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The sensitivity of ecosystem service models to choices of input data and spatial resolution

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ABSTRACT

Although ecosystem service (ES) modeling has progressed rapidly in the last 10–15 years, comparative studies on data and model selection effects have become more common only recently. Such studies have drawn mixed conclusions about whether different data and model choices yield divergent results. In this study, we compared the results of different models to address these questions at national, provincial, and subwatershed scales in Rwanda. We compared results for carbon, water, and sediment as modeled using InVEST and WaSSI using (1) land cover data at 30 and 300 m resolution and (2) three different input land cover datasets. WaSSI and simpler InVEST models (carbon storage and annual water yield) were relatively insensitive to the choice of spatial resolution, but more complex InVEST models (seasonal water yield and sediment regulation) produced large differences when applied at differing resolution. Six out of nine ES metrics (InVEST annual and seasonal water yield and WaSSI) gave similar predictions for at least two different input land cover datasets. Despite differences in mean values when using different data sources and resolution, we found significant and highly correlated results when using Spearman's rank correlation, indicating consistent spatial patterns of high and low values. Our results confirm and extend conclusions of past studies, showing that in certain cases (e.g., simpler models and national-scale analyses), results can be robust to data and modeling choices. For more complex models, those with different output metrics, and subnational to site-based analyses in heterogeneous environments, data and model choices may strongly influence study findings.

1. Introduction

Spatial modeling of ecosystem services (ES)—the value nature provides to people—is a key step in ES assessments (Burkhard, Kroll, Nedkov, & Müller, 2012; Schröter, Remme, Sumarga, Barton, & Hein, 2015) and an increasingly common area of research in sustainability science (Burkhard and Maes 2017). ES modeling is useful to inform national ES assessments (e.g., Rabe, Koellner, Marzelli, Schumacher, & Grêt-Regamey, 2016), ecosystem accounting within the System of Environmental-Economic Accounting (U.N. et al., 2014), and other regional, subnational, and global assessments. A large body of literature, including modeling tools, has developed over the last decade to quantify ES (Bagstad, Semmens, Waage, & Winthrop, 2013a; Martinez-Harms & Balvanera, 2012; Schröter et al., 2015). Meanwhile new data sources derived through remote sensing (Araujo Barbosa, Atkinson, & Dearing, 2015), in combination with sensor networks and crowdsourcing (Johnson & Iizuka, 2016), offer additional data sources to populate models. Modelers now have a diverse body of feasible assessment approaches and an increasing number of global- and national-scale datasets to populate the models. Yet in both data-rich and data-limited environments, determining the most appropriate combination of data and tools for an ES assessment can be challenging.

This challenge also raises the question of replicability in ES assessment: how much difference would the use of different modeling tools and data sources make in an ES assessment for the decision-making process? In response to this challenge, scientists have called for inter- and intra-model comparative studies testing the sensitivity of ES models to choices of input data (Bagstad et al., 2013a; Sharps et al., 2017). Others have recommended the standardization of approaches, while remaining aware of the difficulty of doing so in a still-evolving field (Polasky, Tallis, & Reyers, 2015). Before such standards can be reached, better guidance is needed on navigating the choice and proper use of data and models for ES mapping in support of assessments. More broadly, such model comparison, calibration (where needed data are available), and sensitivity analysis can improve trust in environmental models (Bennett et al., 2013). Similar studies have evaluated the

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impacts of data and model choices for the simulation of ecological phenomena (Martin, Brabyn, & Potter, 2011), hydrologic systems (Bell & Moore, 2000; Geza & McCray, 2008; Koren et al., 1999), and landscape pattern (Rendenieks, Tērauds, Nikodemus, & Brūmelis, 2017).

While ES research has grown substantially in the last 10–15 years, assessments of how data and model choices influence estimates of ES are relatively new. This issue is particularly important when ES assessments are conducted in developing countries, which may have limited data availability and modeling expertise. In this paper, we evaluate the effects of using different input data and spatial resolution when using two different ES modeling tools to conduct a terrestrial/freshwater ES assessment in Rwanda.

Past studies, which we review below, have addressed a number of important questions about model, data input, and data resolution choices in ES assessments, but have most commonly addressed only one, and occasionally two, of these three issues. Additionally, we are unaware of previous studies that make multiple comparisons across multiple modeling tools and ES. Nearly all authors have suggested the need for further research across more diverse study contexts, to better assess the range of application of their findings.

In this study, we modeled carbon sequestration and storage, sediment regulation, and annual and seasonal water yield as part of a national-scale ecosystem accounting project in Rwanda, using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST, Sharp et al., 2016) and Water Supply Stress Index (WaSSI, Caldwell et al., 2013; Sun et al., 2011) modeling tools. Below, we reviewed past studies on the effects of data and model choices on ES assessment results. Next, we tested the similarity of conclusions drawn about ES trends in Rwanda from 1990 to 2010 using the InVEST and WaSSI modeling tools. We then compared the results of InVEST and WaSSI models using input data of varying spatial resolution (30 and 300 m) and three different input land cover datasets to test whether coarser resolution and/or global data give similar results. We compared all results at the national scale, the provincial scale (for Rwanda's five provinces), and used statistical analyses to compare mean values and rank-order correlation at the subwatershed scale. By evaluating the effects of ES data and model choices, we tested whether previous authors' conclusions about data and model selection hold for Rwanda, a small, heterogeneous, and relatively data-limited developing nation in central Africa. We also provided further instruction to guide data and model choice in ES mapping and modeling elsewhere.

1.1. Past studies on the effects of model and data choices on ES assessments

As the ES modeling literature has grown, an increasing number of studies have tested the effects of using different models, data inputs, spatiotemporal resolution, and uncertainty analysis in ES assessments, though such findings have not been broadly synthesized. First, *models* differ widely in their purpose, approach, and output metrics. Given this range, fit for purpose is an important consideration (Schröter et al., 2015). Simpler models may be adequate for addressing screening-level policy questions, while detailed models may be required for high-resolution spatial planning and prioritization. To understand when and where complex models produce more reliable results or whether simpler approaches are satisfactory, it can be useful to compare the results of models that use different methods but share the same purpose (Schulp, Burkhard, Maes, van Vliet, & Verburg, 2014; Sharps et al., 2017; Tallis and Polasky 2011; Willcock et al., in press). Model calibration remains a critical, and often overlooked, aspect of model performance evaluation, especially in data-limited environments (Baveye, 2017).

Second, modelers must choose which *data sources* to use as inputs to ES models. National datasets for key attributes like land cover, soils, or climate may not be available in all countries (particularly in developing nations), raising the question of the adequacy of global data for ES modeling and how much agreement ES model results have when using different global and local datasets as inputs. For instance, Dong, Bryan, Connor, Nolan, and Gao (2016) reported 60–65% per-pixel agreement between different global land cover datasets. Benítez, McCallum, Obersteiner, and Yamagata (2007) found differences of up to 45% in global carbon sequestration estimates for model results that used different global datasets. In a study of crop and fodder production in northern Germany, Kandziora, Burkhard, and Müller (2013) found that European input data overestimated ES provision relative to local data, while Redhead et al. (2016) found that U.K. data produced a better calibration of water models than global data. Finally, Schulp and Alkemade (2011) compared pollination model outputs using national, two European, and two global land cover input datasets, and found results generated using GlobCover to yield the best agreement with those from national data.

Third, choices must be made about the *spatiotemporal resolution* on which to run models. Generally, high-resolution analyses are assumed to be more accurate (though true accuracy assessments require model calibration), but potential gains from progressively higher resolution analysis must be weighed against greater storage and processing requirements, and could reach a point of diminishing returns (Grêt-Regamey et al., 2014; Hamel et al., 2017; Schulp & Alkemade, 2011). Decision-maker needs for both spatial resolution and model accuracy, both of which may be context dependent, should also be considered (Willcock et al., 2016). Continual improvements in data storage and computer processing power mean that moderate-to high-resolution ES analysis is increasingly feasible in developed nations and for many smaller developing countries. Yet for larger middle-income and developing countries, questions of the optimal spatial resolution on which to run ES models remain.

Fourth, data are of different quality, and *data uncertainty* is major source of variability and error in ES modeling (Hamel & Bryant, 2017). At least two recent studies have evaluated the effects of uncertainty related to error in land cover datasets (Dong et al., 2016; Foody, 2015), and further work on this and other types of uncertainty in ES analysis is needed.

Nineteen recent studies focus on the first three types of data and model choices that we address in our study. Each study's characteristics and findings are summarized below (Table 1). We exclude studies from this table that rely on land cover-based benefit transfers (Konarska, Sutton, & Castellon, 2002; Whitham, Shi, & Riordan, 2015) due to this method's well-known limitations (Bockstael, Freeman, Kopp, Portney, & Smith, 2000). We also excluded papers that conducted mapping at different scales but either aggregated fine-scale results (Larondelle & Lauf, 2016) or used different indicators for analysis at different scales (Rabe et al., 2016).

Taken together, these studies reach several broad conclusions. When using different approaches, local ES differences may be evident for small geographic regions but disappear when averaged across larger regions (Bagstad, Semmens, & Winthrop, 2013b; Dong et al., 2016). At national and continental scales, proxy-based results often perform poorly when compared to those of primary ES data or models (Eigenbrod et al., 2010; Schulp et al., 2014). Willcock et al. (in press) generally support this, but found that some complex ES models do not always have the best predictive power.

Geographic aggregation means that infrequent and/or dispersed values (e.g., scattered wetland or forest patches) will be "lost" as they are averaged into coarser scale data, particularly for categorical data like land cover. We thus generally expect fine-resolution data to produce more accurate ES assessment results than coarse-resolution data. This is typically the case (Grêt-Regamey et al., 2014 for all services but carbon sequestration; Grafius et al., 2016). Less divergence is expected in homogeneous environments than in heterogeneous ones, meaning that coarser-resolution analyses may be adequate in relatively homogeneous settings (Grêt-Regamey et al., 2014; Schulp & Alkemade, 2011; Willcock et al., in press). Additionally, a comparison of ES results at very coarse resolutions (1 vs. 10 km for sub-Saharan Africa) found

Table 1
Summary of past studies on ecosystem service model and data selection comparisons.

Analysis	Reference	Location	ES analyzed	Modeling approach[a]	Agreement/Key findings
Model	Bagstad et al., 2013b	San Pedro River, Arizona, USA	Carbon, viewsheds, water yield	ARIES, InVEST	**Good** agreement when quantifying **landscape-scale change; poor** agreement when quantifying **fine-scale change**.
	Dennedy-Frank, Muenich, Chaubey, & Ziv, 2016	Two watersheds in Indiana & Georgia, USA	Water yield	InVEST, SWAT	**Good** agreement in a **flat, cold-temperate agricultural watershed**, **poor** agreement in a **mountainous, warm-temperate forested watershed** (likely due to **different model representation of water storage and baseflow**).
	Eigenbrod et al., 2010	England	Biodiversity, carbon, recreation	Primary data & land cover	**Poor** agreement; best fit between primary data and land cover proxies was carbon, followed by recreation then biodiversity.
	Lüke & Hack, 2018	Chiquito watershed, Nicaragua	Sediment regulation, water yield	InVEST, RIOS, SWAT	**Moderate** agreement of **sediment** models, **limited** agreement between **water yield** models, which used different data and conceptual approaches.
	Schulp et al., 2014	Europe	Carbon, flood regulation, pollination, recreation, sediment regulation	Expert opinion, process-based models, intermediate approaches	**Poor to moderate** agreement between ecosystem service and independent proxy maps. **Greatest agreement** where **consensus exists** for indicators and methods (i.e., **carbon**) **versus** those lacking consensus (i.e., **soil erosion**).
	Sharps et al., 2017	Conwy catchment, Scotland	Carbon, water yield, nutrient regulation	ARIES, InVEST, LUCI	**Some broad agreement** between models but **key differences** observed in **spatial pattern** and **responses to** common **scenarios**.
	Tallis & Polasky, 2011	Willamette Basin, Oregon & Central Valley, California, USA	Carbon, pollination	InVEST (Tier 1 & 2)	**Relatively good** agreement for **carbon** models, in terms of absolute quantity and spatial pattern. **Greater differences** for **pollination** models; simpler models are more appropriate in settings where pollinator communities are less diverse and have less specific habitat needs.
	Vorstius & Spray, 2015	Eddleston Catchment, Scotland	Carbon, pollination, nutrient regulation	EcoServ-GIS, InVEST, SENCE	**Relatively good** agreement for **carbon**. **Relatively poor** for **pollination** and **nutrient regulation** due to differences in model inputs and assumptions.
	Yee et al., 2014	St. Croix, U.S. Virgin Islands	Shoreline protection, recreation, fisheries, natural products	Habitat-based predictors, biophysical models	**Biophysical models** and **habitat-based predictors performed differently,** but **relatively good agreement** in spatial patterns **for different modeling/habitat predictors.**
Model, Resolution	Willcock et al., in press	Sub-Saharan Africa	Carbon, charcoal, firewood, grazing, water yield	Co$ting Nature, InVEST, LPJ, benefit transfer, Scholes methods	**More complex models better** for predicting **carbon**; models **acceptably predict potential ES** but **not flows**. **Minimal difference** between **1 and 10 km resolution** analysis.
Inputs, Model	Van der Biest et al., 2015	Central Campine ecoregion, Northeast Belgium	Crop, livestock & wood production, soil carbon, groundwater recharge, nutrient regulation, sediment regulation, pollination	Expert opinion (qualitative analysis) vs. varied models (quantitative analysis)	**Poor** for **regulating services** but **better** for **provisioning services.** Results from high thematic resolution land cover maps were **more accurate** for **provisioning services** but **less** so for **regulating services**.
Inputs	Benítez et al., 2007	Global	Carbon	Spatial modeling of carbon sequestration potential & cost	Results **differ by up to 45%**, mostly due to differences in key characteristics of the input datasets.
	Kandziora et al., 2013	Bornhöved Lakes area, Germany	Crop production, fodder production	Agricultural statistics data	CORINE data, with **coarser spatial and thematic resolution**, **overestimated service production** as compared to more localized datasets.
	Redhead et al., 2016	U.K.	Water yield	InVEST	**National data** for precipitation & evapotranspiration produced **better calibration** across 42 watersheds **than global datasets**.
Inputs, Resolution	Grêt-Regamey et al., 2014	Four mountain regions in Europe & USA	Agriculture, carbon, flood regulation, timber, viewsheds	Varied models	**Relatively good** agreement for **carbon** but less so for other services. Differences for other services may be due to differences in model complexity & inputs along with differing scale and varying topography.
	Schulp & Alkemade, 2011	Netherlands	Pollination	Spatial pollination model	**GlobCover** data had **better agreement with national data** than other global or continental scale data. Spatial resolution of **250 m** was **adequate to represent pollination**; coarser data could suffice in more homogeneous environments.
	Wang et al., 2018	Fitzroy Basin, Queensland, Australia	Seasonal water yield	InVEST	**Spatial resolution** had a **greater effect** than changes in **data sources** or model coefficients.

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Table 1 (*continued*)

Analysis	Reference	Location	ES analyzed	Modeling approach[a]	Agreement/Key findings
Resolution	Grafius et al., 2016	Towns of Milton Keynes, Bedford, and Luton, U.K.	Carbon, sediment regulation, pollination	InVEST	**Greater** estimates for **carbon storage** and **lower** estimates for **erosion and pollination** with fine than coarse resolution analysis.
	Hamel et al., 2017	Georgia, Hawaii, North Carolina, USA, Puerto Rico, Spain, Kenya	Sediment regulation	InVEST	**Inconsistent** relationship between digital elevation model resolution and erosion across six study sites.

[a] Modeling approach acronyms: ARIES: Artificial Intelligence for Ecosystem Services (Villa et al., 2014), InVEST: Integrated Valuation of Ecosystem Services and Tradeoffs (Sharp et al., 2016), LPJ: Lund-Potsdam-Jena model (Sitch et al., 2003), LUCI: Land Utilisation and Capability Indicator (Jackson et al., 2013), RIOS: Resource Investment Optimization System (Vogl et al., 2018), SENCE: Spatial Evaluation for Natural Capital Evidence (Medcalf, Small, Finch, & Parker, 2012), SWAT: Soil and Water Assessment Tool (Arnold & Fohrer, 2005).

minimal differences between the two (Willcock et al., in press), and in a related study, over 70% of respondents in a survey of African ES experts suggested that 1 km resolution outputs were adequate for their needs (Willcock et al., 2016). In a study of six sites using the InVEST sediment delivery ratio model, Hamel et al. (2017) found an inconsistent relationship between erosion outputs modeled at differing spatial resolution. They note that soil erosion models are highly sensitive to digital elevation model (DEM) resolution, and that the effects of changing resolution are context specific.

In many cases, landscape complexity and the ES being evaluated may dictate whether analysis using complex models (and/or local, high-resolution data) yields a substantial information gain over simpler (and/or global, low-resolution) approaches. In a few cases, simpler models performed adequately (Tallis & Polasky, 2011; Van der Biest et al., 2015 for provisioning ES, Willcock et al., in press for 7 of 12 ES models). In one case (Van der Biest et al., 2015), input datasets with low thematic resolution performed better for regulating services but more poorly for provisioning services (as defined by MEA, 2005). Additionally, we expect high thematic resolution data to provide the greatest information gain in data-rich environments, where the underlying data exist to distinguish the characteristics of more of land cover types.

2. Methods

2.1. Study area

The study occurred within the country of Rwanda, a landlocked, relatively small (26,000 km^2) East African nation with the highest population density in Africa (World Bank, 2017, Fig. 1). The mountainous terrain of western Rwanda becomes more rolling toward the country's eastern border. Annual precipitation patterns follow elevation, with the highest rates occurring in the west, where precipitation exceeds 1600 mm/yr. In the lower elevation eastern section of the country, precipitation is less than 800 mm/yr (U.N., 2010). Dense, mountainous mixed forests supported by high rates of annual precipitation dominate western Rwanda, while agricultural and grazing land can be supported in the lower rainfall areas in the central and eastern part of the country. Forests comprise approximately 20% of Rwanda's land area (U.N., 2010).

2.2. Modeling approach

Through a series of working group meetings convened by the Science for Nature and People Partnership (SNAPP) from September 2015 through March 2017, we defined a list of ES, methods, and data sources and developed and refined ES models together with stakeholders. The working group included representatives from the Rwandan government, civil society (i.e., the Wildlife Conservation Society-Rwanda), and technical experts from the World Bank, U.S. Geological Survey, and Rwandan and U.S. academics. The group identified carbon storage, sediment regulation, and water yield as ES that would add value for decision making and were feasible to quantify using existing data.

We used the InVEST 3.3.3 modeling software (Sharp et al., 2016)—a general-purpose ES modeling toolkit—to quantify carbon storage, sediment regulation (through a sediment delivery ratio model), and annual and seasonal water yield in Rwanda. The InVEST annual water yield model uses the Budyko curve method to estimate actual evapotranspiration (AET), then subtracts AET from precipitation to estimate annual water yield. Its carbon storage model matches land cover to estimated carbon pools in vegetation, soils, and woody debris using a lookup table. The seasonal water yield model quantifies two key metrics: (1) quick flow (runoff during and immediately following storm events), estimated using the Curve Number method, and (2) local recharge, calculated by subtracting quick flow and AET from

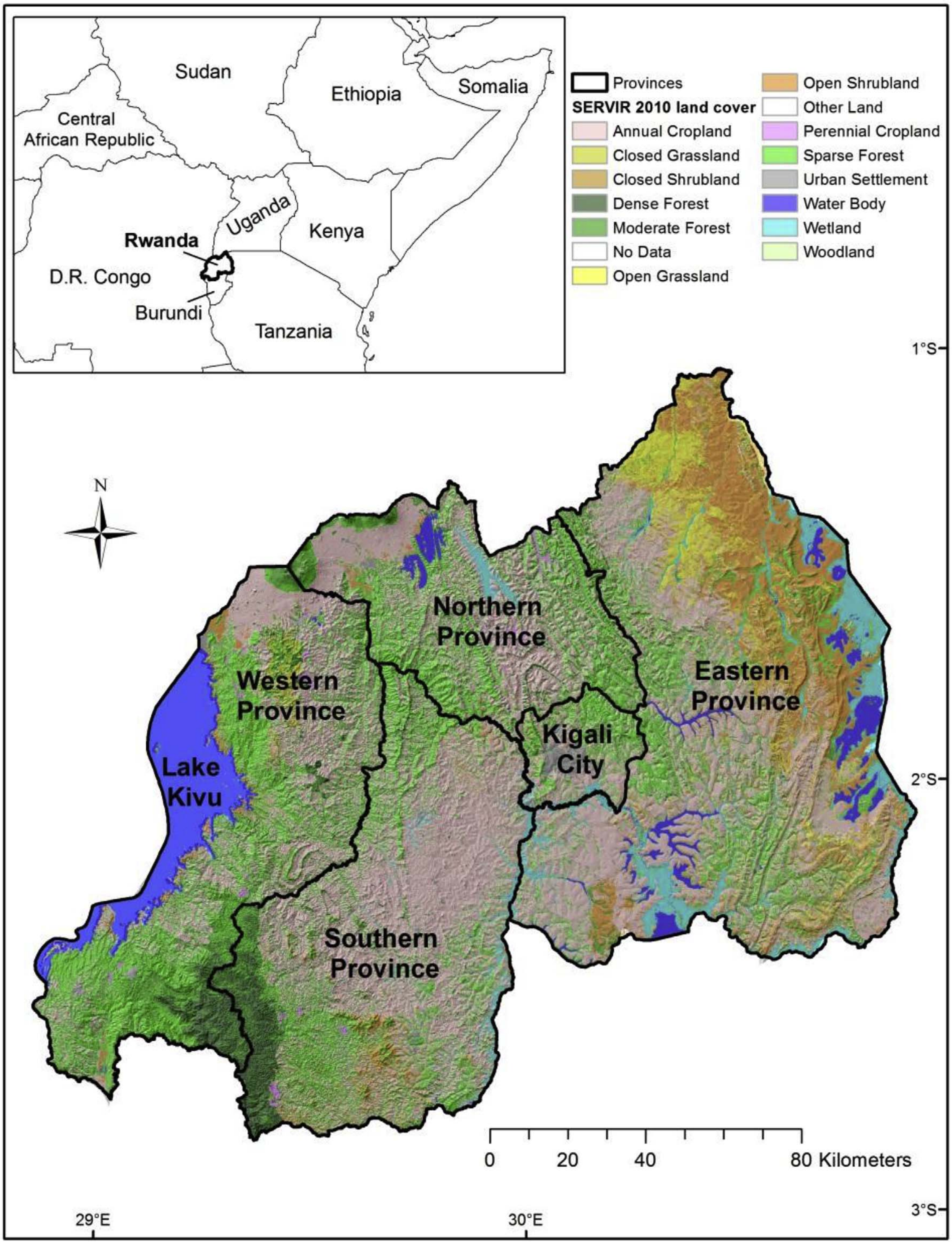

Fig. 1. Study area and 2010 land cover map for Rwanda.

precipitation. The sediment delivery ratio model calculates sediment retention and export using the universal soil loss equation paired with a connectivity index to estimate sediment export (Sharp et al., 2016). Data inputs and model coefficient tables used for InVEST modeling are provided in Appendix 1, and all results are available as a U.S. Geological Survey data release (Ancona & Bagstad, 2018).

McNulty, Cohen, Sun, and Caldwell (2016) had previously applied the WaSSI model (Caldwell et al., 2013; Sun et al., 2011) in Rwanda. WaSSI is an uncalibrated model that calculates monthly water balance by subwatersheds, using leaf area, vegetation type, precipitation, and potential evapotranspiration to estimate AET, which also enables estimation of monthly and annual runoff and net ecosystem exchange (i.e., carbon sequestration, the annual uptake of carbon by vegetation). We evaluated both average annual water yield and dry-season (June–-September) water yield. Data sources used with the WaSSI model are provided in Appendix 2.

All of our analyses are represented in biophysical units although it is possible to apply monetary values to ES using various methods (e.g., market or social cost of carbon).

2.3. Data and model comparison

First, we briefly described InVEST and WaSSI outputs for the years 1990, 2000, and 2010 at the national and provincial scale. InVEST and WaSSI metrics are only directly comparable for average annual water yield. Further reducing the direct comparability of the two approaches, we used slightly different precipitation and soils data for the InVEST and WaSSI model runs (see Appendices 1-2 and Results). This made our comparison more an exercise where analysts choose the best applicable data for use in both their models (e.g., Sharps et al., 2017). We thus considered the two approaches to provide complementary information, which may provide a more nuanced view of spatiotemporal ES trends in Rwanda, particularly for carbon sequestration and storage and dry-season water yield. Seasonal water yield is an important ES metric to track in Rwanda, due to the country's pronounced dry season. We present InVEST and WaSSI results based on model runs at 30 m spatial resolution using SERVIR Scheme II land cover input data (Odour et al., 2016).

Second, we ran an intra-model comparison on the effects of varying spatial data resolution on the results of InVEST and WaSSI models. We initially ran all models using 2010 SERVIR and GlobeLand (Zhang et al., 2016) input data at their native 30 m spatial resolution. Next, we resampled both land cover datasets to 300 m resolution using majority resampling. We also resampled the DEM from its native 30 m–300 m spatial resolution, and used the Fill tool in ArcGIS (Esri, 2017) to remove sinks in the DEM. We compared the difference in results across national, provincial, and subwatershed scales generated using resampled 300 m data against those using the original 30 m data.

Third, we ran another intra-model comparison on the effects of input land cover dataset choice on InVEST and WaSSI model results for the year 2010, using three datasets (Table 2, Fig. 2). We used resampled SERVIR and GlobeLand data at 300 m resolution to avoid confounding the effects of varying spatial resolution (above) and input dataset type. We used European Space Agency-Climate Change Initiative (CCI) data at their native 300 m spatial resolution (UCL-Geomantics, 2015). Tables showing all ES modeling results at national and provincial scales are provided in Appendix 3.

For the first and second analyses, we used the Wilcoxon signed ranks test (the nonparametric analog to a paired *t*-test) to test for statistical differences in the mean value of each ES within Rwanda at the subwatershed level ($n = 101$). For the third analysis, we similarly used the Friedman test (the nonparametric analog of repeated measures ANOVA) to evaluate differences between results generated using three input data sources. None of the data were normally distributed, making parametric statistical tests inappropriate. We also conducted Spearman's rank correlation tests for all comparisons, to test for statistical differences in the rankings of results obtained using corresponding approaches. We conducted all statistical analyses using R version 3.4.2 (R Foundation, 2017).

Table 2
Key attributes of land cover datasets used for comparing effects of data inputs on ecosystem service modeling.

Dataset	Spatial extent	Spatial resolution	Number of classes	Reference
SERVIR-Scheme II	Rwanda	30 m	13	Odour et al., 2016
GlobeLand	Global	30 m	10	Zhang et al., 2016
European Space Agency-Climate Change Initiative (ESA-CCI) v 1.61	Global	300 m	35	UCL-Geomantics, 2015

3. Results

3.1. Water yield and carbon trends quantified by InVEST and WaSSI

Despite the relative incompleteness of streamflow records in Rwanda, annual water yield results using both the calibrated InVEST and the uncalibrated WaSSI models were relatively well correlated with streamflow (R^2 of 0.72 for InVEST and 0.99 for WaSSI, Appendix 1, McNulty et al., 2016). When we compared modeled national-scale AET to a third, global dataset modeled using satellite data, the MODIS MOD16 product (Mu, Zhao, & Running, 2016) for 2008 to 2012, values for WaSSI differed by 1.4–12.2%, and those for InVEST differed by 1.8–10%. However, InVEST overestimated AET relative to MODIS data while WaSSI underestimated it, leading to a national-scale difference in water yield estimates between the two models of 53–58% that was statistically significant ($p \le 0.01$) at the subwatershed scale.

From 1990 to 2010, both models documented a very small (< 1%) increase in annual runoff, with greater changes occurring in the Eastern Province and Kigali City than elsewhere (Fig. 3). The increase was statistically significant ($p \le 0.01$) for the entire time period as modeled using WaSSI and from 2000 to 2010 as modeled using InVEST. Additionally, model results were highly correlated at the subwatershed scale ($p \le 0.01$, Spearman's Rho = 0.79 to 0.82). We observed three key differences in the model results. First, InVEST results predicted a small decline in water yield from 1990 to 2000, and an increase from 2000 to 2010, while WaSSI results showed the opposite trend. Second, differences in runoff between the two models were greatest in the Eastern Province and Kigali City (135–189% difference), and were lesser in the Western Province (17–20% difference). Third, provincial-level changes were greater in InVEST (up to a 10% decline in the Eastern Province), while all WaSSI-modeled changes were less than 2% over the 20-year time period.

Model results gave complementary information about carbon, due to their use of different metrics, i.e., carbon storage (InVEST) and sequestration (WaSSI). Carbon stocks calculated using InVEST declined from 627 MT in 1990 to 535.8 MT in 2000, then rebounded to 551.4 MT in 2010, an overall nationwide decline of 12.1% that was statistically significant ($p \le 0.01$). Provincial-scale carbon stocks declined by 8.7–22.1% from 1990 to 2000, and had more modest declines (1.1–4.3%) or gains (7.8–11.4%) from 2000 to 2010. Net ecosystem exchange (i.e., carbon sequestration) modeled using WaSSI increased from 13.5 MT/yr in 1990 to 14.5 MT/yr in 2000 and 2010 (a 7.5% increase from 1990 to 2000, followed by a 0.1% increase from 2000 to 2010). Carbon sequestration was significantly different from 1990 to 2000 ($p \le 0.01$), but not 2000 to 2010. At the provincial level, carbon sequestration increased by 4.5–15.8% from 1990 to 2000 and had modest declines or increases in the following decade (−3.1% to +1.4%). Annual carbon sequestration ranged from 2.2 to 2.7% of Rwanda's total carbon stock and 8.8–13% of its stock of aboveground and belowground biomass carbon in a given year.

Models also gave complementary information related to dry-season flows. The InVEST seasonal water yield model quantifies quick flow—runoff during and immediately after storms—that is unavailable for local recharge that can support dry-season baseflows. We estimated a 22.5% nationwide increase in quick flow from 1990 to 2010. We observed greater change in the 1990s than the subsequent decade, but found statistically significant differences at the subwatershed scale from 2000 to 2010 only. Provincial-scale quick flow change from 1990 to 2010 ranged from gains of 8.6% (Kigali City) to 48.4% (Western Province). WaSSI more directly quantifies dry-season runoff, and showed that 24% of the annual runoff occurs during the June to September dry season. Dry-season runoff declined from 1990 to 2010, but only very slightly—0.2% nationwide and 0.7% for the Eastern Province, which witnessed the most change. This change largely occurred between 1990 and 2000 (statistically significant at $p \le 0.01$), with non-significant change from 2000 to 2010.

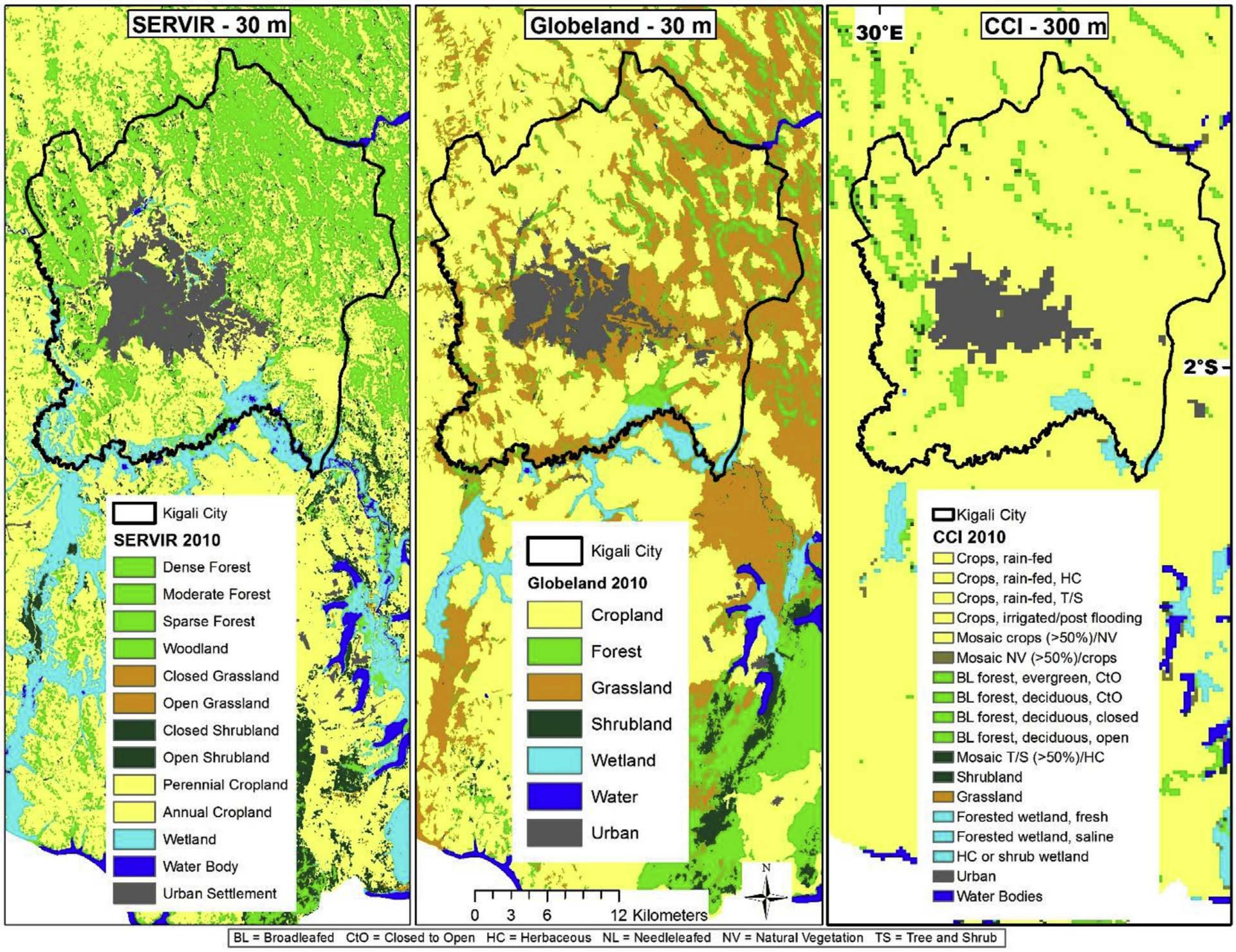

Fig. 2. Land cover for Kigali City: (a) SERVIR Scheme II 30 m, 2010; (b) GlobeLand 30 m, 2010; (c) CCI 300 m, 2010.

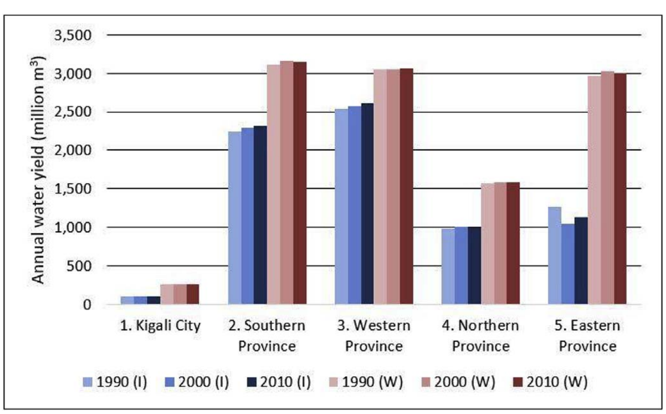

Fig. 3. InVEST (I) and WaSSI (W) annual water yield results by province for Rwanda, 1990–2010.

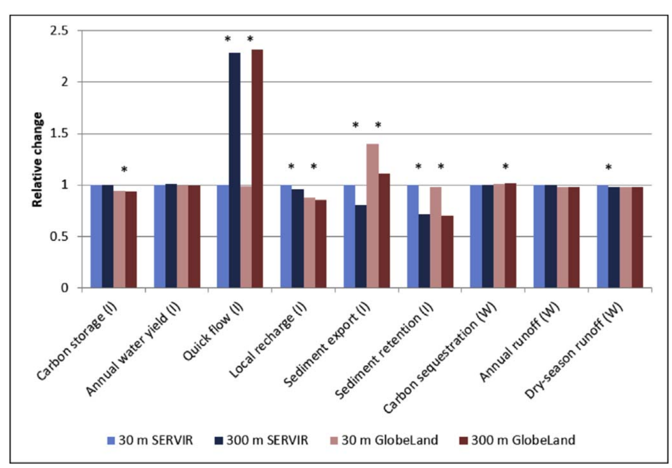

Fig. 4. Effects of spatial resolution on ecosystem service model results: 2010 SERVIR and GlobeLand data at 30 and 300 m resolution using InVEST (I) and WaSSI (W). Values are normalized relative to model results obtained from the 30 m SERVIR data. Asterisks indicate statistically significant differences in mean value by subwatershed between different input resolutions (Wilcoxon signed ranks test; all $p \leq 0.05$).

3.2. Effects of varying spatial resolution

At the subwatershed scale, we observed statistically significant differences when using both SERVIR and GlobeLand data at 30 vs. 300 m resolution for the InVEST quick flow, local recharge, sediment export, and sediment retention results (Fig. 4). Fine-resolution analysis estimated less quick flow (130% nationally, 101–174% provincially) and more local recharge (< 4% nationally, with differences of up to 37% at the provincial scale), and more sediment export and retention (20 and 28% greater, respectively, at the national scale). We also observed significant differences at differing resolution for InVEST and WaSSI carbon models when using GlobeLand data, and for WaSSI dry-season runoff when using SERVIR data. Fine-resolution analysis estimated more carbon storage and less carbon sequestration, and more dry-season runoff, though the magnitude of these differences was much smaller (< 1% nationally and 2% at the provincial scale) than those obtained for the sediment and seasonal water yield models. All

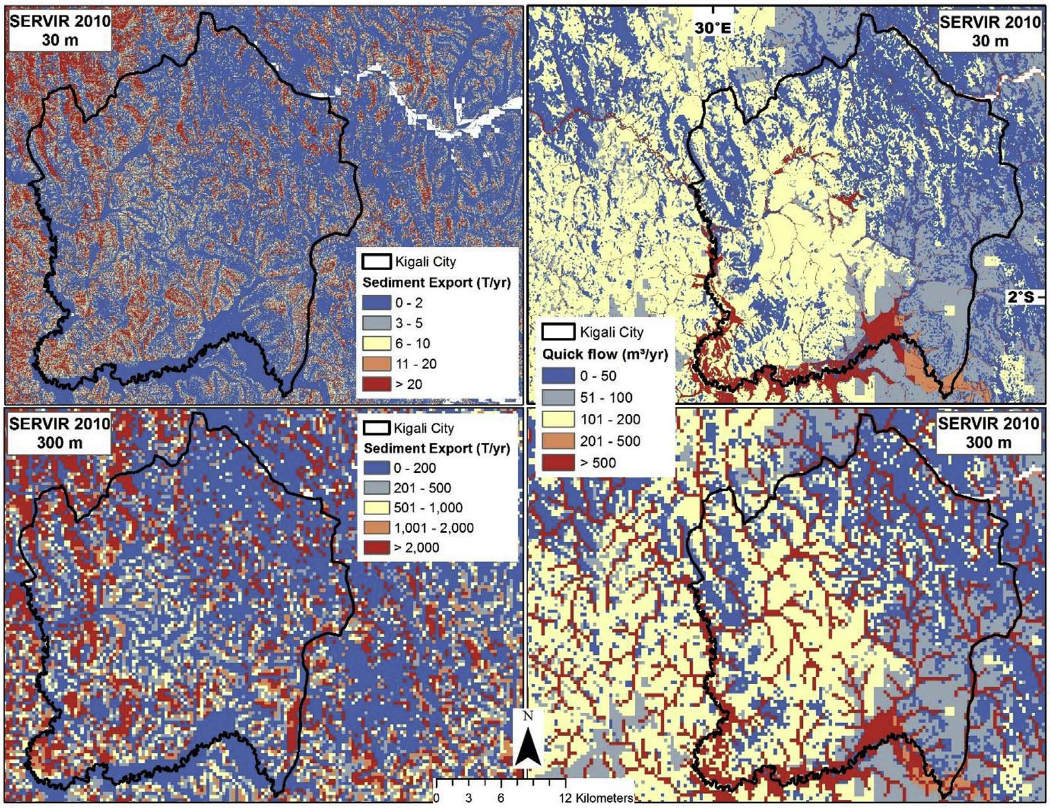

Fig. 5. Sediment export (left) and quick flow (right) results for Kigali City, using SERVIR Scheme II land cover data at 30 m (top) and 300 m (bottom).

differences were significant at $p \le 0.05$. Spearman's rank correlation results were statistically significant ($p \le 0.01$) with high Rho values (0.82–0.99), indicating strong correlation between high- and low-value watersheds for all comparisons.

Sediment export and quick flow maps for Kigali City illustrate key differences (Fig. 5). Generally, patterns of high and low values match well for the high- and low-resolution maps. Greater quick flow in the coarser resolution analysis appears to be caused by larger values in water bodies and floodplains, which are overrepresented at coarse resolution. Greater sediment export seems to be driven by fine-scale topographic features that disappear at coarser resolution. Both trends largely result from Rwanda's highly heterogeneous topography. When we divided sediment export into its two component factors—sediment delivery ratio and revised universal soil loss equation (RUSLE) (per Hamel et al., 2017)—we found differences to be driven primarily by the RUSLE results, which were 39–40% greater in the 30 m model runs. SDR values were 18–19% smaller in the 30 m analysis, which when combined with the RUSLE results led to greater sediment export at 30 m resolution.

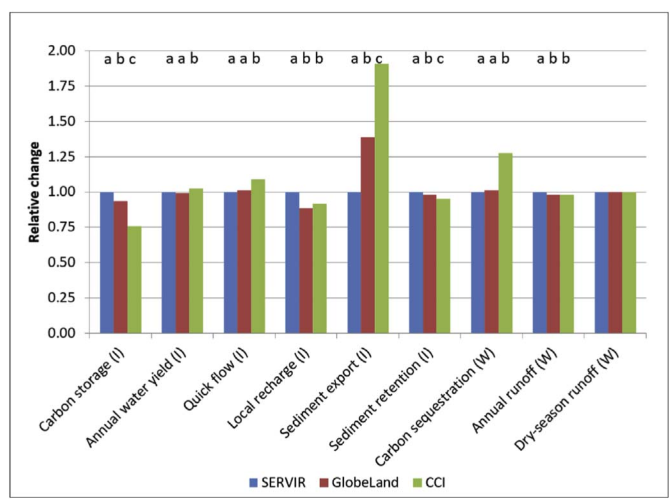

Fig. 6. Effects of spatial data sources on ecosystem service model results: 2010 SERVIR, GlobeLand, and CCI data, all at 300 m spatial resolution using InVEST (I) and WaSSI (W). Values are normalized relative to model results obtained from the 300 m SERVIR data. Letters indicate statistically significant differences in mean value by subwatershed between different data sources (Friedman test; all $p \le 0.01$).

3.3. Effects of varying input land cover data

For the InVEST carbon and sediment results, we observed statistically significant differences across all three input datasets, with national data giving greater carbon storage and sediment retention and less sediment export (Fig. 6). Results were more divergent from SERVIR-generated results when using Climate Change Initiative (CCI) data and less so when using GlobeLand. For the InVEST annual water yield and quickflow and WaSSI carbon sequestration models, SERVIR and GlobeLand data gave similar results but CCI-generated estimates were significantly greater. When comparing InVEST local recharge and WaSSI annual runoff estimates, SERVIR-generated values were significantly greater than those using CCI and GlobeLand. All differences were significant at $p \le 0.01$. For the WaSSI dry-season runoff estimates, we found no statistically significant differences when using different datasets. Spearman's rank correlation results were statistically significant ($p \le 0.01$) with high Rho values (0.77–0.99), indicating strong correlation between high- and low-value watersheds for all comparisons.

The magnitude of national-scale differences between the SERVIR and GlobeLand-generated outputs was relatively small ($\le$6%) for seven of nine models—all but InVEST sediment export (40% greater using GlobeLand) and local recharge (11% lesser using GlobeLand; Fig. 6).

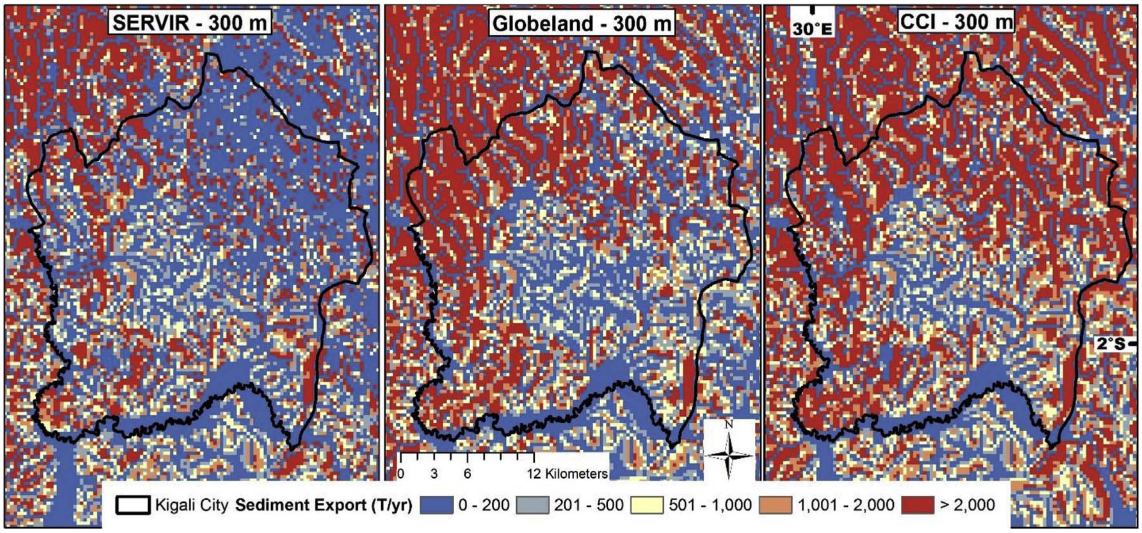

Fig. 7. Sediment export results for Kigali City at 300 m resolution: (a) SERVIR Scheme II; (b) GlobeLand; (c) CCI.

Key differences can be seen for sediment export in Kigali City (Fig. 7). Model results are most different in the northwestern part of the Kigali City, where SERVIR classified land cover as mainly sparse forest, GlobeLand as grassland and cropland, and CCI as cropland (Fig. 2). We also observed relatively small national-scale differences (≤5%) across all three datasets for the InVEST and WaSSI annual water yield, sediment retention, and WaSSI dry-season runoff models. Relative to SERVIR data, CCI data produced substantially smaller values for carbon storage and local recharge, and greater values for quick flow, sediment export, carbon sequestration.

Further differences emerged at the provincial scale. For instance, although all three land cover datasets had fairly close national-scale agreement on annual water yield (< 3% difference in magnitude), GlobeLand data overpredicted water yield in the Northern Province and Kigali City (by 5–7%) and underpredicted water yield in the Eastern Province (by 18%) when compared to SERVIR-based results. We observed similar, relatively close national-scale agreement and wider provincial-scale divergence for quick flow and carbon sequestration (when using GlobeLand data) and for sediment regulation models (when using CCI data, Appendix 3). Only the WaSSI annual and dry-season runoff models had relatively good consensus at both the national and provincial scales when using all three input datasets (though at the subwatershed scale, significant differences in WaSSI-predicted annual runoff were observed when using SERVIR data relative to global data, Fig. 6).

4. Discussion

4.1. Water yield and carbon trends quantified by InVEST and WaSSI

The InVEST and WaSSI annual water yield models both quantified very small nationwide increases in water yield over time, with statistically significant and relatively high Spearman's Rho, though with statistically significant differences in total water yield (Table 3). Key subnational differences (e.g., in the Eastern Province) may stem from calibration data that were limited to certain parts of the country, and to the fact that WaSSI is an uncalibrated model. Carbon and dry-season runoff metrics provide complementary information that is not directly comparable. From 1990 to 2010, carbon storage (quantified using InVEST, which estimates the stock of carbon in four different carbon pools) declined, while carbon sequestration (quantified using WaSSI, which estimates annual carbon uptake through estimates of net ecosystem exchange) increased. Dry-season runoff quantified using WaSSI declined very slightly (0.2%), whereas quick flow quantified using InVEST increased by 22.5%. These trends are complementary, and suggest reductions in local recharge that have negatively impacted dry-season flows. ES changes in Rwanda were largely driven by land cover change trends from 1990 to 2010, including loss of forests and woodlands (−32%), shrubland (−36%), and wetland (−10%), and increasing cover of grassland (+27%), cropland (+78%), and urban areas (+77%).

Although the information that InVEST and WaSSI provide is largely complementary, comparable metrics like annual water yield could be combined in ES model ensembles (Willcock et al., in press), though the resources needed to support running multiple ES models are less likely to be available outside of research contexts.

4.2. Spatial resolution comparison

Differences between the 30 and 300 m resolution analyses were most pronounced for the InVEST seasonal water yield and sediment models, though we lacked data to calibrate our sediment model. We found greater sediment export at higher resolution, driven by larger RUSLE values. Hamel et al. (2017) note the sensitivity of RUSLE-based erosion models to spatial resolution, and that the effects of changing resolution are context dependent. Our findings were similar to Hamel et al.'s (2017) use of the InVEST sediment model for the Cape Fear watershed in North Carolina, USA. For the seasonal water yield model, our finding of greater water yield at coarse resolution is similar to those of Wang et al.'s (2018) application of the same model to the Fitzroy Basin in Queensland, Australia. Other statistically significant differences—of less carbon storage and greater carbon sequestration when using coarse-resolution GlobeLand data, and of less dry-season runoff when using coarse-resolution SERVIR data—were both of smaller magnitude and held for one but not both sets of spatial resolution comparisons. When analyzed using Spearman's rank correlation, all model comparisons had statistically significant and high Rho values, indicating that models produce similar patterns of high and low values across the landscape at different spatial resolution.

The interplay between landscape heterogeneity and analysis resolution has been noted in other ES assessments, with the consensus that coarser-resolution analysis is most likely to produce acceptable results in more homogeneous environments (Grafius et al., 2016; Grêt-Regamey et al., 2014; Schulp & Alkemade, 2011). Our study context is notably heterogeneous in terms of both topography and land cover. Rwanda is a hilly to mountainous nation, particularly in the west, and gradually grades into more rolling terrain in the eastern part of the country. Due to both its topography and agricultural land-use patterns,

Table 3
Summary of key study findings.

Category	Key findings	Implications for modelers
Model comparison (InVEST-WaSSI annual water yield)	• Both models compared favorably to measured streamflow and MODIS AET data • Both models identified similar temporal trends • Model results were highly correlated at subwatershed scale • Key differences emerged in total national & provincial scale water yield	• Both models performed adequately in a relatively data-limited context • Model ensembles may be beneficial
Spatial resolution comparison	• Significantly greater water yield (using seasonal water yield model) and less sediment export at coarser scale • Scale differences were significant for carbon models and WaSSI dry-season water yield for one but not both data sources • No scale differences for annual water yield models • Model results were highly correlated at subwatershed scale	• Consider decision context: fine-resolution analysis is needed for spatial prioritization and payments for ecosystem services, but may not be needed for larger-scale screening studies • Consider the heterogeneity of your context (especially topography and land cover); use finer-resolution analysis in heterogeneous environments • Coarser resolution analysis may be more acceptable for simpler models (e.g., InVEST carbon & annual water yield) than complex models (e.g., InVEST seasonal water yield & sediment delivery ratio) • Coarser resolution analysis may be more acceptable for subwatershed-based models (e.g., WaSSI) than pixel-based models (e.g., InVEST)
Input data comparison	• InVEST carbon and sediment models produced different results across all three input datasets; magnitude of difference was greatest for the sediment model • InVEST annual and seasonal water yield and WaSSI models produced similar results for at least two input datasets • Model results were highly correlated at subwatershed scale	• Consider decision context: global data may be acceptable for screening-level analyses where subnational-scale inaccuracies are not important, or for multinational analyses where common data are needed • Spatial pattern, classification accuracy, and thematic resolution can help determine whether global data are acceptable • Quick assessments of spatial pattern and classification accuracy can be done by comparing data to aerial photos or satellite data • High thematic resolution may be beneficial in data-rich environments, which may enable parameterization of many land cover classes, but less valuable in data-limited contexts

which are dominated by small land holdings, Rwanda's land cover is also highly heterogeneous. Therefore, coarser-resolution analyses will mask fine-grained topographic or land cover features. Despite Rwanda's heterogeneity, simpler InVEST models and WaSSI models were relatively less sensitive to changes in analysis resolution. This supports the conclusions of Grafius et al. (2016), who noted that high-resolution data are most important for more complex ES models, because the data can more accurately identify patterns of both high-value areas and ES flows through a DEM or other layers. WaSSI results are aggregated to the subwatershed scale, which may explain their relative similarity at 30 and 300 m resolution.

4.3. Input data comparison

The InVEST carbon storage and sediment models produced the most divergent results across all three input datasets. However, some models performed similarly when using multiple input land cover datasets. Notably, WaSSI, which classified all land cover into eight classes and reported results at subwatershed scales, gave similar dry-season runoff results regardless of input data, though annual runoff results differed when using SERVIR land cover data or global datasets. The InVEST annual water yield, quick flow and WaSSI carbon sequestration estimates were similar to SERVIR-based results when using GlobeLand data, but dissimilar when using CCI data. Our Spearman's rank correlation analysis found all comparisons to be statistically significant with high Rho values, indicating that models produce similar patterns of high and low values across the landscape when using different input land cover datasets.

For ES modeling, the spatial pattern, classification accuracy, and thematic resolution of land cover datasets all matter. Differences were evident in the pattern and classification of land cover for our sediment export analysis (Figs. 2 and 7). Additionally, differing thematic resolution (i.e., CCI data have 35 classes, GlobeLand 10, and SERVIR Scheme II 13) matters when data exist to distinguish different levels of ES provision between a large number of classes. In other words, thematic resolution need not go beyond the quality of field data available to parameterize models, which in Rwanda was roughly limited to the 13 SERVIR Scheme II classes. In data-rich contexts that can support the full use of high thematic resolution data, analysts should expect to observe greater differences than we did between results generated using different input land cover datasets (Kandziora et al., 2013, Van der Biest et al., 2015).

Most other studies have found that different inputs yield diverging results (Benítez et al., 2007; Kandziora et al., 2013; Redhead et al., 2016; Van der Biest et al., 2015), though this finding was not uniform (Wang, Lechner, & Baumgartl, 2018). Our results suggest that for some models, certain global-scale data may be adequate for ES assessments. This is particularly true for national-scale screening analyses and continental to global scale ES assessments, for which analysis of fine-scale subnational differences is not required.

4.4. Conclusions

Building on others' findings about data and model selection for ES mapping and a national-scale case study in Rwanda, we make recommendations below that ES modelers can use in choosing data and models to map ES (Table 3). Such studies have previously helped guide modelers in the fields of hydrology (Bell & Moore, 2000; Geza & McCray, 2008; Koren et al., 1999), ecology (Martin et al., 2011), and landscape ecology (Rendenieks et al., 2017), and are increasingly available to guide ES analysts (Table 1). In Rwanda, InVEST and WaSSI annual water yield models both had relatively good predictive power, giving greater confidence in their outputs, despite their differences. The models offer different advantages that may be favored by different users. For instance, WaSSI provides monthly data, while InVEST allows analysis of ES beyond water and carbon. InVEST also provides pixel-level outputs, which may be useful in the interpretation of results for some models (though not, e.g., its annual water yield model, Sharp et al., 2016). Scientists and decision makers should consider desired ES metrics, their sensitivity to change, and the availability of calibration data for before selecting a particular ES modeling technique. Investment in calibration and monitoring data remains important for Rwanda (where we only had calibration data for the InVEST water models) and other nations, to more accurately track changes in their ES and natural capital (Baveye, 2017).

We found that certain models gave similar results when using coarser resolution analysis and/or global data (Figs. 4 and 6, Table 3). Specifically, simpler InVEST models and all WaSSI models (which produce results at subwatershed scale) were less sensitive to changes in spatial resolution than the InVEST seasonal water yield and sediment models. Encouragingly, despite statistically significant differences in mean ES values for some of our comparisons, we found consistently high levels of rank correlation, indicating that regardless of input data and models, similar patterns of high and low values were produced by comparable approaches.

Generally, analysts will gravitate toward using the best available (i.e., high resolution, national to local) data. This is particularly important for analyses that require fine-scale accuracy, such as scenario analysis or targeting of conservation incentives like payments for ecosystem services, though in some contexts users may not require high-resolution maps (Willcock et al., 2016). Coarser-scale and/or global data approaches could be appropriate for screening-level analysis, where national summaries are needed but lower subnational accuracy is acceptable. Further, the heterogeneity of the region being modeled, scale of analysis, and model complexity can guide the choice of analysis resolution. Coarser resolution analyses may be more acceptable for large spatial extents, simpler models, and homogeneous environments (e.g., large, flat expanses of forests, deserts, grasslands, or farmland), with finer resolution analyses needed for small spatial extents, more complex models, and heterogeneous environments (e.g., hilly or mountainous topography, fragmented natural areas, urban areas, or forest/agricultural mosaics). Others have tested the effects of spatial resolution on ES assessments at finer (Grafius et al., 2016, 5 vs. 25 m) and coarser (Willcock et al., in press, 1 vs. 10 km) resolutions, and their conclusions provide guidance on the effects of scale on model results outside the range of spatial resolution that we tested.

Our analysis identifies key areas of comparability and non-comparability when making different choices about ES data and models for Rwanda, a highly heterogeneous and somewhat data-limited environment. Experimental work remains worthwhile in other settings to determine when and where different ES models provide the needed accuracy for their decision context without sacrificing the quality and affordability of needed ES information. In particular, since just one of the studies we reviewed addresses marine ecosystem services (Yee, Dittmar, & Oliver, 2014), such comparative studies for coastal and marine ES are needed. Scientists and decision makers should be aware that data and model choices can influence ES assessment outcomes, with potential implications for ES-based decision making. Ultimately, scientists and decision makers are responsible for determining acceptable margins of error for their needs (e.g., Willcock et al., 2016), ideally based on informed decisions about tradeoffs between different models, analysis resolution, and data sources.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2018.02.005.

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