red List of Threatened Species. Data and background information are available online from World Bank Open Data.

2.2.4. Conservation spending

Two datasets provided information on country-level spending on conservation:

(xiv) We used information about total average annual spending (in \$ US million 2005) from 2001 to 2008 as estimated by Waldron et al. (2013). This includes all flows of funding estimated: international donors, domestic governments, trust funds, and self-funding via user payments. We also used a database of REDD+projects sourced through a number of dedicated multilateral and bilateral climate funds to include (xv) the amount of climate finance and (xvi) the amount of REDD funding countries received from 2003 to 2013. Data and background information are available online

(http://www.climatefundsupdate.org/data).

2.2.5. Civil society involvement in conservation

We followed McCreless et al. (2013) and focused on three datasets that measure the extent to which civil society is involved in conservation efforts for many countries. It is challenging to measure or quantify the extent of civil society involvement in conservation at a national scale. These three broad estimates of complex, local occurrences allow us to quantitatively compare involvement in conservation among many different countries, through both international NGOs and multilateral agencies. Our study does not address the reasons why people may be more involved in some countries (i.e. socioeconomic factors) or the impacts of more involvement, but focuses on whether people in places with higher rates of involvement in conservation organizations are more likely to use ES models. (xvii) BirdLife International (BLI) is the largest global partnership of conservation organizations in the world. We used data on citizen membership in BLI partner organizations available online (www.birdlife.org/worldwide/national/index.html). We standardized NGO membership numbers by country population to represent the proportion of a county's population that belongs to a leading local conservation NGO. (xviii) IUCN is the largest global environmental organization in the world. The Environmental Sustainability Index provides a country level estimate of the number of IUCN organizations per million people. These data are available online (www.yale.edu/esi/c_variableprofiles.pdf). (xix) Local Agenda 21 initiatives are "measures undertaken and overseen by local authorities to address problems of environmental sustainability, and represent the involvement of civil society in environmental governance". The Environmental Sustainability Index provides a country level estimate of the number of local Agenda 21 initiatives per million people available online (www.yale.edu/esi/c_variableprofiles.pdf).

2.3. Analysis

We examined the relationships that use of ES models has with each of the country-level variables. We also examined relationships that carbon model use and habitat model use have with particular variables. We used nonparametric Spearman rank correlations because the individual datasets did not meet the assumptions required for parametric correlations such as data having normal distributions (Crawley, 2007). All data analyses were conducted in the statistical platform R (R, 2011).

We tested for correlation among country-level variables and used principal components analysis (PCA) to reduce two groups of highly correlated variables with correlation coefficients >0.70: Governance and Biodiversity (Dormann et al., 2013). We used the first principal component to capture over 90% of the variance for these two groups of variables (Table 2). We then used model selection to rank all possible linear combinations of variables to identify those statistical models that could best explain the outcome variable of InVEST model usage. We used the R package MuMIn (multi-model inference) for model selection, and ranked models based on AICc values to identify the explanatory variables present among the top models (Barton, 2014). We performed model selection with only the variables that have data for all countries so that submodels would not be fitted for different datasets. All possible combinations of our 8 predictor variables resulted in 256 evaluated models.

For our analysis on trainings, we initially narrowed our focus to 9 trainings that occurred within our study period and that had at least 10 model runs within 30 days before and after the training. We defined InVEST trainings as organized meetings of Natural Capital Project staff with registered event participants in order to introduce and train people in the use of InVEST models. We gathered information on trainings from Natural Capital Project

Table 2
Correlation results comparing model use with country level variables. Bold rows indicate positive and significant correlations. N is the number of countries for which those data are available. We calculated the first principal component of Governance and Biodiversity variables to capture >90% of the variance in the underlying variables. "Governance PC" includes government effectiveness, regulatory quality, and control of corruption (for pairwise correlations, rho=0.91, 0.95, and 0.87). "Biodiversity PC" includes GEF Benefits Index of Biodiversity and mammals (rho=0.77).

Variable comparison	N	Spearman's rho	95% CI	p-value
Total model use~…				
Capacity				
GDP per capita	**94**	**0.347**	**(0.155, 0.513)**	**0.00062** **
Population	**94**	**0.482**	**(0.309, 0.624)**	**1.8E−7** **
Internet	**94**	**0.316**	**(0.121, 0.487)**	**0.0019** **
Computers	**86**	**0.237**	**(0.0269, 0.428)**	**0.028** *
Trainings	**94**	**0.273**	**(0.0748, 0.451)**	**0.0077** **
Governance				
Governance PC	**94**	**0.335**	**(0.142, 0.504)**	**0.00095** **
Environmental quality				
Biodiversity PC	**94**	**0.317**	**(0.122, 0.488)**	**0.0019** **
EPI	**94**	**0.262**	**(0.062, 0.441)**	**0.011** *
EPI Forests	86	−0.0179	(−0.229, 0.195)	0.87
EPI biodiversity	94	0.131	(−0.0732, 0.325)	0.21
Conservation spending				
Conservation spending	**92**	**0.603**	**(0.454, 0.719)**	**2.1E−10** **
REDD	31	0.0580	(−0.136, 0.540)	0.76
Climate finance	94	0.00992	(−0.193, 0.212)	0.92
Civic engagement in conservation				
BLI	62	-0.248	(−0.468, 0.00241)	0.052 +
IUCN	89	0.0885	(−0.122, 0.291)	0.41
Agenda 21	**74**	**0.0867**	**(0.000496, 0.435)**	**0.46**
Carbon model use~…				
EPI Forests	86	0.0252	(−0.188, 0.236)	0.82
REDD	31	0.127	(−0.238, 0.461)	0.50
Climate finance	94	0.0311	(−0.173, 0.232)	0.77
Habitat model use~…				
Biodiversity PC	**94**	**0.244**	**(0.043, 0.425)**	**0.018** **
EPI	**94**	**0.236**	**(0.0352, 0.419)**	**0.022** *
EPI Forests	86	0.0153	(−0.197, 0.226)	0.89
EPI biodiversity	94	0.153	(−0.0509, 0.345)	0.14

** $p < 0.01$.
* $p < 0.05$.
+ $p < 0.1$.

records, including meeting agendas, participant lists, training evaluation surveys, and facilitator notes.

We defined a "Before" period of time as the 13 weeks (approximately 90 days) before a training, "After 1" as the 13-week period following a training, and "After 2" as the next 13-week period (Fig. 1). We computed a change factor as the ratio of model runs between the "Before" and "After 1" periods. We also calculated average weekly usage in these time periods to estimate the prolonged effect of trainings on InVEST model usage.

To evaluate the effect of trainings statistically, we created a generalized linear mixed model with country as a random effect and period as a fixed effect. We assumed a Poisson distribution for weekly usage data and tested whether usage was different in the periods "Before", "After 1", and "After 2" with a type III Wald chisquare test.

Finally, we combined our quantitative results with a qualitative analysis of documents from these trainings, including detailed facilitator notes and participant surveys (Creswell, 2009). This review focused on lessons learned by the training facilitators and the following open-ended questions given to participants:

– Please identify two things you found the most useful from this course (favorite parts).
– What recommendations do you have for improving the course (least favorite parts)?
– What subject(s) would you like to see offered in future training sessions?
– Do you have any additional comments?

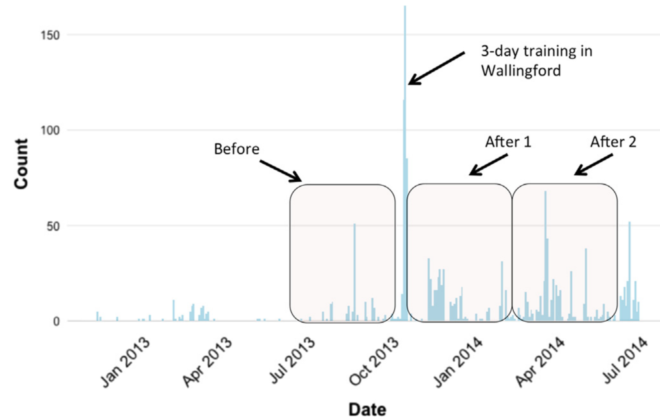

Fig. 1. : Example of a training in the UK. Model use spikes during the training. We compared the number of models runs and average weekly use for one 13-week period before and two 13-week periods after trainings.

3. Results

The use of InVEST models increased over the 25-month study period (Fig. 2). A significant amount of overall use occurred in the U.S., but most of the growth over time occurred in non-U.S. countries.

Across all countries, ES models related to habitat, water yield, carbon, sediment, and nutrients were used most often (Fig. 3).

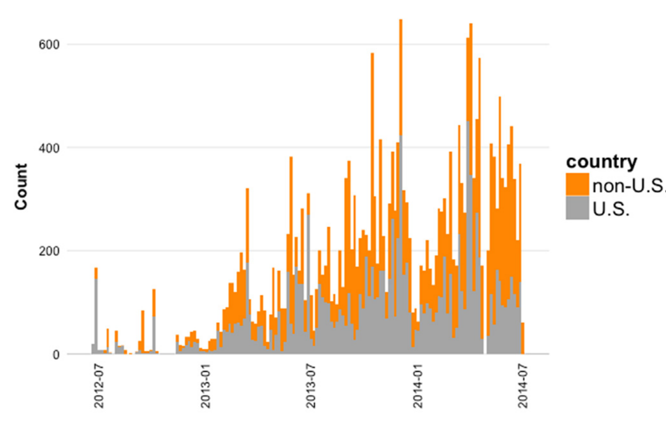

Fig. 2. : Growth in the use of InVEST models over time. Model use occurred in 102 different countries with 44% of all use occurring in the U.S. For non-U.S. countries, there were 14,301 model runs with 43% of use occurring in 5 countries: the UK (1554), Germany (1491), China (1209), France (1074), and Colombia (780).

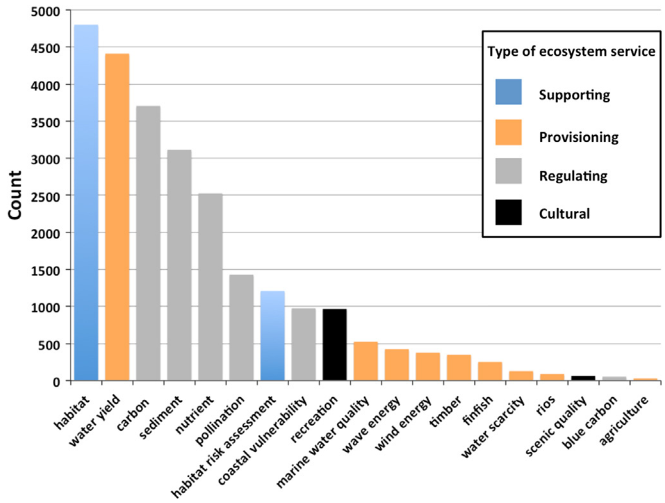

Fig. 3. Types of ecosystem service models used. 46% of all model use is for regulating services. "Rios" focuses on freshwater provisioning services but includes other service types as well.

Based on the ES classifications provided by the Millennium Ecosystem Assessment (MEA, 2005), we identified each service as provisioning, regulating, supporting, or cultural and found that 46% of model use was for regulating services (Appendix A).

We found a number of positive and significant correlations between total use of ES models and the country-level variables (Table 2). These relationships exist in all of the hypothesized categories, especially for variables related to Capacity. For carbon model use, none of the hypothesized relationships showed positive correlations. For habitat model use, the Biodiversity PC and EPI variables had positive and significant correlations. We examined whether trainings were more likely to occur in particular kinds of places and did not find that trainings were significantly correlated with any of the other country-level variables.

Model selection shows which variables are present in the statistical models that best explain InVEST usage (Table 3). "Population," "Training," and "Internet" were found to be the most common and important variables in the top 10 models. Other variables such as those for biodiversity and the Environmental Performance Index appear in some statistical models, but not as consistently.

In analyzing the effect of trainings, we found that the average use of ES models in countries with trainings was over two times larger than in countries without trainings (Fig. 4). For the 9 trainings we analyzed, we typically observed a burst of usage during the training and then more activity in the After 1 periods than the Before periods (Fig. 4; Appendix B). The change factors (ratio of model runs in After 1 period to model runs in Before period) showed that all but one of the cases had an increase in model use following a training (Table 4). The average change factor for 1-day

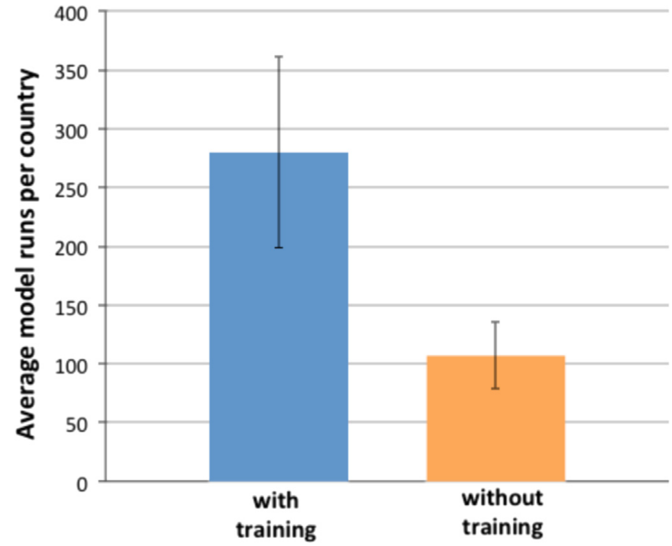

Fig. 4. : Comparison of average use in non-U.S. countries with and without trainings. Error bars depict standard error. There was a significant difference in the average use for countries with (mean=280, sd=81) and countries without (mean=107, sd=29) trainings ($t(22.6)=2.0$, $p=0.05$).

Table 4
Comparison of ES model use before and after trainings. Change factor is the ratio of use in 13-week periods after/before training.

Country	Date of training	Model use before training	Model use after training	Change factor
Argentina[a]	9/12/2013	14	52	3.71
Cambodia[b]	6/17/2013	6	13	2.17
Canada[a]	2/04/2013	64	92	1.44
Chile[b]	9/09/2013	17	82	4.82
Korea[c]	9/11/2012	46	54	1.17
Peru[b]	5/27/2013	18	40	2.22
Spain[a]	11/18/2013	13	175	13.46
UK1[b]	10/15/2013	137	661	4.82
UK2[c]	3/07/2013	50	23	0.42

[a] 2-day training.
[b] 3-day or longer.
[c] 1 day training.

trainings was 0.80 ($n=2$), 2-day trainings was 6.2 ($n=3$), and 3-or-more-day trainings was 3.5 ($n=4$). Using the generalized linear mixed model with country as a random effect, we found a positive and significant effect of trainings on model use (Fig. 5. $\chi_2^2 = 154.8$; $p<0.001$).

The qualitative assessment of training evaluations further illuminated place-specific factors than help explain use of ES models, such as connections to a university course or a funded project with deadlines. Among the 7 cases reviewed, change factors were

Table 3
Model selection results for the top 10 statistical models by AICc value. Statistical models are listed by row in rank order (the first has the lowest AICc value corresponding to best fit) with a check mark for variables that are included in the statistical model. Only the 8 variables that contained data for all countries were included in model selection.

Model	Biodiversity_PC	EPI	EPI biodiversity	GDP	Governance_PC	Internet	Population	Training	df	Log likelihood	ΔAIC_c
1	–	–	–	–	–	✓	✓	✓	5	−652.62	0.00
2	–	–	✓	–	–	✓	✓	✓	6	−652.25	1.55
3	✓	–	–	–	–	✓	✓	✓	6	−652.27	1.58
4	–	✓	–	–	–	–	✓	✓	5	−653.47	1.70
5	–	✓	–	–	–	✓	✓	✓	6	−652.52	2.09
6	–	–	–	–	✓	✓	✓	✓	6	−652.61	2.26
7	–	–	–	✓	–	✓	✓	✓	6	−652.62	2.27
8	–	–	–	–	–	✓	✓	–	4	−654.89	2.31
9	–	–	–	–	✓	–	✓	✓	5	−654.04	2.83
10	–	–	✓	–	–	✓	✓	–	5	−654.23	3.22

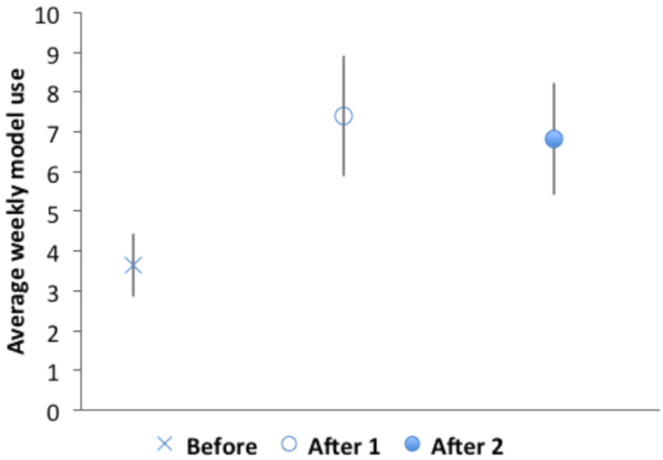

Fig. 5. The positive effect of trainings on model usage across 9 cases. "Before" is average weekly model use and standard error for a 13-week period (approximately 90 days) before a training. "After 1" is for a 13-week period after a training and "After 2" is for the following 13-week period.

highest for trainings that offered case studies and demonstrations relevant to participants' on-going projects and when a specific deliverable using InVEST was due soon after the event. Training attendees valued the opportunity to interact with experienced analysts and developers of the InVEST models. This in-person support served to narrow the user-developer divide that is a known barrier to decision-support tool uptake (Haklay and Tobon, 2003). After establishing a rapport with training facilitators, participants felt more comfortable applying the tool and requesting support following the event.

4. Discussion and conclusion

Using a unique global dataset, we conduct the first quantitative analysis of the use of ecosystem service modeling tools. We show that general capacity to use these kinds of tools (i.e., population, GDP/capita, computer technology) as well as specific capacity building for the tool in question (i.e., trainings) are the strongest predictors of model use in a given country. While the effect of trainings varied widely among countries, in general trainings had a positive and enduring effect on tool use. Understanding the factors that encourage uptake and use of scientific tools can help target trainings, improve tool design, and improve impact of scientific knowledge on decisions.

Formal trainings can build on a country's existing capacity to use decision support tools. Why do some trainings have a bigger impact than others? Trainings that are longer than 1-day probably have a larger effect because they allow trainers and participants to spend more time learning the details of how to use the tools. Extended trainings include time for repeatedly running models and practice working through the different steps of an ES assessment (Rosenthal et al., 2014). Other, site-specific factors related to a training can explain the places where we observe larger impact, such as countries with reliable Internet access and more spending on conservation-related research. Regardless of these local factors, problem-based exercises that are simple, well designed and include detailed guidance (e.g., step-by-step tutorials) show promise as an entry point for a range of potential tool users (Verutes and Rosenthal, 2014). Further research on effective ways to sequence introductory to more technical content for a diverse range of audiences can inform creative approaches to building local capacity that actively engage participants in learning a new technology.

Can country-level variables help us identify new, underserved audiences for computer-based decision support tools, or understand which technologies may be most relevant to a local place? We found evidence that country-level conditions can be used to estimate the capacity for using InVEST models generally, but did not find that country-level conditions were highly correlated with the use of carbon or biodiversity ES models. It is likely that other variables beyond those we tested are associated with tool use. These include some of the site-specific factors uncovered in our qualitative assessment, such as a funded ES project with deadlines, as well as factors related to the presence of ES concepts in government policies, overall amounts of science research activity, and levels of education in a population.

Limitations to this study are worth noting. First, as mentioned above, some ES models (i.e. marine models) were not included in our data set, so we almost certainly underestimated the impacts of trainings that focused in part on these models. Second, our data capture where a given model is used, not the location where ES are being evaluated. Researchers in one country can run InVEST models focused on another, and some InVEST trainings included participants from other countries, who likely went on to use InVEST outside the country where the training was held. Excluding the US from our analyses removes the largest source of this issue, but further subsetting to countries where we are certain models are being used in-country reduces the size of our dataset rapidly. Our analyses therefore pertain to where models are used rather than where they are applied. Third, our analyses focused on InVEST, but of course several other ES models and computer-based tools exist. We are not aware of equivalent tracking data for any other tool, but we expect they would display patterns associated with national-scale capacity and training opportunities.

Future research in this area would benefit from in-depth qualitative analyses to better understand the factors that lead to differences in effectiveness of trainings. In addition, understanding the relationships among users (e.g., through surveys of users) could help to illuminate how technology diffuses through social networks (Haythornthwaite, 1996). User surveys could also help to clarify user demographics, the decision contexts in which the tools are used, and the ways in which outputs are used to inform decisions (McKenzie et al., 2014). Finally, model developers could make several simple additions to the information reported for each model use, including location of the region being assessed, and saving records for later reporting if the computer is not connected to the Internet.

People may use an ES model for any of a number of reasons: they receive training, they find decision support tools useful for a particular context, they have project deadlines or an academic adviser nudging them to produce results, etc. Efforts to increase use of these models should therefore focus equally on understanding these drivers, building capacity generally, and providing specific training in the tools. Formal training opportunities that provide locally-relevant demonstrations of the tool and follow-up activities to reinforce what was learned are an effective way to support the continued usage of spatial models in ES assessments. If country-level factors can predict use along with trainings, then we need to be aware of which countries have the basic capacity to use these models. And we need to think about more than just trainings – having key conditions in place, such as the capacity variables illuminated in this study, will enable people to use what they learn. Tracking and explaining tool use can lead to more strategic deployment of technology and smarter applications of these models for informing real world decisions.

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Appendix A. Categories and ES type for InVEST models.

InVEST model category	Ecosystem service type	Specific models included
Agriculture	Provisioning	"agriculture"
Blue carbon	Regulating	"blue_carbon" "blue_carbon_biophysical" "blue_carbon_preprocessor"
Carbon	Regulating	"carbon_biophysical" "carbon_biophysical/" "carbon_combined" "carbon_valuation"
Coastal vulnerability	Regulating	"coastal_vulnerability"
Finfish	Provisioning	"finfish_aquaculture"
Habitat	Supporting	"habitat_quality" "biodiversity_arc" "biodiversity_biophysical" "biodiversity_biophysical/"
Habitat risk assessment	Supporting	"hra" "HRA_LaunchGUI_arc" "hra_preprocessor"
Marine water quality	Provisioning	"marine_water_quality_biophysical" "marine_water_quality_biophysical/"
Nutrient	Regulating	"nutrient"
Pollination	Regulating	"pollination" "pollination_biophysical" "pollination_valuation"
Recreation	Cultural	"recreation_client" "recreation_client_init" "recreation_client_scenario"
Rios	Provisioning	"rios" "rios_0.3.0" "rios_sediment"
Scenic quality	Cultural	"aesthetic_quality" "scenic_quality"
Sediment	Regulating	"sediment" "sediment_biophysical"
Timber	Provisioning	"timber" "timber/"
Water scarcity	Provisioning	"water_scarcity"
Water yield	Provisioning	"hydropower_valuation" "hydropower_water_yield" "water_yield" "water_yield/"
Wave energy	Provisioning	"wave_energy" "wave_energy_biophysical" "wave_energy_biophysical/" "wave_energy_valuation"
Wind energy	Provisioning	"wind_energy" "wind_energy_biophysical" "wind_energy_uri_handler"
Removed from analysis, either with development activity or separately to filter out non-model use		
Overlap	–	"overlap_analysis" "overlap_analysis_mz" "OverlapAnalysis_arc"
Scenarios	–	"scenario_generator"
Other model types in data log	–	"#VALUE!" "adept" "adept_core" "coastal_vulnerability_post_processing" "crop_production" "developme" "development" "fisheries"

"GridSeascape_arc"
"habitat_suitability"
"malaria"
"monthly_water_yield"
"monthly_water_yield_old"
"ntfp"
"percent_land"
"pollination_10_arc"
"recreation_init"
"recreation_scenario"
"rios_beer"
"rios_porter"
"rios_rsat"
"routedem"
"scenario_generator_summary"
"sdr"
"test"
"test_invest_2"
"test_string_submission"
"test!!! version number?"
"viewshed_grass"
"wind_energy_valuation"

Appendix B. Model use over time and average weekly model use (with standard error) in 13-week periods before and after trainings. We analyzed the effect of trainings in detail for these 9 trainings

See Fig. B1, Fig. B2, Fig. B3, Fig. B4, Fig. B5, Fig. B6, Fig. B7, Fig. B8.

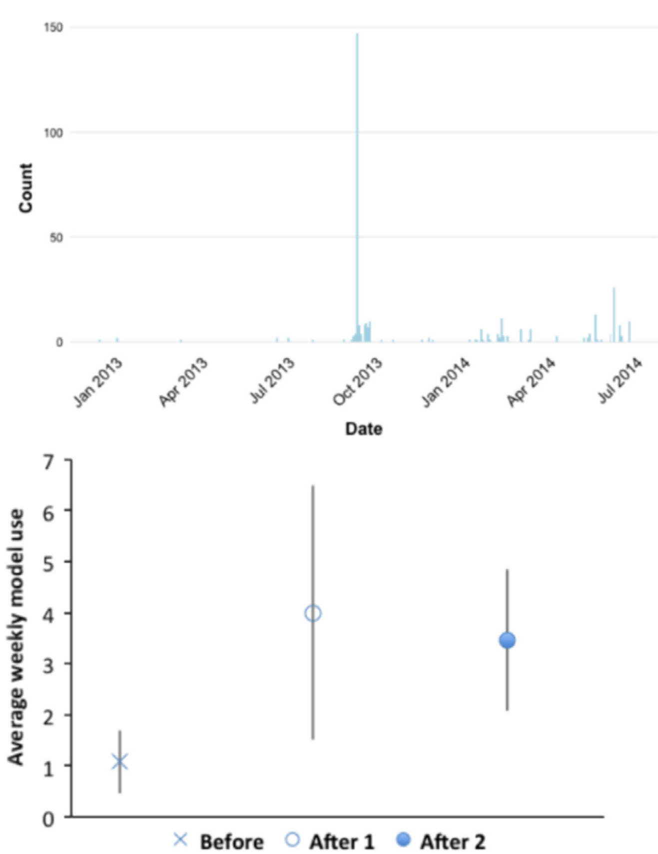

Fig. B1. Argentina 2-day training 9/12/2013.

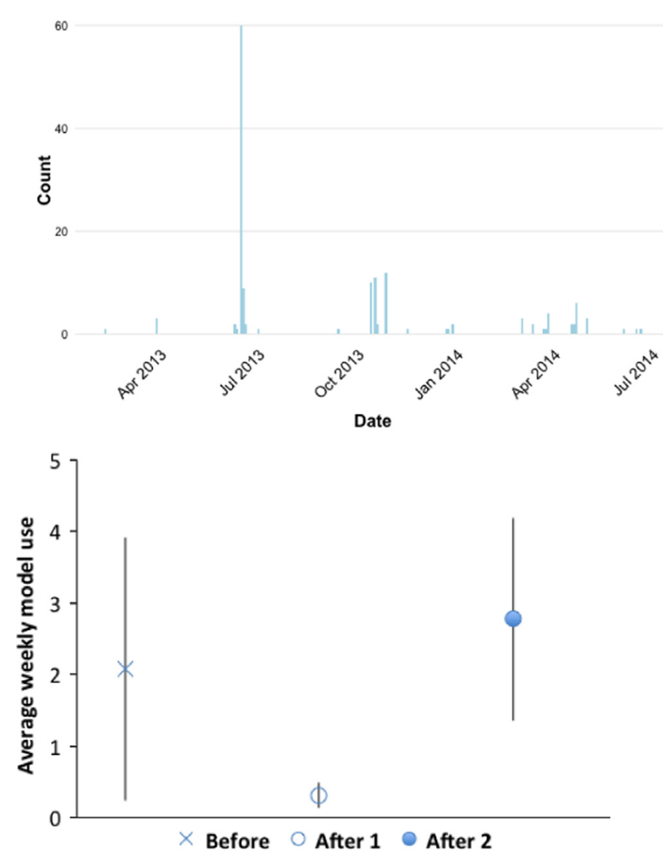

Fig. B2. Cambodia 3-day training 6/17/2013.

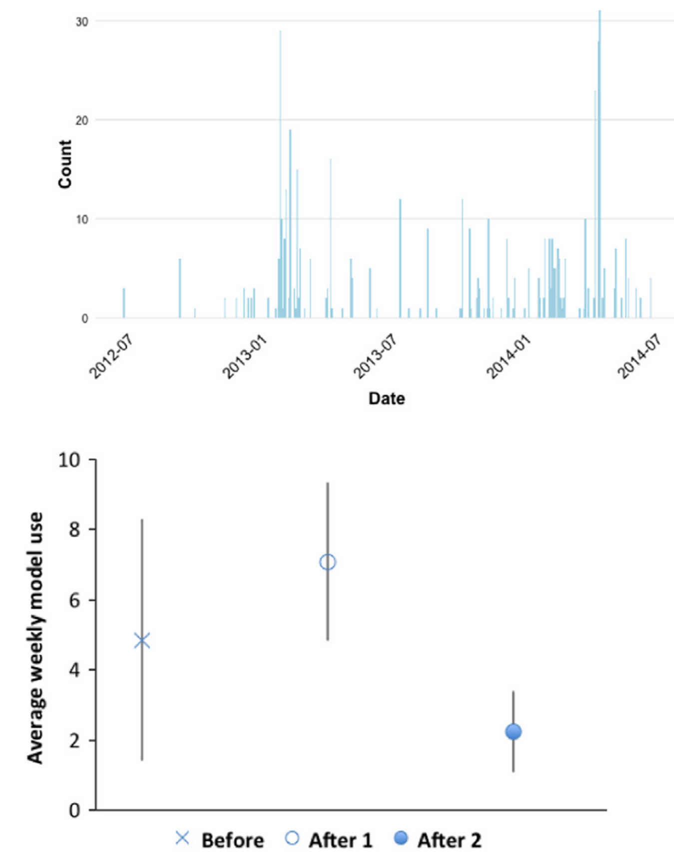

Fig. B3. Canada 2-day training 2/04/2013.

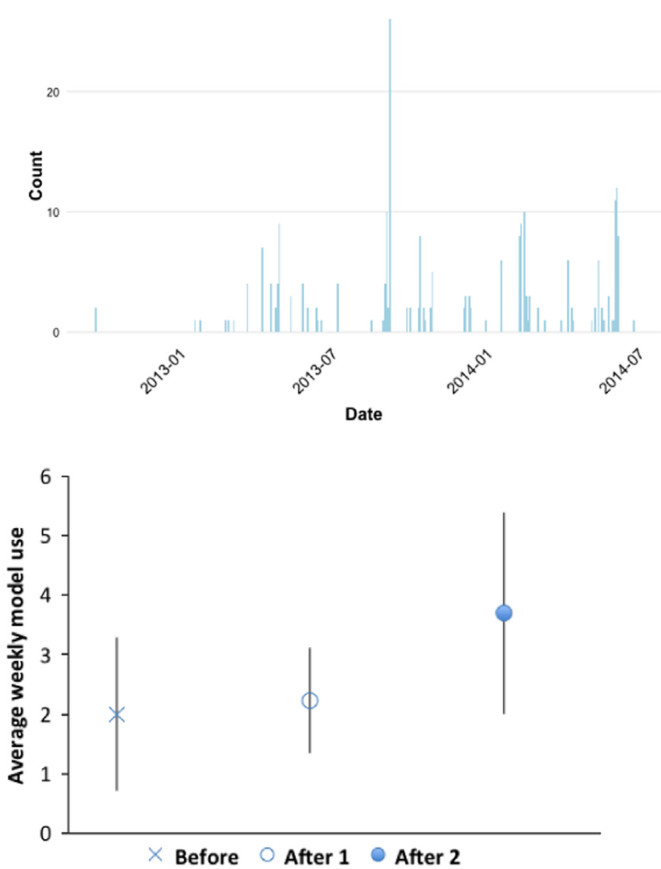

Fig. B4. Chile 3-day training 9/09/2013.

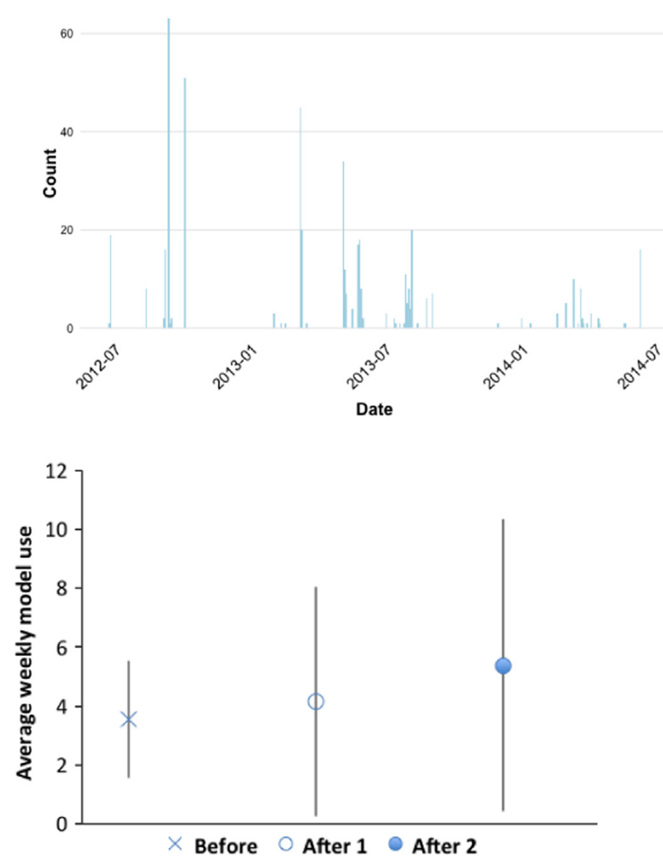

Fig. B5. Korea 1-day training 9/11/2012.

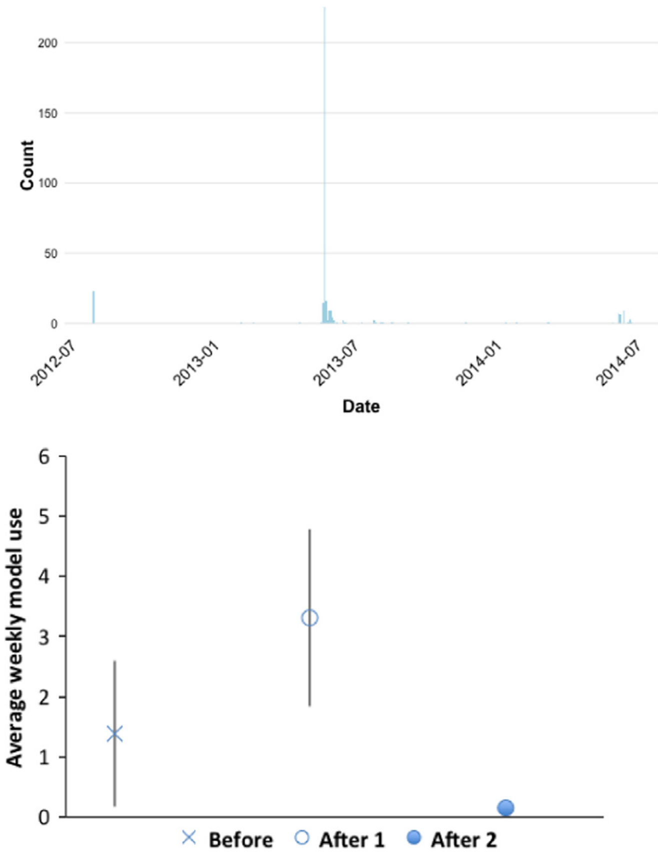

Fig. B6. Peru 3-day training 5/27/2013.

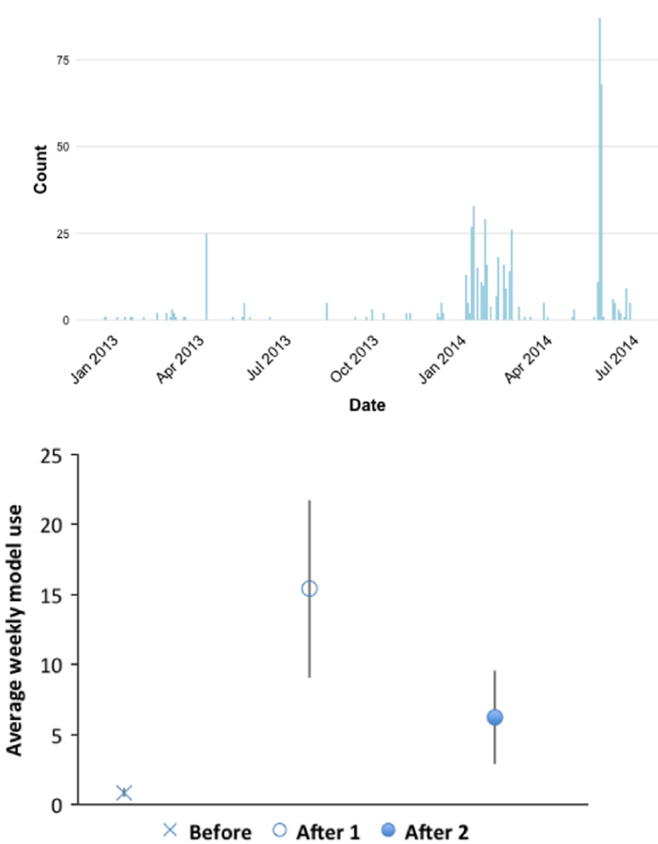

Fig. B7. Spain 2-day training 11/18/2013.

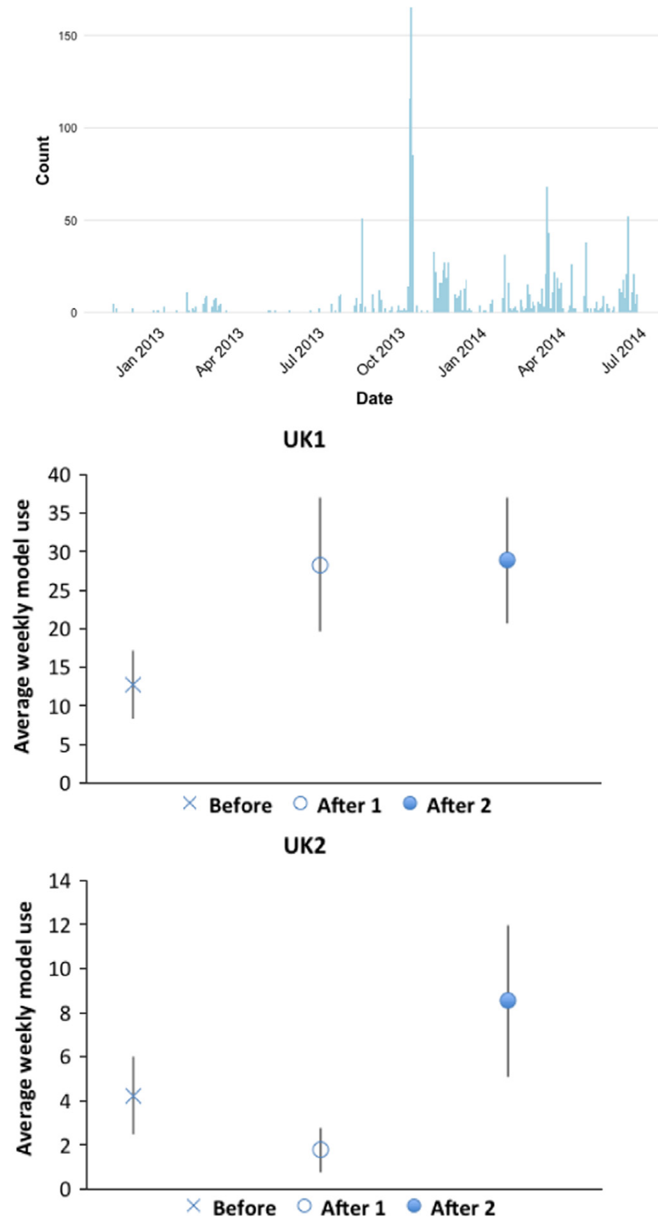

Fig. B8. UK1 3-day training 10/15/2013 and UK2 1-day training 3/07/2013.

References

Abson, D.J., Wehrden, H.V., Baumgartner, S., Fischer, J., Hanspach, J., Hardtle, W., et al., 2014. Ecosystem services as a boundary object for sustainability. Ecol. Econ. 103, 29–37.

Bagstad, K.J., Semmens, D.J., Waage, S., Winthrop, R., 2013. A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosyst. Serv. 5, 27–39.

Bagstad, K.J., Villa, F., Batker, D., Harrison-Cox, J., Voigt, B., Johnson, G.W., 2014. From theoretical to actual ecosystem services: mapping beneficiaries and spatial flows in ecosystem service assessments. Ecol. Soc. 19 (2), 64.

Barton, K., 2014. MuMIn: R Package for Multi-Model Inference. CRAN Project, USA.

Braat, L.C., Groot, R.D., 2012. The ecosystem services agenda: bridging the worlds of natural science and economics, conservation and development, and public and private policy. Ecosyst. Serv. 1 (1), 4–15.

Burkhard, B., Crossman, N., Nedkov, S., Petz, K., Alkemade, R., 2013. Mapping and modelling ecosystem services for science, policy, and practice. Ecosyst. Serv. 4, 1–3.

Cerbu, G.A., Swallow, B.M., Thompson, D.Y., 2011. Locating REDD: a global survey and analysis of REDD readiness and demonstration activities. Environ. Sci. Policy 14 (2), 168–180.

Crawley, M.J., 2007. The R Book. John Wiley & Sons Ltd., West Sussex, England.

Creswell, J.W., 2009. Research Design: Qualitative, Quantitative, and Mixed Methods Approaches, 3rd ed. Sage Publications, Thousand Oaks, Calif..
Crossman, N.D., Burkhard, B., Nedkov, S., 2012. Quantifying and mapping ecosystem services. Int. J. Biodivers. Sci., Ecosyst. Serv. Manag. 8 (1–2), 1–4.
Daily, G.C., Matson, P.A., 2008. Ecosystem services: from theory to implementation. Proc. Natl. Acad. Sci. USA 105 (28), 9455–9456. http://dx.doi.org/10.1073/Pnas.0804960105.
Daily, G.C., Polasky, S., Goldstein, J., Kareiva, P.M., Mooney, H.A., Pejchar, L., et al., 2009. Ecosystem services in decision making: time to deliver. Front. Ecol. Environ. 7 (1), 21–28. http://dx.doi.org/10.1890/080025.
Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carre, G., et al., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36 (1), 27–46. http://dx.doi.org/10.1111/J.1600-0587.2012.07348.X.
Fisher, B., Turner, R.K., Morling, P., 2009. Defining and classifying ecosystem services for decision making. Ecol. Econ. 68, 643–653.
Goldstein, J.H., Caldarone, G., Duarte, T.K., Ennaanay, D., Hannahs, N., Mendoza, G., et al., 2012. Integrating ecosytem-service tradeoffs into land-use decision. Proc. Natl. Acad. Sci. 109 (19), 7565–7570.
Haklay, M., Tobon, C., 2003. Usability evaluation and PPGIS: towards a user-centered design approach. Int. J. Geogr. Inf. Sci. 17 (6), 577–592.
Haythornthwaite, C., 1996. Social network analysis: an approach and technique for the study of information exchange. Libr. Inf. Sci. Res. 18 (4), 323–342.
Holzman, D.C., 2012. Accounting for nature's benefits: the dollar value of ecosystem services. Environ. Health Perspect. 120 (4), 152–157.
Hsu, A., Johnson, L., Lloyd, A., 2013. Measuring Progress: A Practical Guide From the Developers of the Environmental Performance Index (EPI). Yale Center for Environmental Law & Policy, New Haven.
Kareiva, P.M., Tallis, H., Ricketts, T.H., Daily, G.C., Polasky, S., 2011. Natural Capital: Theory and Practice of Mapping Ecosystem Services. Oxford University Press, Oxford: UK.
Kaufmann, D., Kraay, A., Mastruzzi, M., 2011. The worldwide governance indicators: methodology and analytical issues. Hague J. Rule Law 3 (2), 220–246. http://dx.doi.org/10.1017/S1876404511200046.
Lawler, J.J., Lewis, D.J., Nelson, E., Plantinga, A.J., Polasky, S., Withey, J.C., et al., 2014. Projected land-use change impacts on ecosystem services in the United States. Proc. Natl. Acad. Sci. 111 (20), 7492–7497.
Lin, L., Pattanayak, S.K., Sills, E.O., Sunderlin, W.D., 2012. Site selection for forest carbon projects. In: Angelson, A. (Ed.), Analysing REDD. CIFOR, Indonesia.
Lin, L., Sills, E., Cheshire, H., 2014. Targeting areas for Reducing Emissions from Deforestation and forest Degradation (REDD+) projects in Tanzania. Glob. Environ. Chang. Hum. Policy Dimens. 24, 277–286. http://dx.doi.org/10.1016/J.Gloenvcha.2013.12.003.
McCreless, E., Visconti, P., Carwardine, J., Wilcox, C., Smith, R.J., 2013. Cheap and Nasty? The potential perils of using management costs to identify global conservation priorities. PLoS One 8 (11), e80893.
McKenzie, E., Posner, S., Tillmann, P., Bernhardt, J.R., Howard, K., Rosenthal, A., 2014. Understanding the use of ecosystem service knowledge in decision making: lessons from international experiences of spatial planning. Environ. Plan. C: Gov. Policy 32 (2), 320–340.
MEA, 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC.
Mermet, L., Laurans, Y., Lemenager, T., 2014. Tools for What Trade? Analysing the Utilization of Economic Instruments and Valuations in Biodiversity Management. Agence Francaise de Developpement, Paris.
Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, D.R., et al., 2009. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. Front. Ecol. Environ. 7 (1), 4–11. http://dx.doi.org/10.1890/080023.
Pandey, K.D., Buys, P., Chomitz, K., Wheeler, D., 2006. Biodiversity Conservation Indicators: New Tools for Priority Setting at the Global Environmental Facility. World Bank, Development Economics Research Group and Environment Department, Washington, DC.
Peh, K.S.H., Balmford, A., Bradbury, R.B., Brown, C., Butchart, S.H.M., Hughes, F.M.R., et al., 2013. TESSA: a toolkit for rapid assessment of ecosystem services at sites of biodiversity conservation importance. Ecosyst. Serv. 5, 51–57.
R, 2011. R: A Language and Environment for Statistical Computing: R Development Core Team.
Rosenthal, A., Verutes, G., McKenzie, E., Arkema, K.K., Bhagabati, N., Bremer, L., et al., 2014. Process matters: a framework for conducting decision-relevant assessments of ecosystem services. Int. J. Biodivers. Sci., Ecosyst. Serv. Manag. 11 (3), 190–204.
Ruckelshaus, M., McKenzie, E., Tallis, H., Guerry, A., Daily, G., Kareiva, P., et al., 2015. Note from the field: lessons learned from using ecosystem service approaches to inform real-world decisions. Ecol. Econ. 115, 11–21.
Sherrouse, B.C., Clement, J.M., Semmens, D.J., 2011. A GIS application for assessing, mapping, and quantifying the social values of ecosystem services. Appl. Geogr. 31 (2), 748–760.
Sharp, R., Tallis, H.T., Ricketts, T., Guerry, A.D., Wood, S.A., Chaplin-Kramer, R., Nelson, E., et al., 2015. InVEST Version 3.2.0 User's Guide. The Natural Capital Project. The Nature Conservancy, and World Wildlife Fund, Stanford University, University of Minnesota.
Smith, R.J., Muir, R.D.J., Walpole, M.J., Balmford, A., Leader-Williams, N., 2003. Governance and the loss of biodiversity. Nature 426 (6962), 67–70. http://dx.doi.org/10.1038/Nature02025.
Smith, R.J., Muir, R.D.J., Walpole, M.J., Balmford, A., Leader-Williams, N., 2007. Revisiting the links between governance and biodiversity loss. Conserv. Biol. 21 (4), 899–900. http://dx.doi.org/10.1111/J.1523-1739.2007.00726.X.
Verutes, G.M., Rosenthal, A., 2014. Using simulation games to teach ecosystem service synergies and trade-offs. Environ. Pract. 00 (0), 1–11.
Villa, F., Bagstad, K.J., Voigt, B., Johnson, G.W., Portela, R., Honzak, M., et al., 2014. A methodology for adaptable and robust ecosystem services assessment. PLoS One 9 (3), e91001.
Waldron, A., Mooers, A.O., Miller, D.C., Nibbelink, N., Redding, D., Kuhn, T.S., et al., 2013. Targeting global conservation funding to limit immediate biodiversity declines. Proc. Natl. Acad. Sci. 110 (29), 12144–12148.