Identifying governance strategies that effectively support ecosystem services, resource sustainability, and biodiversity

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Conservation scientists, national governments, and international conservation groups seek to devise, and implement, governance strategies that mitigate human impact on the environment. However, few studies to date have systematically investigated the performance of different systems of governance in achieving successful conservation outcomes. Here, we use a newly-developed analytic framework to conduct analyses of a suite of case studies, linking different governance strategies to standardized scores for delivering ecosystem services, achieving sustainable use of natural resources, and conserving biodiversity, at both local and international levels. Our results: (*i*) confirm the benefits of adaptive management; and (*ii*) reveal strong associations for the role of leadership. Our work provides a critical step toward implementing empirically justified governance strategies that are capable of improving the management of human-altered environments, with benefits for both biodiversity and people.

adaptive governance | Convention on Biological Diversity | knowledge leadership | Millennium Ecosystem Assessment | policy making

As ecosystems degrade and loss of biological diversity accelerates, it is becoming increasingly urgent to identify governance strategies that successfully mitigate human impact (1). Although many different approaches have been proposed, their effectiveness has rarely been compared systematically for different conservation outcomes, and samples of case studies are often small. Before 2004, only 35% of studies of natural resource management had five or more cases (2). Almost all studies with larger samples were multisite comparisons for a single theme at subnational level, with very few attempts at analyses at an international scale (3–5). This lack of basic empirical evidence on the performance of different governance strategies has led to polarized debates among conservationists (6), wastage of scarce financial resources, and a risk of poorly designed and ineffective conservation programs. In this study, we analyze a suite of 34 local and international case studies to identify governance strategies that may benefit three conservation outcomes, namely: (*i*) enhancing delivery of ecosystem services; (*ii*) ensuring sustainable use of natural resources; and (*iii*) maintaining biodiversity.

An early contention that common-pool resources are inevitably overexploited, in a "tragedy of the commons," has been replaced by understanding that common property institutions under strong communal management can provide effective stewardship for the conservation of biodiversity (7, 8), especially when central or local protective regulation is effectively enforced (4, 9). Governance strategies adopted for conservation therefore vary widely, embracing community management as well as centrally controlled, state-run protected areas and private property regimes. The Convention on Biological Diversity (CBD) encourages devolution of management responsibilities and has drawn attention to the importance of adaptive management (i.e., regular monitoring to enable "learning through doing") (10) to complement protected-area governance (11, 12). Moreover, growing recognition of the often hidden values of ecosystem services (13, 14) now supports CBD's recommendation to use economic or social instruments to promote effective conservation (6). Examples include waste-trading schemes, eco-labeling, creation of knowledge networks and, especially, public payment for maintenance of certain ecosystem services, for example through Reduced Emission from Deforestation and environmental Degradation (REDD) (15). However, discussion continues on the relative merits of protective regulation or positive social and economic incentives for conserving biodiversity within and beyond protected areas (16–18). To address socio-environmental objectives, it is therefore important to consider a range of processes and socio-economic tools within an envelope of institutional capacities, including a potential role for leadership (typically, in the form of providing knowledge on complex issues) that has recently come to the fore (19).

Critically, many regulatory tools (such as restrictions on access or use) and social or economic tools (such as moratoria, taxes, and subsidies) are applied as political expedients without instituting appropriate studies to assess their effectiveness. These tools have costs that affect their social sustainability. The performance of conservation schemes needs to be assessed, and it seems essential for such evaluations to move beyond single-

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factor analyses. We developed an analytic framework to assess the relative importance of a suite of governance strategies for effective biodiversity conservation (20), based on measuring indicator variables in four main categories (Fig. 1*A*): (*i*) initial capacity; (*ii*) management priorities; (*iii*) main processes and tools aimed at those priorities; and (*iv*) environmental response variables that potentially depend on (*i*)–(*iii*). Using standardized questionnaires and expert judgment (*Materials and Methods*), we collected continuous and categorical data for 34 case studies across two levels of scale (Table S1). A total of 26 cases examined the management of study areas at local to subnational scale: 15 of these studies came from eight European countries, two from the United States, and nine from different developing countries. Eight additional cases involved the use of specific ecosystem services at an international scale, including organic agriculture around the Baltic Sea, North Sea fisheries, and a 27-country European Union-wide survey of six recreational activities dependent on wild resources.

For our sample of local case studies, we used information-theoretic (IT) modeling techniques to examine which factors, whether singly or in combination, best predicted variation in three environmental response variables (Fig. 1*B*): (*i*) provision of ecosystem services; (*ii*) sustainability of resource use; and (*iii*) conservation of biodiversity. As predictor variables, we identified—from an initial set of 22 putative variables—5 indicators of governance strategies that had been measured or assessed objectively, and which were of strong a priori interest based on major debates in conservation science (Fig. 1*B*, Table S2, and Table S3). By ensuring that each logical stage of our analytic framework was represented in the models (Fig. 1 *A* and *B*), we were able to assess the relative importance of these different stages in achieving successful conservation outcomes. We omitted from our IT models all variables for the setting of management priorities: This approach both minimized the number of predictor variables (reducing the risk of spurious relationships) and ensured that key analyses were strictly based on objectively measured predictors (*Materials and Methods*, Fig. 1*B*, and Table S2). An alternative analytical technique, Ragin's Qualitative Comparative Analysis (21), could only be implemented with a restricted dataset (*Materials and Methods*), but its results corroborated those from the IT models, and are therefore not reported in detail. Although similarly comprehensive analyses were not possible with our more limited sample of eight international case studies, we used key results from our local-site IT analyses as candidate hypotheses for examining selected univariate relationships.

Results

Provision of ecosystem services was associated with both adaptive management (Fig. 2*A*) and knowledge leadership—a measure of the frequency with which a higher authority was consulted. Both predictors approached significance when they were included in the same model (Table S4*A*), despite being highly intercorrelated ($r_{26} = 0.701$, $P < 0.0001$). Dropping one of the two variables from the full model resulted in a strong positive relationship (at $P < 0.01$) for the variable remaining in the model. There was also a negative effect of regulatory tools when adaptive management was excluded (Fig. 2*A* and Table S4*A*). Considering the sustainability of resource use, the relationship with knowledge leadership was significantly positive when using five predictors, and that with adaptive management became strongly positive when knowledge leadership was removed (Fig. 2*B* and Table S4*B*). However, the model-averaged parameter estimate was higher for knowledge leadership ($\beta = 0.76$) than for adaptive management ($\beta = 0.52$) when the alternative variable was dropped. Finally, for conservation of biodiversity, both knowledge leadership and regulatory tools independently showed strong positive relationships in the full five-predictor model (Fig. 2*C* and Table S4*C*), whereas adaptive management had a significant effect when knowledge leadership was dropped.

Taken together, knowledge leadership had a strong positive effect on all three environmental response variables, whereas adaptive management was independently associated with the provision of ecosystem services but was otherwise interchangeable with knowledge leadership. Meanwhile, regulatory tools showed strong relationships with two response variables—negative for the provision of ecosystem services and positive for the conservation of biodiversity. Private ownership of land and state responsibility for land management, two of the three variables

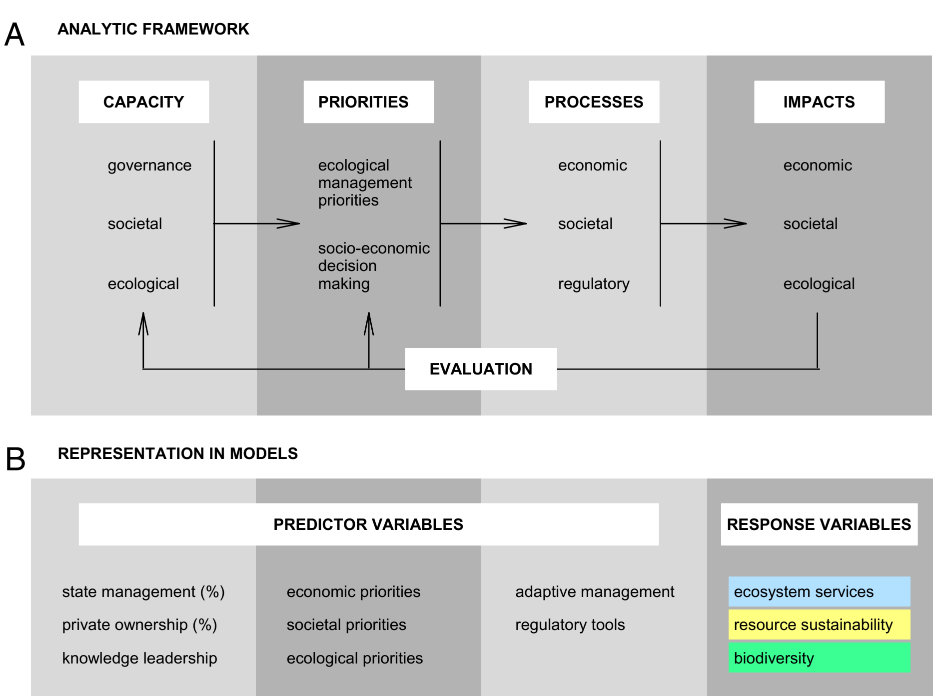

Fig. 1. Conceptual framework for analyzing the performance of different governance strategies. (*A*) The framework grouped variables into four main categories: (*i*) initial capacity; (*ii*) management priorities; (*iii*) main processes and tools aimed at those priorities; and (*iv*) the economic, societal, and ecological impacts of these governance strategies. Impacts were subsequently assessed and procedures were evaluated (no variables were included for this category). (*B*) For statistical analyses, variables were chosen that represented the logical structure of the framework. IT models were then used to examine which (combination of) variables from categories (*i*)–(*iii*) best explained variation in three environmental response variables of category (*iv*): provision of ecosystem services; sustainability of resource use; and conservation of biodiversity. Potential associations with the three priority-setting variables were analyzed separately, for reasons explained in *Materials and Methods*. For details on variable selection, see *Materials and Methods*, Table S2, and Table S3, and for results, see main text, Fig. 2, and Table S4.

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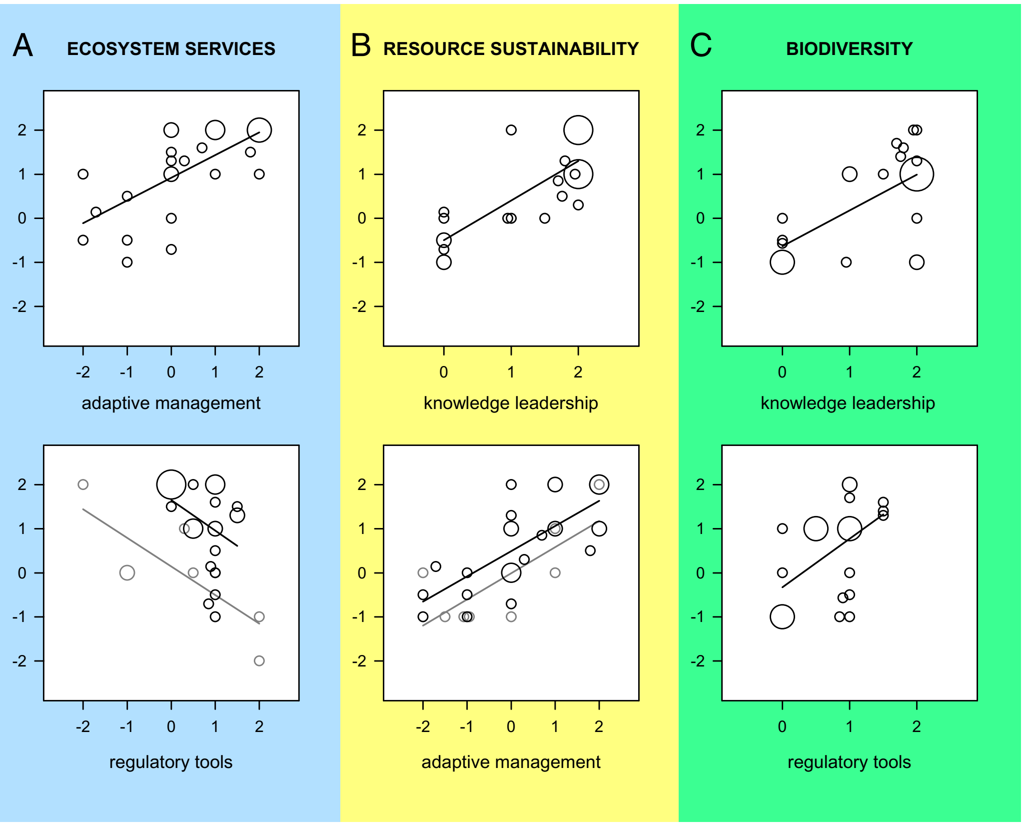

Fig. 2. Key associations between governance strategies and three environmental response variables. (*A*) Provision of ecosystem services. (*B*) Sustainability of resource use. (*C*) Conservation of biodiversity. Based on the independent assessment of case studies (*Materials and Methods*), variables were assigned along a three- or five-point scale, with all three environmental response variables ranging from −2 for "very low" status or ">10% decrease in 10 years" as a trend, to +2 for "very high" status or ">10% increase in 10 years" as a trend. Although statistical analyses were conducted separately for local (black open symbols and black lines) and international (gray open symbols and gray lines) case studies (see main text and *Materials and Methods*), some panels show data for both levels of scale to illustrate consistency of patterns. Putative relationships at the local scale were examined in IT models using multiple predictor variables, and results served as candidate hypotheses for targeted testing of associations at international level (for results, see main text). Symbol size is proportional to the number of overlapping data points (i.e., case studies), some adjacent data points are jittered slightly for clarity, and lines are best fits from univariate linear regressions. Two local case studies, which had been omitted from IT models because of missing data, are included in plots for completeness, where appropriate. For a schematic illustration of the underlying analytic framework, see Fig. 1.

characterizing initial capacity (Fig. 1, *A* and *B*), showed no significant associations in any of the models.

The setting of management priorities also appeared to have strong effects on our three environmental response variables. An emphasis on ecological priorities was positively associated with the conservation of biodiversity (r_{26} = 0.717, P < 0.0001), whereas setting of economic and social priorities was associated with the provision of ecosystem services (r_{26} = 0.645, P < 0.0001, and r_{26} = 0.667, P < 0.0001, respectively) and the sustainability of resource use (r_{26} = 0.626, P = 0.001, and r_{26} = 0.502, P = 0.009, respectively).

At an international scale, the provision of ecosystem services decreased with the relative importance of regulatory tools (Fig. 2*A*; r_8 = –0.794, P < 0.019), whereas sustainability of resource use increased with the degree of adaptive management (Fig. 2*B*; r_8 = 0.747, P < 0.033). Both results confirm patterns observed for the local case studies (Fig. 2 *A* and *B* and Table S4, *A* and *B*). Likewise, as in our local-scale IT analyses, knowledge leadership was positively associated with both the sustainability of resource use (r_8 = 0.363, P < 0.377) and the conservation of biodiversity (r_8 = 0.620, P < 0.101) (compare Fig. 2 *B* and *C*). However, these relationships failed to reach significance with our limited sample size of only eight international case studies (relationships were highly significant for all three environmental response variables when pooling local and international data; r_{34} > 0.55, P < 0.001).

Discussion

Strong benefits of community tenure or management would have resulted in negative relationships between other tenure or management regimes and ecosystem service status or sustainability. In view of the strong and consistent positive relationships with adaptive management and knowledge leadership, there was a striking lack of association with private land ownership or state management responsibility. In part, this lack of effects may reflect having to choose these particular variables purely on statistical grounds (Table S2), thereby ignoring weak positive relationships of resource-use sustainability with community management in preliminary regression-based analyses (20). However, effects of ownership and management also tend to depend on the social institutional setting (8), so their detection might have required interaction terms with variables not considered in our models. A candidate variable would be the duration of conservation management, because almost all our studies were in Europe, North America, or special conservation areas (Table S1), where balances of state, private, and community tenure and management institutions were perhaps already relatively favorable, so that the greatest remaining variation was in short-term tools and processes such as regulations, leadership, and adaptive management.

Adaptive management, incorporating monitoring and feedback, has long been proposed as a powerful tool to ensure successful conservation outcomes (10, 22). Indeed, we found that adaptive management had strong, positive associations with all three environmental response variables, providing empirical support for the recommendation of recent international agreements that implementing adaptive management, and concomitant devolution of governance, are needed to ensure the sustainable use of biodiversity (12, 23). Future studies should investigate whether, at least under certain circumstances, benefits of adaptive management and knowledge leadership are an alternative to effective tenure or management institutions, and what additional advantages they can provide when both approaches are combined.

Although biodiversity conservation seemed to benefit from setting of ecological priorities and was associated positively with regulations, the provision of ecosystem services was correlated strongly and positively with economic priorities, and was at the same time negatively associated with regulations, at both local and international scales. These results confirm the importance of different regulatory emphases, in a dual approach to conservation that incorporates both protection and use (6, 24). Sometimes this duality may best be achieved by the spatial separation of areas for protection or use of resources (25). In areas where conservation is to be promoted through use of ecosystem services, our analyses indicate a need for cautious use of regulations. More generally, our finding that the three investigated conservation outcomes were associated with different sets of governance strategies carries the important implication that, if all three outcomes are desired simultaneously, a joint (or compromise) set of strategies has to be implemented; governance strategies that benefit one outcome may not necessarily support the other two.

Using a newly-developed analytic framework and extensive survey data, our study succeeded in identifying governance strategies that best explain, across two levels of scale, the provision of ecosystem services, sustainability of resource use, and conservation of biodiversity. We suggest that future work should focus on two main goals. First, further studies are required that replicate and refine our analyses by using more accurate measurements of socio-economic factors and environmental variables (26). Second, and perhaps more importantly, our study sets the scene for investigating causality through planned experiments. We envisage coordinated, large-scale trials of different approaches across administrative areas within countries—as a socio-economic equivalent to landscape-scale experiments in ecology—that test key predictions derived from correlational analyses, such as those presented here. Taken together, such work will help establish empirically justified governance strategies that can help improve the management of human-altered environments, with benefits for both biodiversity and people (27).

Materials and Methods

Data Collection. Twenty-two teams collected data for the Governance and Ecosystem Management for the Conservation of Biodiversity project (20) from 34 case study sites (Table S1). Teams were selected for their ability to identify a wide range of terrestrial and aquatic ecosystems within different jurisdictions in countries at various stages of development. Nineteen teams were tasked with assessing/quantifying one to three local to subnational case studies that already existed in 19 countries, yielding 26 cases for analysis, termed "local cases." Meanwhile, three teams were tasked with assessing/quantifying eight case studies across multiple countries, termed "international cases." Standard questionnaires were used at each site to collect a range of 80–85 ecological, economic, and social datapoints, from which 22 variables (Table S2) were later derived, using a priori processing rules (Table S3 and ref. 20).

Of the 22 putative predictor variables, 14 for "initial capacity" were based (Table S2) on: (a) measuring or estimating proportions of state, private, or community management (variables 1–3 in Table S2) or ownership (variables 5–8) across the study site; (b) whether 1, 2, or 3 of these types of management (variable 4) or ownership (variable 9) were present; (c) scores from "best professional judgment" of whether vertical integration (variable 10), horizontal social integration (variable 11), local community participation (variable 12), and multilevel governance (variable 13) was considered high (+2), good (+1), basic (0), scarce (−1), or very low (−2); and (d) whether major external sources of advice were consulted, and if so, whether more than once annually (giving scores of 0, 1, and 2 for knowledge leadership; variable 14). For "management priorities," ecological (variable 15), economic (variable 16), and social (variable 17) priorities were assessed (e) as not appropriate (−1), at minimal levels (0), or appropriate levels (+1). For "processes and tools," knowledge generation (variable 18) was scored like variables 10–13, whereas adaptive management (variable 19) was constructed (f), according to whether monitoring and management were absent (−2), management of species (−1) or ecosystems (0) was present without monitoring, or species (+1) or ecosystems (+2) were managed with monitoring; finally (g), there was a five-point scale from high (+2) to absent (−2) constructed from answers to 3–5 questions about listed abundance, implementation, awareness and acceptance of market, regulatory and social tools (variables 20–22).

In addition to the 22 variables mentioned above, three environmental response variables (provision of ecosystem services; sustainability of resource use; conservation of biodiversity) were scored through best professional judgment, using a five-point scale ranging from −2 (very low or >10% decrease in 10 y) to +2 (very high or >10% increase in 10 y). Several questions in our standard questionnaire prompted observer teams to identify appropriate topics for assessment in their allocated case studies. Anticipating a large range of potential topics across a diverse set of case studies, we considered it important for this part of the survey to provide teams with a certain amount of freedom in data collection (see below). For example, observers were allowed to examine any number of topics for a given response variable (Table S1), and it was left to their expertise and personal judgment to synthesize diverse data for inclusion in their final report (for each case study, scores were entered in an "executive summary table," which was submitted to the project organizers; ref. 28). Although scoring of the three response variables was inevitably less standardized than for other variables used in our analyses, we considered this approach essential for effectively capturing the status and trends of very different ecosystems and for assessing case studies of varying data availability and quality. Importantly, from an analytical point of view, our approach will only have added noise to our dataset, thereby making detection of effects less likely. If there was systematic under- or overestimation of success by teams across the environmental response variables, this bias could have increased similarity of effects detected for the different response variables, but would generate neither the observed relationships with predictor variables nor the differences in results between response variables.

With our study approach and project resources, it was not feasible to assess "biodiversity" with quantitative diversity measures or proxy indicators (26); rather, where appropriate (Table S1), observers examined the status and trends of selected, relevant species. This approach enabled us to identify important relationships with our suite of (governance) predictor variables (see below), setting the scene for more elaborate future analyses (see main text).

Variable Selection. For the IT analyses (see below), we identified a reduced set of predictor variables from the 22 listed in Table S2 (which were also intended for a suite of other analyses; ref. 28). With a sample of 26 local case studies, we expected to have sufficient replication for fitting a maximum of five predictor variables, because "the residual mean square will tend to stabilize and approach the true value of σ^2 as the number of variables increases, provided that all important variables have been included, and the number of observations greatly exceeds the number of variables in the fitted equation—five to ten times as many" (29). We selected variables that were objective, of intrinsic scientific interest (for a priori reasons), and which covered the first four stages of our analytic framework (Fig. 1, *A* and *B*). Thus, our full IT models included as predictors: (*i*) percentage of state-managed land; (*ii*) percentage of land owned privately; (*iii*) knowledge leadership; (*iv*) adaptive management; and (*v*) regulatory tools. These variables correspond, respectively, to categories (a), (a), (d), (f), and (g) described above. By using only a small subset of the predictor variables available, we also addressed conclusions of an earlier project report, which cautioned not to "overfit" statistical models (28).

Although our three environmental response variables (provision of ecosystem services, sustainability of resource use, conservation of biodiversity) were scored, and not measured, this approach is unlikely to have created spurious relationships with the five chosen predictor variables (or vice versa). Two important aspects of our experimental design sought to reduce scope for systematic bias. First, all five predictor variables (Table S2) were either assessed directly (land ownership and management) or constructed from multiple data points after the survey, using a priori defined rules (Table S2 and Table S3). For example, knowledge leadership and adaptive management were each constructed from the answers given to two basic survey questions. This way, observers could not know, at the time of conducting

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their evaluation, how their answers would later combine to produce data for particular variables. Second, our 26 local studies in 19 countries were assessed by 19 different observer teams, with participants who had not managed the projects they scored, minimizing scope for systematic bias. Furthermore, the measures and scores for activities in six of the eight cases at the international level were averages of data provided by single observers in each of 5–25 countries.

For two reasons, none of the variables for setting management priorities (Fig. 1*B* and Table S2) were included in our IT models. First, based on model-economy considerations, we could only accommodate five predictors with our given sample size. Second, the priority-setting variables were the only variables of interest that were represented as simple scores; the other five predictor variables, and all three environmental response variables, had been either measured directly, or constructed from quantitative variables (see above). Because the priority-setting variables may have been prone to some subjectivity (those observers who were strongly orientated toward a particular priority may have been also more likely to be positive about particular management outcomes), we examined them in separate, univariate tests and interpreted results cautiously.

Statistical Analyses. We chose an IT modeling approach to analyze our dataset of local case studies. IT analyses are similar to multiple regression analyses, but circumvent problems associated with conventional stepwise procedures that inflate Type-1 error rates (30). Our IT modeling followed standard methodology (refs. 31 and 32 and Table S4 legend), and used previously reported algorithms (32) run in "R" (33). We ran models with a normal error structure (based on linear least-squares regression) on the original scores, because Kolmogorov–Smirnov, Ryan–Joiner, and Anderson–Darling tests indicated normality of errors based on residuals of a full model with all five predictors fitted to each of the three response variables (all tests were $P > 0.10$; compare Table S4). We used the adjusted version of Akaike's information criterion (AICc) to control for bias, as the ratio of the number of observations ($n = 24$) to the number of predictors ($n = 5$) was much less than 40 (31). Two case studies had to be excluded from analyses owing to missing values (but were included in plots in Fig. 2, where appropriate).

We calculated 95% "confidence sets" of models fitted to each dataset (32). A confidence set is the smallest subset of candidate models for which the Akaike weights sum to 0.95 (i.e., we had 95% confidence that this set contained the model best approximating the true model). For example, Table S4, *A* to *C*, show all model combinations within the 95% confidence set of models (31, 32), with the best-fitting at the top (e.g., the best-fitting model for ecosystem services, with $w_i = 0.124$, included knowledge leadership and adaptive management alone; Table S4*A*). We assessed the importance of each individual predictor based on the summed Akaike weights (SAWs) across all models in the 95% confidence set containing that predictor. The statistical significance of each sum was determined relative to that of a randomly generated null predictor (with zero mean, SD of 0.5, and data between −2 and 2, i.e., comparable with our real data) by using 100 randomization runs (Table S4). For all three environmental response variables, we ran models with all five predictors, as well as reduced models without knowledge leadership and without adaptive management, respectively, because they were highly intercorrelated (see main text).

We also explored analytical approaches that are routinely used in the social sciences, such as Qualitative Comparative Analysis (QCA) or fuzzy set QCA (fsQCA) (21). Although these are powerful, established techniques, their utility can be limited in certain scenarios, because: (*i*) meaningful variation in the dataset is lost, because variables must be condensed into binary form before analysis (i.e., to scores of 0 or 1) (e.g., in our case, the percentage of land ownership in our study sites cannot meaningfully be classified as 0 or 1); and (*ii*) missing values in the dataset greatly reduce effective sample size (rows with missing data are excluded from analyses). IT techniques do not suffer from these limitations, and were therefore our method of choice, but we decided to investigate informally whether QCA would produce similar results and corroborate our key findings. We first conducted a "crisp-set" analysis, which used the actual (untransformed) data, including only data where we had actual scores of 0 and 1 (i.e., even if a predictor scored 0.99, rather than a 1, it was excluded). In the next step, we used the most inclusive "fuzzy-set" rule, in which any predictor that scored ≥ 0.51 was given a 1 and any scoring ≤ 0.49 a 0. The results for the minimum-model output showed high consistency for both QCA and IT analyses.

Comprehensive IT analyses were not possible with our sample of eight international case studies. However, our key results from local case studies allowed the formulation of clear candidate hypotheses, which we could examine by conducting targeted, univariate Pearson's correlations.

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32. Whittingham MJ, Swetnam RD, Wilson JD, Chamberlain DE, Freckleton RP (2005) Habitat selection by yellowhammers *Emberiza citrinella* on lowland farmland at two spatial scales: Implications for conservation management. *J Appl Ecol* 42:270–280.
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Supporting Information

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Table S1. Local and international case studies

Name	Country	Area, km^2	Humans per km^2	Conservation priorities	ES*	RS†	BD‡
Local case studies							
Macin Mountain National Park	Romania	113	44	Biodiversity, cultural	14	—	—
Lake Kerkini	Greece	800	36	Provisioning, cultural	14	3	—
Kozep Tisza Protected Landscape	Hungary	84	82	Biodiversity, cultural, provisioning	13	13	—
Gullmar Fjord Catchment	Sweden	1,700	7–16	Supporting, provisioning	3	1	1
Danube Delta Biosphere Reserve	Romania	5,800	4.6	Biodiversity, provisioning, cultural	15	15	2
Kävlinge River Catchment	Sweden	1,200	35–238	Supporting, biodiversity, provisioning	2	2	1
Rönne River Catchment	Sweden	1,900	43–91	Supporting, provisioning	1	1	1
Moritzburg Hill	Germany	54	40	Provisioning, biodiversity	5	6	55
Chianti Classico	Italy	900	76	Provisioning, cultural, supporting	20	4	3
Velka Fatra National Park	Slovakia	438	34	Biodiversity	5	4	—
Só út Area	Hungary	70	41	Biodiversity, cultural, provisioning	13	13	3
Biosphere Reserve Schorfheide-Chorin	Germany	1,292	25	Biodiversity, provisioning, cultural	13	13	5
Biosphere Reserve Rhön	Germany	1,849	91	Biodiversity, provisioning, cultural	14	14	1
Moritzburg Forest	Germany	59	42	Provisioning, biodiversity	9	10	3
Catskill/Delaware Watershed	USA	4,209	18	Regulating	10	1	—
Järna (organic food area)	Sweden	105	80	Provisioning, supporting	13	5	1
Maine (beginning with habitat plan)	USA	43,400	30	Biodiversity	7	—	—
Shahsevan Rangelands	Iran	2,200	33	Provisioning, cultural, biodiversity	15	5	2
Camili Biosphere Reserve	Turkey	25,258	26	Biodiversity, cultural, provisioning	6	3	5
Borano Community Conserved Land	Ethiopia	45,620	12	Provisioning, cultural	9	9	4
Danau Sentarum National Park	Indonesia	1,320	7.5	Biodiversity, provisioning	3	2	1
Zinder Pastoral Region	Niger	80	3–100	Cultural, provisioning, supporting	7	12	1
Gobi Gurvan Saikhan National Park	Mongolia	4,300	0.12	Biodiversity, provisioning, cultural	14	14	1
Chitwan National Park	Nepal	1,678	300	Biodiversity	5	5	5
Parapeti River Basin	Bolivia	61,000	1.6	Biodiversity, provisioning, supporting	7	1	2
Picomayo River Basin	Argentina	200,000	2.2	None	9	9	12
Summary for local cases							
Total number of assessments (sum)					246	165	109
Median number of topics assessed per case study					9	5	2
Range in number of topics assessed per case study					1–20	1–15	1–55
International case studies							
Northsea fisheries	Maritime	850,000	n/a	Provisioning, supporting	3	1	8
Baltic organic agriculture	Circum-Baltic	245,300	58	Provisioning, supporting	5	5	3
Hunting birds	EU	4,300,000	114	Cultural, provisioning	(25)	7	9
Hunting ungulates	EU	4,300,000	114	Cultural, provisioning	(23)	7	8
Angling	EU	4,300,000	114	Cultural, provisioning	(20)	1	8
Gathering fungi	EU	4,300,000	114	Cultural, provisioning	(19)	7	7
Wild plant products	EU	4,300,000	114	Cultural, provisioning	(13)	7	8
Watching birds	EU	4,300,000	114	Cultural	(23)	7	8
Summary for international cases							
Total number of assessments (sum)					(131)	42	59
Median number of topics assessed per case study					(19)	7	8
Range in number of topics assessed per case study					3–(25)	1–7	3–8

*Ecosystem services—"Cultural" through recreation, tourism, education, heritage and other knowledge, aesthetic and spiritual pleasure; "provisioning" of food, fuel, fiber, pharmaceuticals, dyes, and flavors from the wild, as fungi, herbs, honey, nuts, wood, wild animals, or evolved resources for syntheses, and through organic or other cultivation of plant crops, fish, livestock, and trees; "regulation" of climate, floods, erosion, pests, and disease; "supporting" through pollination and refreshing air and water.

†Resource sustainability—Change in capacity for recreational, touristic, educational, aesthetic, spiritual, heritage, and other knowledge culture; change in capacity for production of wild animal and plant products, fuel, and genetic resources; change in soil, aquatic habitats, and support systems for wild and cultivated animals, plants, and fungi.

‡Biodiversity—Many bird, mammal, reptile, insect, plant, and fungi taxa, in some cases associated specifically with grassland, farmland, sylvo-pastoral, wetland, and aquatic habitats.

Conservation priorities are listed in the order given by assessors, using categories developed by the Millennium Ecosystem Assessment (1). "Biodiversity" is listed only where this was a stated priority; provisioning was inferred when agriculture, forestry, and use of wild resources were listed; supporting was listed where priorities were to mitigate negative impacts of provisioning (e.g., pollution, erosion, or overexploitation); and cultural services could involve tourism or maintenance of local traditions. The final three columns state how many different aspects of the three response variables (ES, ecosystem services; RS, resource sustainability; BD, biodiversity) were assessed for each case study (values in parentheses for international case studies are numbers of countries in which the aspect named in the first column was assessed for ES, in each country across the number of habitats in RS, and number of taxa in BD), with summary statistics provided separately for local and international cases.

1. Millennium Ecosystem Assessment (2005) *Ecosystems and Human Well-Being: Synthesis* (Island, Washington, DC).

Table S2. Variable selection

No.	Analytic framework	Variable	Objective?	Notes
1	Initial capacity	**State management (%)**	Yes	Variables 1–3 have a "unit-sum constraint," and variable 4 is also derived from these three variables, so only one of them needs to be included in IT models*
2		Private management (%)	Yes	
3		Community management (%)	Yes	
4		Multiple managed	Yes	
5		State ownership (%)	Yes	Variables 5–8 have a unit-sum constraint, and variable 9 is also derived from these four variables, so only one of them needs to be included in IT models[†]
6		**Private ownership (%)**	Yes	
7		Community ownership (%)	Yes	
8		Free access (%)	Yes	
9		Multiple ownership	Yes	
10		Vertical integration	No	Observer expectation
11		Horizontal integration	No	Observer expectation
12		Local role	No	Observer expectation
13		Multilevel instruments	Probably	Expectation unclear
14		**Knowledge leadership**	Yes	Chosen for objectivity and a priori reasons[‡]
15	Management priorities	*Ecological priorities*	No	Observer expectation;[§] variables *not* included in main IT models, but examined in separate univariate tests
16		*Economic priorities*	No	
17		*Social priorities*	No	
18	Processes/tools	Knowledge generation	No	Observer expectation
19		**Adaptive management**	Yes	Chosen for objectivity and a priori reasons[¶]
20		Market tools	Probably	Expectation unclear; 3 cases missing
21		**Regulatory tools**	Probably	Chosen for objectivity and a priori reasons[‖]
22		Social tools	Probably	Expectation unclear; 3 cases missing

*This variable was selected because it has negative correlations with all other types of management (note that, on a priori grounds, "community management" could have also been chosen).
[†]This variable was selected because it is highly variable and has negative correlations with all other types of ownership.
[‡]This variable was selected for a priori reasons (1–3), and because it was constructed from two unambiguously quantified questions (*Materials and Methods*).
[§]Observers who favored priority-setting may also have been most positive about management outcomes (*Materials and Methods*).
[¶]This variable was selected for a priori reasons (4–6), and because it was constructed from two unambiguously quantified questions (*Materials and Methods*).
[‖]Many examples of regulation benefiting conservation provide strong a priori reasons for selecting this variable. Furthermore, counting from lists of conventions and laws was considered less ambiguous than scoring market or social tools, and there were also no missing values (therefore providing a larger sample size).

The original survey produced data for 22 variables, 15 of which described unique aspects of the case studies (other variables were redundant because of unit-sum constraints; see footnotes). For information-theoretic (IT) models, variables were selected, which were considered objective (e.g., measured directly or constructed from measured variables; see text) and of a priori scientific interest, and which together represented the logical structure of the analytic framework (see Fig. 1 *A* and *B*). The variables used in the IT models (see Table S4) are highlighted in bold, and those examined in separate, univariate analyses (management priorities; see main text) are italicized.

1. Manolis JC, et al. (2009) Leadership: A new frontier in conservation science. *Conserv Biol* 23:879–886.
2. Berry JK, Gordon JC (1993) *Environmental Leadership: Developing Effective Skills and Styles* (Island, Washington, DC).
3. Dietz JM, et al. (2004) Defining leadership in conservation: A view from the top. *Conserv Biol* 18:274–278.
4. Holling CS (1978) *Adaptive Environment Assessment and Management* (Wiley, London).
5. Walters K (1986) *Adaptive Management of Renewable Resources* (Macmillan, New York).
6. Convention on Biological Diversity (2004) *Addis Ababa Principles and Guidelines for the Sustainable Use of Biodiversity* (Secretariat Conv Biol Divers, Montreal).

Table S3. Survey questions for predictor variables

Category	Survey questions (and **variables**)	Selected?
a	Identify the model of management regime used in the area; if a combination of models is used, provide a measure of the proportion of each (e.g., 10% state, 90% private) **(variables 1–3)**	Yes
	Identify the proportion of land under different ownership regimes (e.g., 30% state owned, 50% private and 20% community) **(variables 5–8)**	
b	Are 1, 2, or 3/4 of these types of management **(variable 4)** or ownership **(variable 9)** present?	No
c	What is the "Voice and accountability" of citizens in the country (World Bank Scores); what is the level of vertical trust between stakeholders and institutions (structured interview); how many institutional levels are involved in the regulation of biodiversity conservation; is the level of institutional interaction during the implementation of regulations positive or negative; is there significant collaboration among local stakeholders; do governance processes positively or negatively affect the level of vertical trust? **(variable 10)**	No
	What is the level of horizontal trust between stakeholders and institutions (structured interview); how many different stakeholder groups are involved in the management of ecosystems and biodiversity; are there informal policy networks of key persons representing institutions and stakeholders across organizational levels; is there a clear leadership role of certain stakeholders or agencies in the management process; do governance processes positively or negatively affect the level of horizontal trust? **(variable 11)**	
	What mechanisms exist within national legislation or action plans to support collaborative management at local level, and how well are they implemented; do informal policy networks exist of key persons representing institutions and stakeholders across organizational levels at local level? **(variable 12)**	
	What mechanisms exist within national legislation or action plans to support collaborative management at local level, and how well are they implemented; do informal policy networks exist of key persons representing institutions and stakeholders across organizational levels; is there a clear leadership role of certain stakeholders or agencies in the management process? **(variable 13)**	
	Is local knowledge and experience incorporated into management planning; what is the public awareness of the services from biodiversity conservation; what is the public perception of disservices or costs from biodiversity? **(variable 18)**	
d	Is there a clear leadership role of certain stakeholders or agencies in the management process; if so, is there consultation more than once annually or less frequently? **(variable 14)**	Yes
e	Are ecological objectives in relation to biodiversity conservation appropriate (e.g., conservation and sustainable use), basic (e.g., focusing on few ecosystem goods and services) or not appropriate (e.g., maximizing natural resource exploitation only for commodities) **(variable 15)**; are economic objectives appropriate (e.g., sustainable economic development), basic (e.g., economic development with equitable sharing of benefits) or not appropriate (e.g., unconstrained economic growth) **(variable 16)**; are social objectives appropriate (e.g., increasing quality of life for population), basic (e.g., maintenance of social minimum standards) or not appropriate (e.g., no social objectives)? **(variable 17)**	In part; see Table S2 and text
f	Are ecosystems managed with an ecosystem approach or as separate natural resources; is monitoring used to change the management plan or is the management plan evaluated in other ways? **(variable 19)**	Yes
g	List the market tools and incentives in place to support the management of ecosystems or components within them; what proportion of the tools and incentives are used for biodiversity conservation; what is the awareness of current tools among stakeholders? **(variable 20)**	Only **21**; see Table S2 and text
	List the binding and nonbinding multilateral agreements that influence nature policy either positively or negatively and the key legislation used to manage biodiversity at national level; identify the most important nonenvironmental legislation that impacts biodiversity; is licensing for use allowed; what is the level of enforcement and compliance with each of the identified pieces of legislation and regulations? **(variable 21)**	
	What is the public awareness of the services from biodiversity conservation; how is the use of the natural resources monitored over time; of the lists of legislation and regulations above, what is the level of implementation and the importance of each within the area? **(variable 22)**	

The suite of 22 variables (variable identification numbers are shown in bold) developed to assess governance strategies were based on the above-listed questions (taken from ref. 1), which were addressed systematically by each of the 22 teams that surveyed case studies. Variables were selected for analysis for a priori reasons and because they were objectively quantified with minimal scope for influence by observer expectation (for variable selection, see Table S2). Categories a–g refer to those used in *Materials and Methods*.

1. Galaz V, Hahn T, Terry A (2006) Governance and Ecosystems Management for the Conservation of Biodiversity: ecosystem governance in Europe. http://www.gemconbio.eu/downloads/report_on_governance_types_and_ecosystem_management_characteristics_CTMIUCN.pdf. Accessed February 18, 2011.

Table S4. Results of information-theoretic models for three environmental response variables. (*A*) Provision of ecosystem services; (*B*) sustainability of resource use; and (*C*) conservation of biodiversity

The table columns show Akaike's information criterion (corrected for small sample size) (AICc), the delta weight (Δ_i) (the difference between the AICc for a given model and the best-fitting model), and the Akaike weight (w_i) (the likelihood of a model being the best model). Each table includes all model combinations within the 95% confidence set of models (1, 2), with the best-fitting model in the top row. For example, for ecosystem services in Table S4*A*, the value of 0.124 for w_i in the top row represents the probability that the model including knowledge leadership and adaptive management alone would be the best-fitting model if the data were collected again. The w_i scores are summed for each predictor across all models in the 95% confidence set in which that predictor occurs, as "Summed Akaike Weights" (SAWs). We used a randomly derived predictor with a mean of zero and a SD of 0.5 (this generated data of the same range as some of our actual predictors, given that values were bounded by –2 and +2) to estimate mean and confidence intervals for SAWs (2). To estimate 1% confidence intervals, we generated SAWs for 100 datasets containing this randomized null predictor and all five other predictor variables; the 95% confidence limit was estimated by the fifth highest value. Thus, in Table S4*A*, the highest random score for SAW was 0.97 out of 100 runs, so any score >0.97 indicates a probability value of $P < 0.01$, and SAWs > 0.75 are $P < 0.05$. SAWs were also estimated for models omitting either knowledge leadership (exKL) or adaptive management (exAM), because of the strong correlation between these two predictors ($r_{26} = 0.701$, $P < 0.0001$; see main text). Formatting highlights significant (bold) and marginally significant (italics) effects, respectively. Finally, to estimate the direction of the relationships, we also estimated slope coefficients (β) for each predictor, by averaging the value (weighted by the w_i scores) across all models in which that predictor occurred in the 95% confidence set (1).

(A) Ecosystem services

	State management	Private ownership	Knowledge leadership	Adaptive management	Regulatory tools	AICc	Δ_i	w_i
	—	—	1	1	—	56.56	0	0.124
	1	—	1	1	1	56.58	0.02	0.123
	—	—	1	—	1	56.70	0.14	0.116
	—	—	—	1	—	57.31	0.75	0.086
	—	—	1	1	1	57.36	0.79	0.083
	1	—	1	—	1	57.45	0.89	0.080
	1	—	1	1	—	58.12	1.55	0.057
	1	—	—	1	—	58.21	1.64	0.054
	1	—	—	1	1	59.20	2.63	0.033
	—	1	—	1	—	59.41	2.84	0.030
	—	—	1	—	—	59.52	2.95	0.028
	—	—	—	1	1	59.54	2.98	0.028
	—	1	1	1	—	59.74	3.18	0.025
	—	1	1	—	1	59.90	3.33	0.023
	1	1	1	1	1	60.46	3.90	0.018
	1	1	—	1	—	60.61	4.04	0.016
	—	1	1	1	1	60.88	4.32	0.014
	1	1	1	—	1	61.00	4.44	0.014
SAWs	0.425	0.180	*0.730*	*0.723*	0.554			
β	0.003	−0.0003	0.412	0.324	−0.343			
SAWs exKL	0.430	0.251	n.a.	**0.996**	0.308			
SAWs exAM	0.367	0.164	**0.996**	n.a.	**0.843**			
Null interval	0.15–0.97 (mean = 0.27)							
95% limit	0.75							

Knowledge leadership and adaptive management were consistently the most important predictors (both positively, i.e., greater levels of knowledge leadership and adaptive management were correlated with increase in ecosystem services). There was a negative influence of regulatory tools when adaptive management was dropped from the model.

Table S4. Cont.

(B) Resource sustainability

	State management	Private ownership	Knowledge leadership	Adaptive management	Regulatory tools	AICc	Δ_i	w_i
	1	—	1	—	—	48.75	0	0.244
	—	—	1	—	1	50.10	1.35	0.124
	1	—	1	1	—	50.30	1.56	0.112
	—	—	1	1	—	50.43	1.68	0.105
	1	—	1	—	1	50.51	1.76	0.101
	—	—	1	—	—	51.34	2.60	0.067
	—	—	1	1	1	51.86	3.11	0.052
	1	1	1	—	—	51.92	3.18	0.050
	1	—	1	1	1	53.24	4.49	0.026
	—	1	1	—	1	53.32	4.57	0.025
	—	1	1	1	—	53.66	4.91	0.021
	1	1	1	1	—	53.90	5.15	0.019
	1	1	1	—	1	54.10	5.35	0.017
SAWs	0.575	0.162	**0.990**	0.356	0.358			
β	–0.004	0.00005	0.755	0.078	–0.135			
SAWs exKL	0.299	0.278	n.a.	**0.988**	0.183			
SAWs exAM	0.640	0.167	**0.999**	n.a.	0.414			
Null interval	0.16–0.99 (mean = 0.29)							
95% limit	0.80							

Knowledge leadership was the most important predictor of resource sustainability. The relationship was positive (i.e., greater levels of knowledge leadership correlated with increase in resource sustainability), with adaptive management only becoming significant (again positively) when knowledge leadership was dropped from the model.

(C) Biodiversity

	State management	Private ownership	Knowledge leadership	Adaptive management	Regulatory tools	AICc	Δ_i	w_i
	—	1	1	—	1	50.79	0	0.362
	—	—	1	—	1	51.02	0.22	0.324
	—	—	1	1	1	53.71	2.92	0.084
	—	1	1	1	1	53.95	3.16	0.075
	1	—	1	—	1	54.22	3.43	0.065
	1	1	1	—	1	54.36	3.56	0.061
SAWs	0.151	0.509	**0.995**	0.187	**0.999**			
β	–0.00007	0.003	0.802	0.021	1.249			
SAWs exKL	0.165	0.171	n.a.	**0.942**	**0.998**			
SAWs exAM	0.155	0.521	**0.999**	n.a.	**0.999**			
Null interval	0.15–0.98 (mean = 0.27)							
95% limit	0.86							

Knowledge leadership and regulatory tools were the two best predictors of biodiversity (both positively, i.e., greater levels of knowledge leadership and regulatory tools were correlated with increase in biodiversity) and adaptive management became significant when knowledge leadership was dropped from the model.

1. Burnham KP, Anderson DR (2002) *Model Selection and Multimodel Inference* (Springer, New York).
2. Whittingham MJ, Swetnam RD, Wilson JD, Chamberlain DE, Freckleton RP (2005) Habitat selection by yellowhammers *Emberiza citrinella* on lowland farmland at two spatial scales: Implications for conservation management. *J Appl Ecol* 42:270–280.