Modelling how conservation initiatives go to scale

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Abstract

A significant portion of the planet's land and sea is managed to conserve biodiversity, yet little is known about the extent, speed and patterns of adoption of conservation initiatives. We undertook the first quantitative exploration of how area-based conservation initiatives go to scale by analysing the adoption of 22 widely-recognised and diverse initiatives, from across the globe. We use a standardised approach for comparing the potential of different initiatives to reach scale. While our study is not exhaustive, our analyses reveal consistent patterns across a variety of initiatives: adoption of most initiatives (82% of our case studies) started slowly before rapidly going to scale. Consistent with diffusion of innovation theory, most initiatives exhibit slow-fast-slow (i.e., sigmoidal) dynamics driven by interactions between existing and potential adopters. However, uptake rates and saturation points vary among the initiatives and across localities. Our models suggest that the uptake of most of our case studies is limited; over half of the initiatives will be taken up by <30% of their potential adopters. We also provide a methodology for quantitatively understanding the process of scaling. Our findings inform us how initiatives scale up to widespread adoption, this will facilitate forecasts of the future level of adoption of initiatives, and benchmarking their extent and speed of adoption against those of our case studies.

Introduction

Rapidly increasing human pressures[1,2] have created the Anthropocene and led to the 6th extinction crisis[3]. Massive scientific investment has identified the primary threats to biodiversity, estimated the speed and patterns of biodiversity loss, and measured their ecological and social consequences[4-6]. In contrast, comparably little research has examined the speed and patterns of adoption and spread (scaling) of policies, programmes, and projects (hereafter "initiatives") that are designed to conserve biodiversity[7]. Characterising and explaining the scaling of conservation initiatives addresses a critical scientific knowledge gap in policy deliberations around the world[7-9]. We undertake a quantitative exploration of how conservation initiatives go to scale, revealing dynamics shared across a diverse range of initiatives.

To examine the speed and extent of conservation initiative adoption, we compiled a temporal database of 22 area-based conservation initiatives from around the globe (Figure 1, Supplementary Table 1). These diverse initiatives range from village-designated locally managed marine areas to international World Heritage Sites, including state and privately protected areas, and various forms of community based resource management. Initiatives were selected during an expert working group of conservation scientists and practitioners with knowledge of community-based, private, and state-led biodiversity conservation initiatives worldwide (the authors MM, MBM, HP, RW, SG, ND, CR, DB and a representative from UNEP-WCMC).

Our database spans terrestrial and marine biomes, low to high-income countries, and local, national and international scales. It includes some of the earliest and most recent conservation initiatives of the modern era including privately protected areas, international treaties and community based conservation; implemented by government agencies, non-governmental organisations, and individuals. This database represents research effort by dozens of organisations that operate in varied locations across the globe. For example, cataloguing the spread of locally managed marine areas (Figure 1) required face-to-face interaction between NGOs and hundreds of village chiefs across three island nations (see data collection in methods and Supplementary Table 1). Only conservation initiatives for which data on the date of adoption and the adopter were known, and where we could estimate the number of potential adopters (Supplementary Table 1, column D and G) were included. Our case studies represent a significant, but not comprehensive, subset of conservation initiatives; future studies should still investigate patterns in the adoption and spread of other conservation initiatives including for example a wider variety of conservation measures on private land, payments for ecosystem services and certification programs, as these initiatives were not included in this study.

We explore the mechanisms driving the spread of each initiative by fitting three competing models to time series data on adoption. Each model represents a different mechanism (i.e. process) of spread; their relative fit to the observed data offers support for different mechanisms that could be driving or limiting adoption[10]. Examining how adoption dynamics for a particular initiative vary across different localities, or how multiple initiatives proceed in the same location, can help to isolate the factors that influence adoption[11]. Adoption is a complex process, influenced by a range of interacting factors (e.g. relative advantage, communication and supporting policies) and these data are not available across initiatives so we do not assess the influence of individual drivers statistically. However, we do discuss differences among patterns in adoption and provide theory-based hypotheses for these differences.

Mechanisms, extent and speed of scaling

Across our database of case-studies, two of our candidate models (the "fast-slow" and the "slow-fast-slow" model), each representing a different mechanism of spread, best described cumulative adoption through time (Figure 2, Supplementary Table 2). Only a few parameters were needed to describe the adoption dynamics: uptake rate (α for the fast-slow model or β for the slow-fast-slow model), the initial number of adopters A_0, and the number of resistant individuals R, that is, the number who will never adopt the initiative in its current form (*Methods*) within the total pool of potential adopters, (K).

Most initiatives (83%) were best described using a slow-fast-slow model (i.e., sigmoidal adoption dynamics), consistent with the adoption dynamics predicted by the diffusion of innovation theory[9,13]. Diffusion of innovation theory predicts that information about a particular initiative spreads from successful adopters to potential adopters through learning and persuasion. Early adoption rates are slow, because the small number of initial adopters limits the diffusion of the information. Among our case studies, the time between the first and subsequent adoption was as long as 54 years (the first and second country to adopt protected areas). Thus, even initiatives that eventually achieve high levels of adoption can begin slowly (Figure 4), and a slow initial uptake rate is therefore not sufficient grounds for abandoning an initiative. Slow initial growth gives way to a rapid growth phase, as an increasing number of adopters share their experiences with a large pool of potential adopters. Over time, the uptake rate slows again as the pool of potential and willing adopters declines. Eventually, a point of saturation is reached where all individuals that have been exposed to the initiative have either adopted it, or are resistant to the initiative in its current form. Because the processes of initial spread and saturation are governed by independent parameters (β and K respectively), it is difficult to estimate the eventual penetration of an initiative based on early adoption dynamics.

The remaining conservation initiatives followed a fast-slow pattern of adoption, suggesting a fundamentally different mechanism of spread, particularly in the early adoption phase. Under a fast-slow model, each potential adopter has a constant probability of engaging in the initiative, independent of the current number of adopters. The result is an initial burst of adoption, followed by a constant deceleration as the pool of potential adopters declines. In our dataset, fast-slow models are characteristic of more highly-regulated initiatives, where adoption faces bureaucratic hurdles and political negotiation (Figure 2, Supplementary Figure 1). Examples include international environmental treaties such as the natural World Heritage Areas, and the Man and the Biosphere Reserves. It also includes community-based initiatives that were strongly driven by NGOs and/or governments, such as Wildlife Management Areas in Tanzania and locally managed marine areas (lmmas) in Samoa. The latter was proactively communicated to potential adopters e.g. [13], and the rate-limiting factor could be the number of potential adopters, rather than access to information on the initiative.

Adoption dynamics can be shaped by local context, as well as the type of initiative. For example, the model of adoption of lmmas - where coastal communities implement a resource management system within their local waters – was fast-slow in Samoa and slow-fast-slow in the Solomon Islands and Fiji. The adoption of lmmas in these different countries may reflect the incentives, motivations, and capacities for adoption. In Samoa, the government actively promoted lmmas and incentivised adoption by providing boats and aquaculture resources to adopting villages[14]. The active intervention of a top-down organisation meant that the initial rate of uptake was not limited by interactions between adopters and potential adopters, and the best fit model was therefore fast-slow. In contrast, local residents of Fiji and Solomon Islands had a stronger bottom-up role in the adoption and spread of lmmas, where they are more closely aligned with objectives of community empowerment and strengthening traditional governance[15]. Past research on adoption highlights that the spread of any initiative will lie in a continuum between pure diffusion (i.e., unplanned, mediated by peers) to active dissemination (i.e., managed, through or dependent on vertical hierarchies)[16], and these differences are likely to be reflected through different adoption dynamics (e.g. pure diffusion is best represented by slow-fast-slow models).

We constrained the parameters across the models fit to different time series, and using information theory (AIC) to identify the most parsimonious models, we tested (1) whether the dynamics of a single initiative varies significantly between locations and (2) whether the dynamics of different initiatives within the same location vary significantly. The results showed that separate fits were justified for most of our case studies (Figure 3, Supplementary Figure 1-6, Supplementary Table 3). Thus, even when the spread of conservation initiatives occur via consistent mechanisms (e.g., conservation covenants in Australia shared a slow-fast-model), the precise uptake rate and extent of adoption was shaped by unique factors associated to the location or the initiative.

In the Philippines, for example, the design of marine reserves is similar across the country – small, no-take areas established under local (municipal) government ordinances, primarily to enhance local fisheries[17]. Given this consistency, we expect the model of adoption to be consistent across separate regions. Indeed, in most (90%) regions the slow-fast-slow model provided the best fit to the time series. However, the dynamics of these slow-fast-slow models were sufficiently different in each location to justify unique fit parameters (according to AIC; Figure 3, Supplementary Table 4). There were only a few regions for which models that shared uptake rate or resistant population were as good as the separate models (e.g. shared proportion of adopters for the Philippines region IV-A, IV-B and XI Supplementary Table 5). Each regions' parameter will vary with the drivers of the uptake rate and the proportion of adopters. For example, high uptake rates could be attributed to "cross-site visits" that encourage peer-to-peer communication about the benefits of marine reserve establishment[18]. In contrast, regions which lacked such communication, due to either funding constraints, remoteness, or social conflict, may exhibit different uptake rates and proportions resistant to adoption.

Our best fit models predict our case study initiatives generally reach low percentages of the total pool of potential adopters. Over half (n=12) will never be adopted by more than 30% of potential adopters (i.e., actors who could establish and/or implement the initiative). Locally-implemented initiatives were particularly unlikely to have large uptake across their potential adopters (0.13-51%; although Northern Rangelands Trust Communal Conservancies in Kenya were an exception, with 99% predicted adoption). In contrast, national initiatives had a comparatively high penetration (84-100%). Although low percentages of adopters were predicted for most initiatives, practitioners should remember that the population that is resistant to adoption within the total pool of adopters can change with significant changes to the relative advantage of participating in these initiatives[12].

Decision makers across the world are seeking conservation initiatives that display both rapid uptake and large-scale adoption[19]. Our results, however, suggest that to date our case studies have not been able to exhibit both these desirable attributes. The 18 widely-recognized conservation initiatives in our dataset that follow a slow-fast-slow model display an apparent trade-off between the speed of uptake and the final proportion of adopters. Figure 4 contrasts the uptake speed with the predicted maximum adoption proportion, where both parameters have been standardised across the different initiatives. Those initiatives in the bottom right of this figure (shown in green) exhibited rapid uptake, but were adopted by a relatively small proportion of potential adopters (i.e., a large proportion of the potential pool were resistant). In contrast, the initiatives in the top left (highlighted in blue) were adopted by almost all potential users, but took a long time to achieve this. The dataset also contained a set of initiatives at the bottom left (shown in red) which exhibited both slow uptake and low levels of adoption. These results suggest the presence of a Pareto frontier for our case studies displaying slow-fast-slow dynamics, and allow practitioners and funders to benchmark their initiatives with these dynamics against ours.

Implications for policy and practice

Insights gained from our models can help scientists forecast how much existing initiatives can contribute towards global policy targets, such as those articulated within the Convention on Biological Diversity (CBD) and the U.N. Sustainable Development Goals (SDG). For example, we found a large potential for further adoption of lmmas in the Solomon Islands (Figure 2a). These initiatives will directly contribute towards strengthening the resilience of the fisheries (SDG Target 14.2) and reaching the Aichi Targets for marine protected area coverage, where the Solomon Islands currently falls short. Model projections are uncertain in the earliest stages of adoption (Figure 2), but can still help to identify initiatives with the highest future return on investment. For example, our study also suggests that the adoption of some initiatives has waned (e.g., Chilean Territorial Use Rights for Fishing, Philippine marine reserves; Figure 2a): at this stage, demonstration sites are probably ineffective at further increasing adoption, and conservation efforts should shift towards sustaining the implementation of existing projects, or towards the adoption of complementary initiatives[20].

Our results have revealed consistent patterns of adoption worldwide for government and privately protected areas, international treaties and community based conservation, but more research is needed to incorporate the durability and impact of these initiatives into our models. Our datasets include many sites where an initiative has never been effectively implemented[21] or where a project has been abandoned[22]. Given the long time-scales required for ecological recovery, it is important to consider the dynamics of ongoing action, as well as adoption (e.g. [23]). Doing so will require theories explaining spread, such as the diffusion of innovation theory, to be integrated alongside new insights into the factors that enable robust governance of natural resources[24,25]. Understanding the influence of context will also be vital: future models of the adoption should focus on understanding the complexity of adopters (e.g. privately protected areas can be managed by individual, groups or organisations), and how they are influenced by a heterogeneous spatial (e.g., via oceans or mountains inhibiting interactions) and temporal (e.g., via shocks or the implementation of policy and incentives) environment e.g. [26]. Future work should also engage with alternative models, such as "escalation", where there is another period of growth in uptake rate after it initially slows down[27] as a result of changed conditions or an altered intervention. To engage with this complexity, analyses of context will require the collation of larger and more detailed datasets of conservation initiatives.

The persistence of biodiversity and ecosystem services depends on the adoption of effective conservation initiatives at a pace and scale that matches or exceeds environmental threats. Scientists spend enormous effort working out which initiatives, if applied, deliver the greatest biodiversity benefits[28,29]. However, for an initiative to be truly effective, it must also be applied at a meaningful scale. Our results show, for the first time, that the dynamics of adoption are consistent and comprehensible. Such insights are critical if scientists are to understand the drivers of adoption and match the scale of its response to the vast challenges of the Anthropocene. While our results only begin to address this research gap, they offer the first insights, directions, and tools for further progress.

Methods

Data

To model adoption of conservation initiatives, we collected information on the number of adoptions through time for each initiative and estimated the total number of potential adopters. Adoption has been interpreted in different ways in the diffusion of innovation literature, varying with respect to: the decision to adopt; degree and extent of implementation[30]. The process of adoption for conservation initiatives varies widely, some require very little bureaucracy, while others have long and complicated processes of implementation. We aimed to collect the existing data on the start of the implementation process, the moment where the decision to adopt is made. However, for many case studies the only data available are the dates of registration so they are the data we used (see Supplementary Table 1). The date of adoption represents the first time that entity starts the adoption process or registers that type of initiative. We use the word entity to represent the unit of adoption (e.g., individual people, communities, local government, etc.). The type of adopter was decided for each individual initiative in collaboration with experts of that particular initiative. Adoption decisions however are not always clearcut. For example, in some villages the adoption decision was made by the individuals within a community as well as the community leaders, while in others they may depend solely on the community leader. The impact of heterogeneity in the adoption decision should be investigated in future studies. The method used to estimate the total number of adopters also varies for each case study and is explained in detail in Supplementary Table 1. For example, the total pool of adopters for conservation covenants relied on tenure maps, the size of properties and criteria from NGOs defining what property would and would not be considered. In contrast, the total pool of adopters for locally managed marine areas relied only on previous estimates of the number of coastal villages in the different Pacific countries. The source of information on the number of adoptions and potential number of adoptions is provided in Supplementary Table 1.

Model Descriptions

We model the spread of adoption as a simple differential equation. In the ***fast-slow***, adoption occurs at a rate proportional to the number of entities susceptible to adopting the conservation initiative. At any time, each entity can either be susceptible to adoption, resistant to adoption, or an adopter. Let the number of adopters at time t be A(t). We assume the number of entities resistant to adoption, R, and the total number of entities, K, does not change through time. If α is the fixed per entity uptake rate, then

$$\frac{dA}{dt} = \alpha \, (K - R - A(t)). \qquad (1)$$

Note that $K - R - A(t)$ is just the number of susceptibles at time t. Given an initial number of adopters, A_0,this model can be solved exactly to be fast-slow

$$A(t) = K - R - (K - R - A_0) \, e^{-\alpha t}, \qquad (2)$$

using the standard technique of integrating factors for linear first order differential equations.

The ***slow-fast-slow model*** is similar, but susceptible entities can only adopt when they contact an adopter. Assuming random mixing of entities, and a successful contact-conversion rate parameter β, then the uptake rate is

$$\frac{dA}{dt} = \beta \, A(t) \, [K - R - A(t)]. \qquad (3)$$

This has the closed form, sigmoidal, solution,

$$A(t) = \frac{(K-R)\,A_0}{A_0 + (\,K-R-A_0)\,e^{-\beta(K-R)t}}. \qquad (4)$$

Equation (4) can be achieved by noting that (3) is equivalent to the logistic equation, with carrying capacity, $K - R$, and density independent intrinsic growth rate β.

Finally, the third candidate model is the constant model, which assumes adoption occurs at a fixed rate, α, until there are no more susceptible individuals left to adopt (only resistant individuals). This model is

$$\frac{dA}{dt} = \begin{cases} \alpha, A(t) < K - R \\ 0, A(t) \geq K - R \end{cases} \qquad (5)$$

Which has the solution

$$A(t) = \min\ (A_0 + \alpha t, K - R). \quad (6)$$

Model fitting and selection

To fit the models to the data we minimised the sum of square errors between the observed number of adopters at each time step and the predicted number of adopters from equations (2), (4), and (6), using the function 'fmincon' in MATLAB.

Three fitting parameters were needed to describe the adoption dynamics: uptake rate (denoted by α in the fast-slow model and β in the slow-fast-slow model), the initial number of adopters A_0, and the number of resistant individuals R who will never adopt the initiative

To generate the error envelopes around the predicted number of adopters we used block bootstrapping with a block size of 3 years. Block bootstrapping is a method for calculating the distribution of model parameters given the correlated nature of time series data (for details see [31]). We repeat the model fitting procedure above for each block bootstrap resampled set of data. This gives us a predicted number of adopters for each time step in each sample. We then use the 1% and 99% quantiles of those predictions as the error envelopes in Fig 2.

We used Akaike Information Criteria, corrected for small sample sizes (AICc) to compare the relative support for each model given the data[32]. Specifically, with n data points, and p parameters in the model we computed

$$AIC_c = n \log\left[\frac{1}{n}\sum_{i=1}^{n}\left(A_{t(i)} - A(t(i))\right)^2\right] + 2p + \frac{2p(p+1)}{n-p-1}. \quad (7)$$

Several of our initiatives occur across multiple sites. To test whether sites share the same uptake rate, α, we used the above AICc formula on the aggregated data across each site. In the shared α models the number of parameters is reduced with only the total available number of adopters, K – R, varying at each site.

Data and code availability

Supplementary Table 1 lists all the sources of the data used to estimate the total number of potential adopters and number of adoptions for each intervention per year. The data that support the findings of this study are available from the corresponding author upon request. Correspondence and requests for materials should be addressed to Morena Mills.

All code for the modelling is available on GitHub (https://github.com/MikeBode/Diffusion_of_innovation_fitting).

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Author contributions: MM, MB, MBM, HPP conceived the idea and led study design, MM, RW, SG, ND, HG CLA, CR, LG and RN collected and collated quantitative data, MM, MB and MH conducted analysis. All authors drafted the paper, reviewed and edited the paper.

Competing interests

The authors declare no competing interests.

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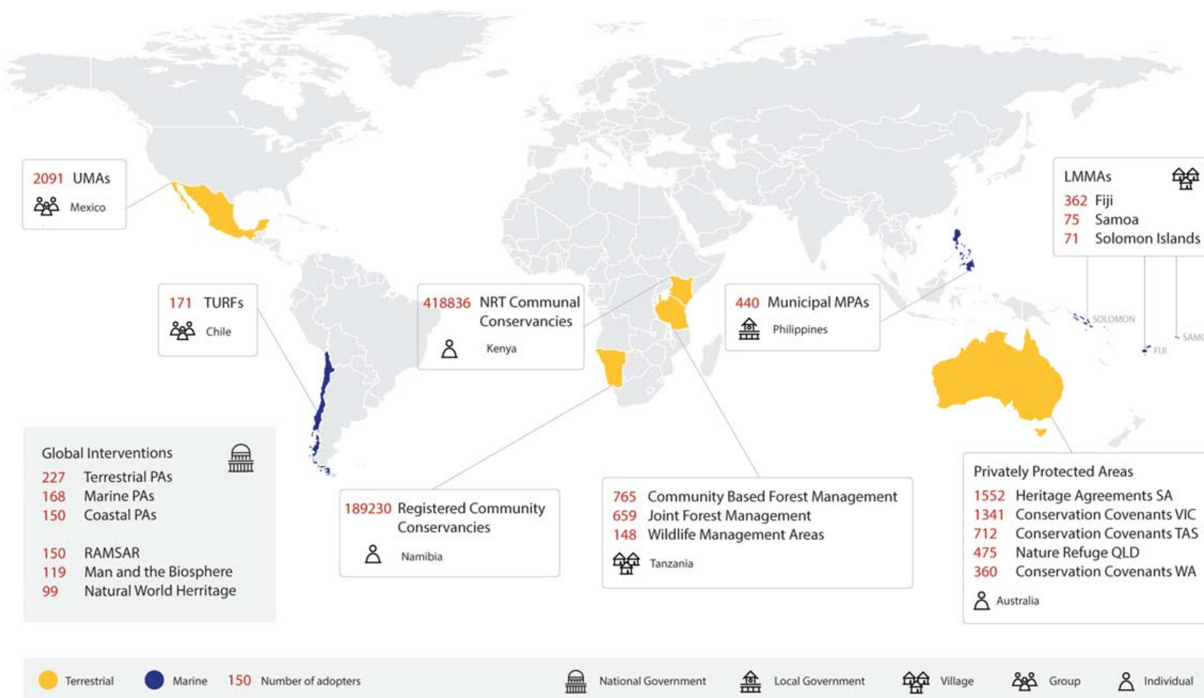
Figure 1. Location of the area-based biodiversity conservation initiatives analysed. Legend indicates the number of adoptions, type of adopter used for analysis, and the marine/terrestrial biome. The act of adoption varies across case studies and can represent the initial step in a process of establishment (e.g., Community Based Forest Management in Tanzania) or the legal designation of management (e.g., Heritage Agreements in Australia). See Supplementary Information for full data.



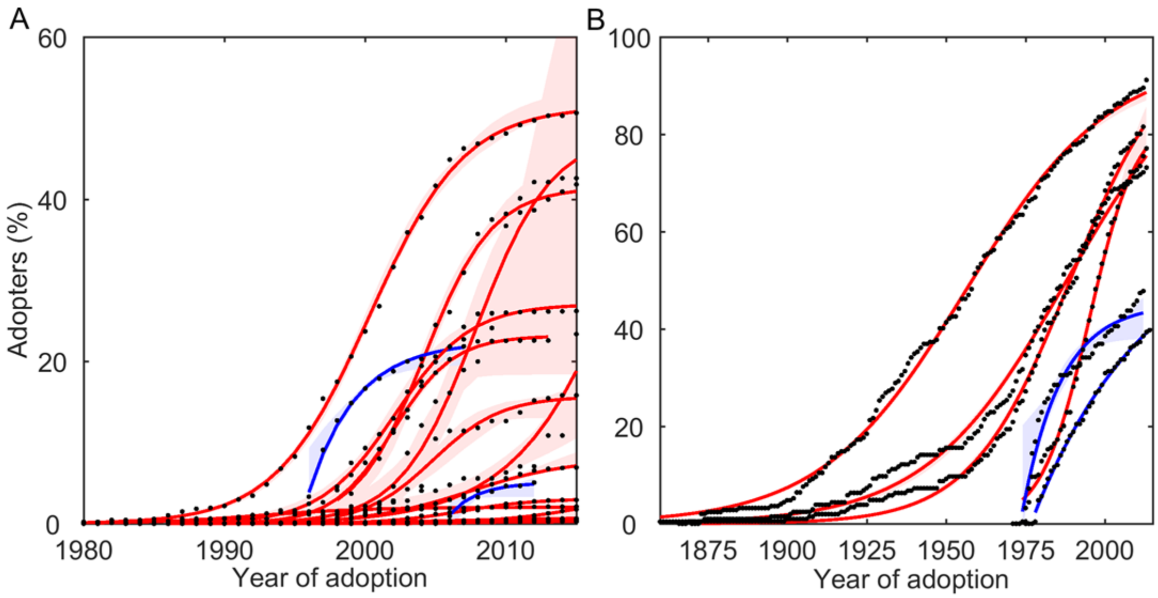


Figure 2. The cumulative percentage of adopters of conservation initiatives at (A) local and (B) national scales. Each line represents the best fit model for an initiative, points represent the data, and shading represents uncertainty in the model fit (see Supplementary Methods). Local scale adopters include individuals, communities, villages and local governments. Adoptions at a national scale represent the first time the initiative (e.g., a protected area) was implemented by that country. Red lines represent initiatives that are best described by the slow-fast-slow model, blue lines represent initiatives that are best described by a fast-slow model.

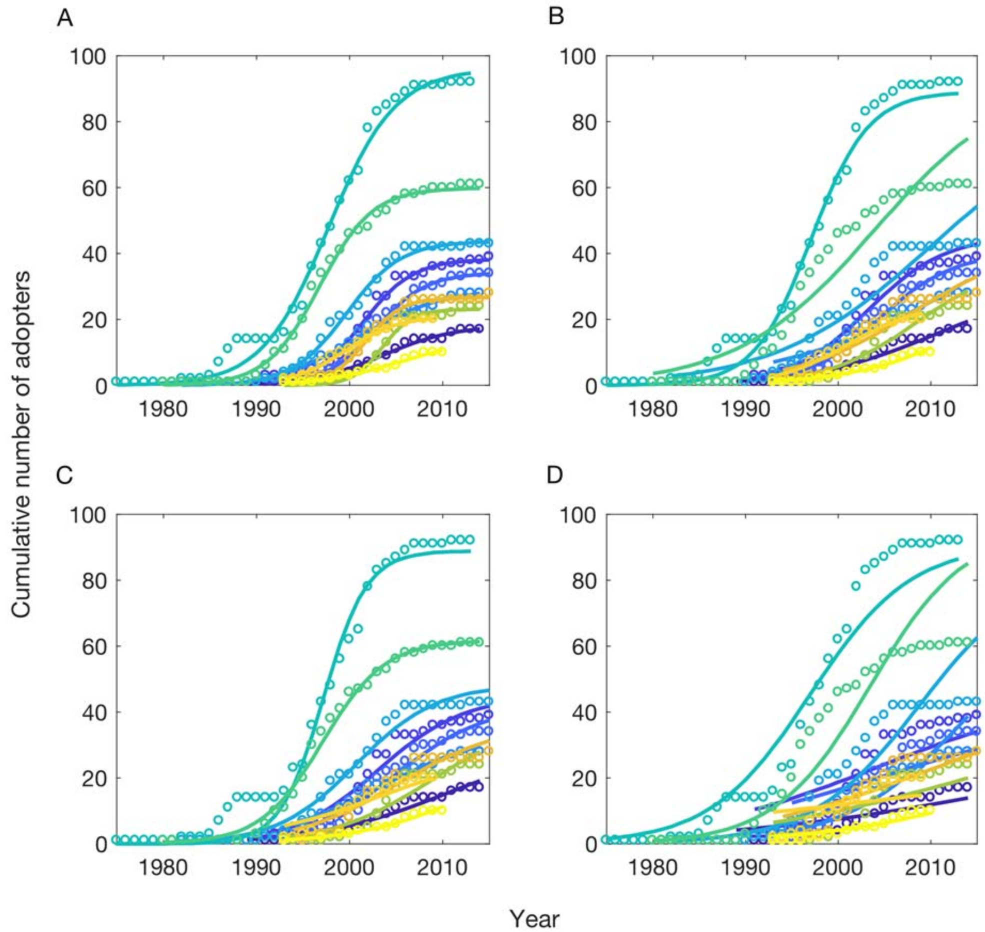


Figure 3. Slow-fast-slow models describing adoption of marine reserves by municipalities in the Philippines. Each colour represents a different municipality, with the circles denoting the observed number of adopters, and the lines showing the model fits. (A) Models where the uptake rate and proportion of resistant entities are fitted individually. (B) Models where the proportion of resistant entities is shared but the uptake rate is fit separately. (C) Models where the uptake rate is shared while the proportion of resistant entities is fit separately. (D) Models with shared uptake rate and proportion of resistant entities. See Supplementary Methods and Supplementary Table 5 for full details.

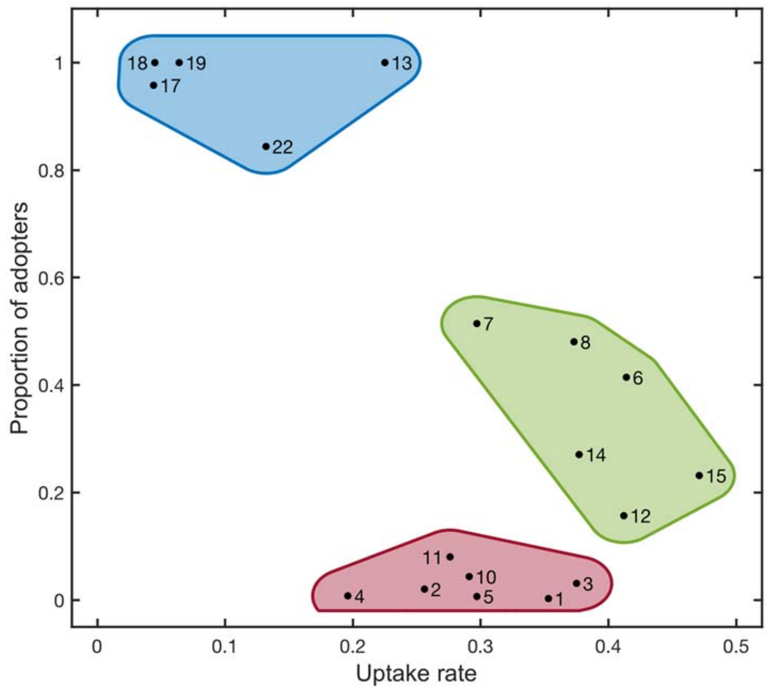
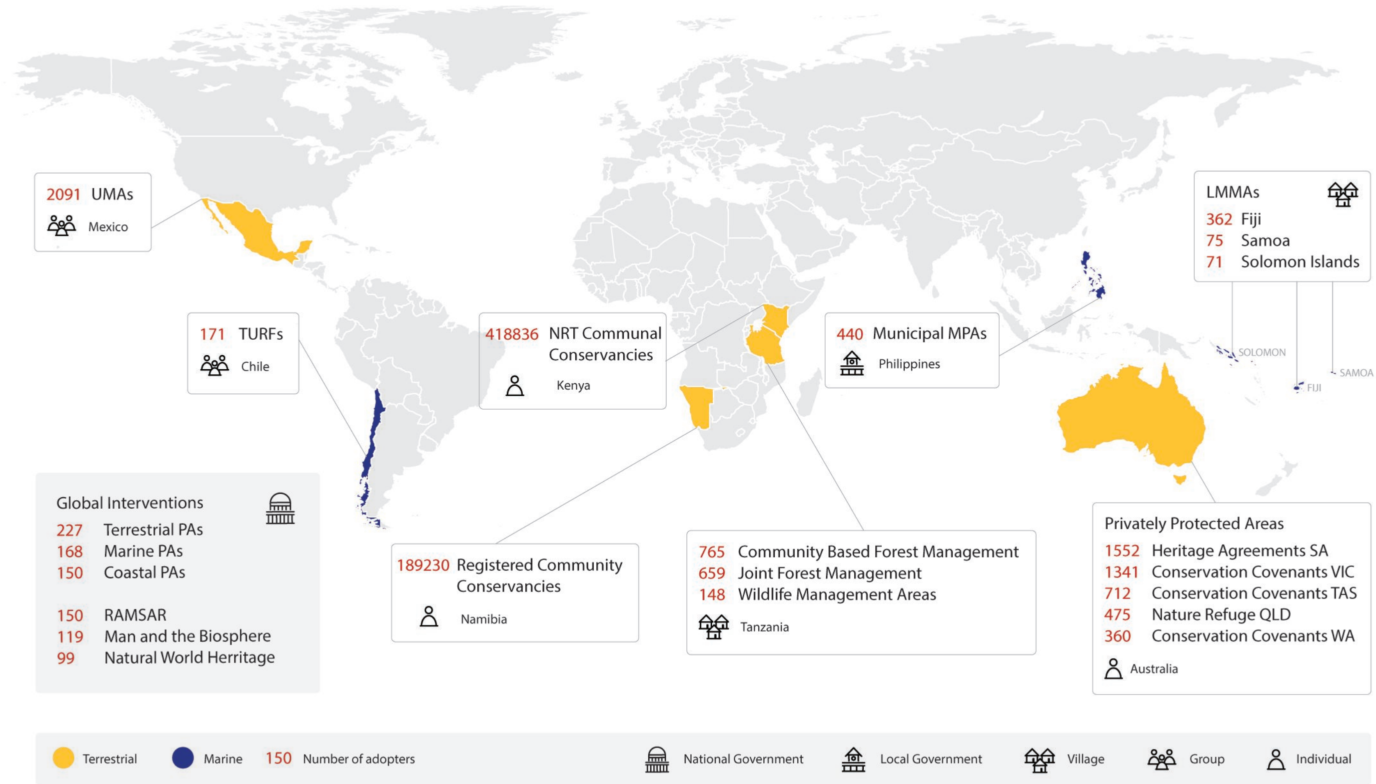
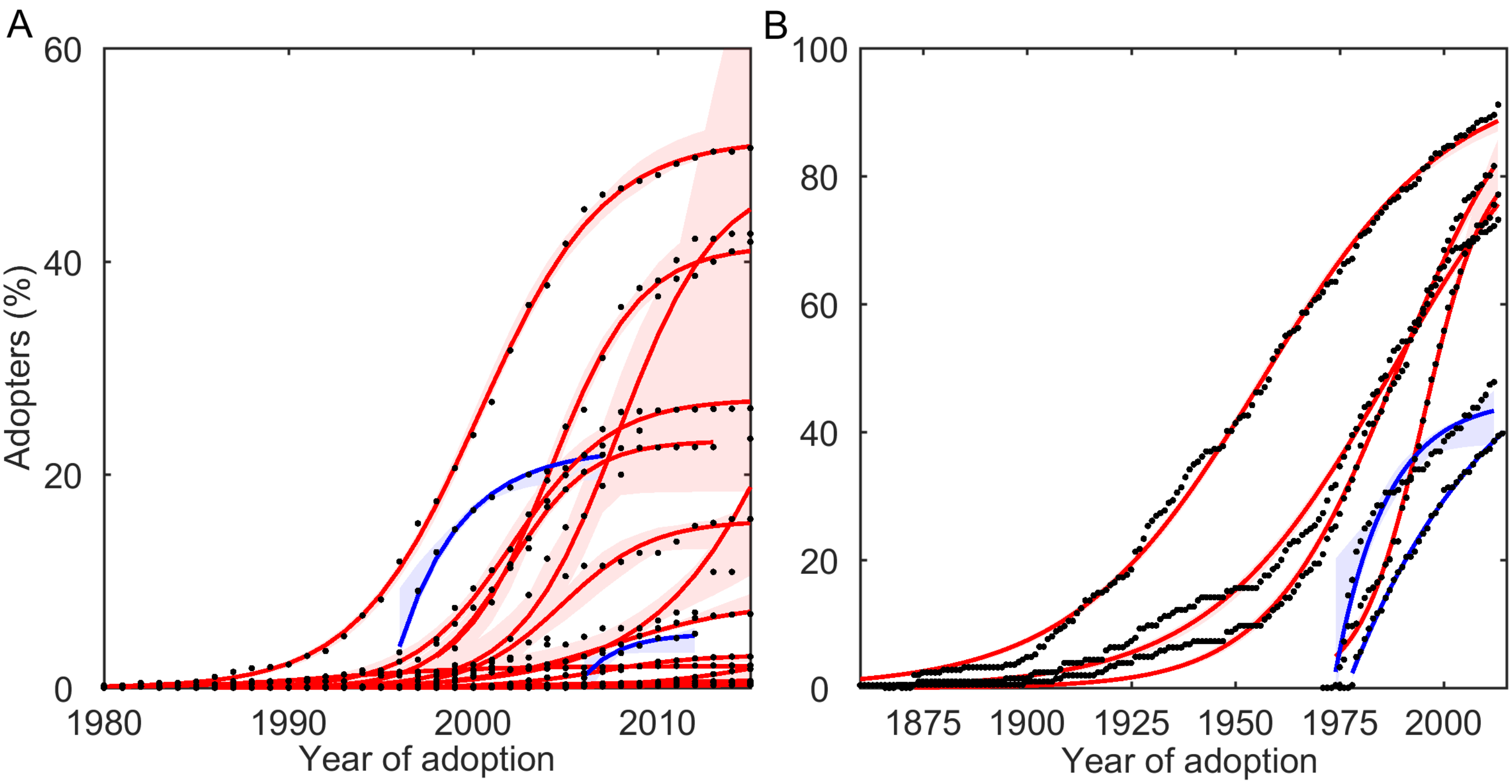
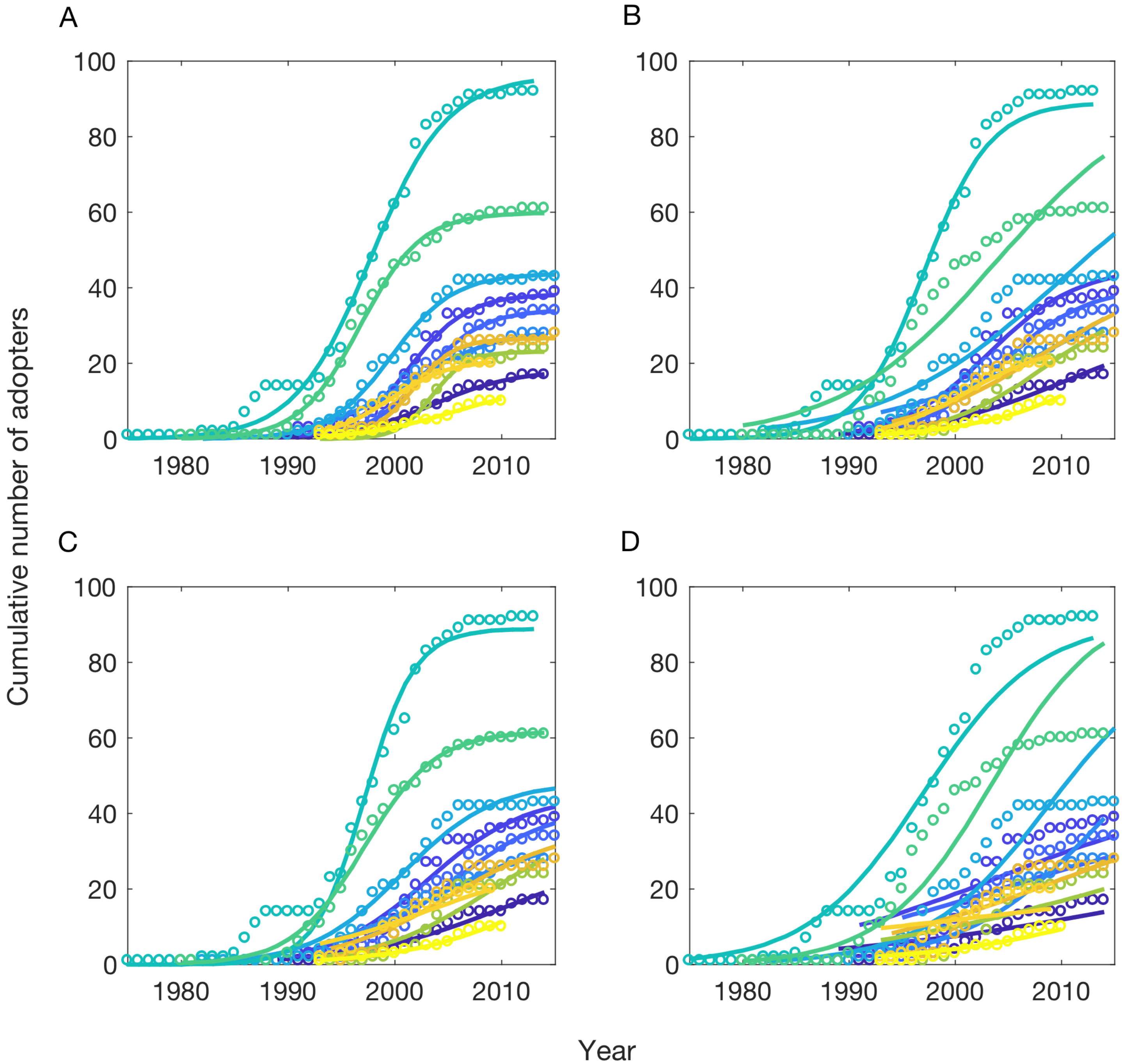


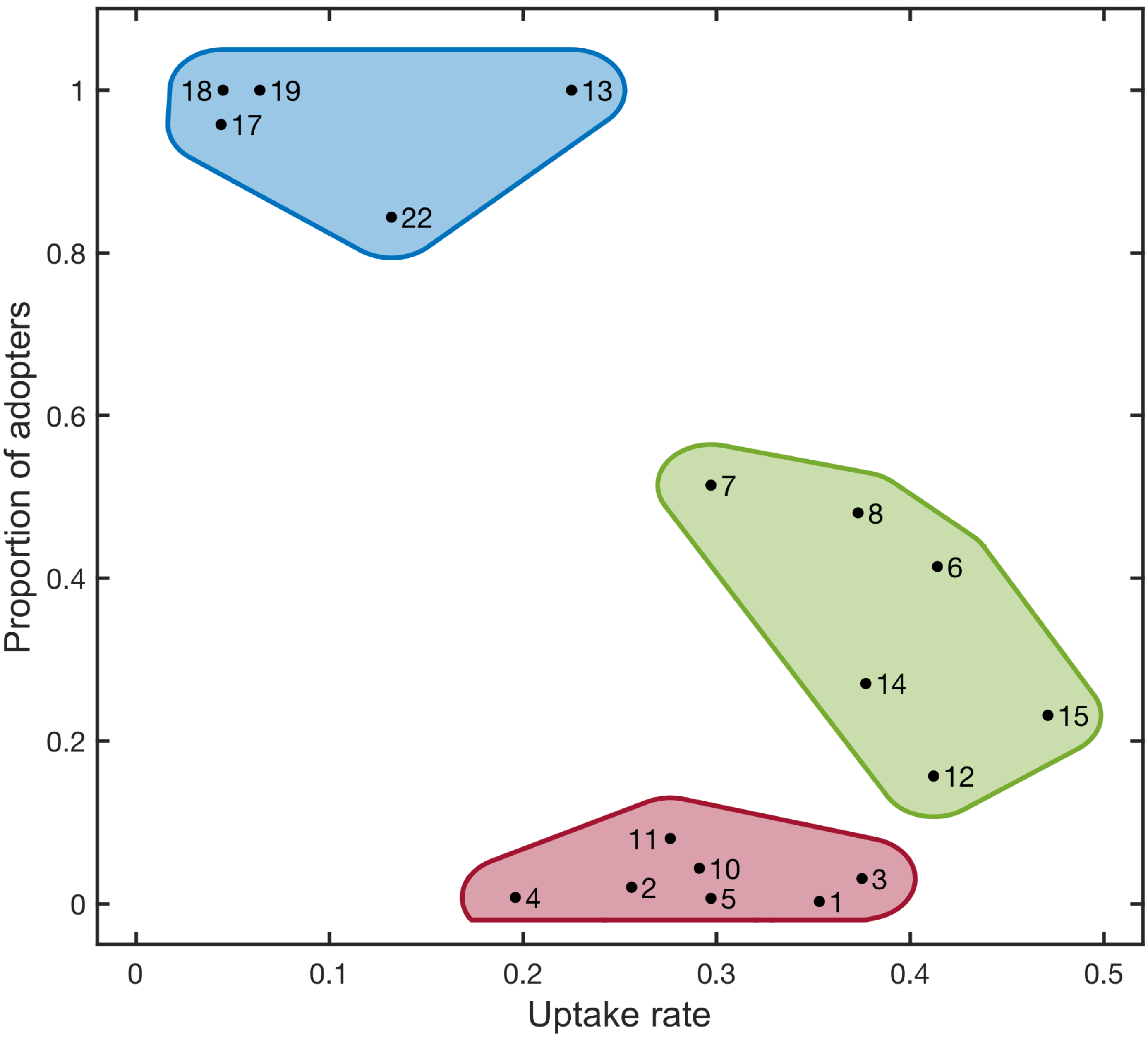
Figure 4. Trade-off between the proportion of potential adopters that are predicted to adopt an initiative (y-axis) and the uptake rate (x-axis), for the conservation initiatives that follow the slow-fast-slow model. Initiatives were divided into 3 groups: high eventual adoption and slow uptake (blue), low eventual adoption and rapid uptake (green) and both low eventual adoption and slow uptake (red). Labels indicate: 1, Nature Refuge Conservation Covenants in Queensland; 2, Heritage Agreements in South Australia; 3, Conservation Covenants in Tasmania; 4, Conservation Covenants in Victoria; 5, Conservation Covenants in Western Australia; 6, Territorial User Rights Fishing in Chile; 7, MPAs established under municipal ordinanaces in the Philippines; 8, Locally Managed Marine Areas in Fiji; 10, Locally Managed Marine Areas in Solomon Islands; 11, Unidades de Manejo in Mexico; 12, Registered Community Conservancies in Namibia; 13, Northern Rangelands Trust Communal Conservancies in Kenya; 14, Community Based Forest Management in Tanzania; 15, Joint Forest Management in Tanzania; 17, Terrestrial Protected Areas; 18, Coastal Protected Areas; 19, Marine Protected Areas; 22, RAMSAR sites.


2091 UMAs
Mexico
171 TURFs
Chile
418836 NRT Communal Conservancies
Kenya
440 Municipal MPAs
Philippines
LMMAs
362 Fiji
75 Samoa
71 Solomon Islands
SOLOMON
FIJI
SAMOA
Global Interventions
227 Terrestrial PAs
168 Marine PAs
150 Coastal PAs
150 RAMSAR
119 Man and the Biosphere
99 Natural World Herritage
189230 Registered Community Conservancies
Namibia
765 Community Based Forest Management
659 Joint Forest Management
148 Wildlife Management Areas
Tanzania
Privately Protected Areas
1552 Heritage Agreements SA
1341 Conservation Covenants VIC
712 Conservation Covenants TAS
475 Nature Refuge QLD
360 Conservation Covenants WA
Australia
Terrestrial
Marine
150 Number of adopters
National Government
Local Government
Village
Group
Individual



A
B
Adopters (%)
Year of adoption
Year of adoption
0
20
40
60
1980
1990
2000
2010
0
20
40
60
80
100
1875
1900
1925
1950
1975
2000


A
B
C
D
100
80
60
40
20
0
1980
1990
2000
2010
Cumulative number of adopters
Year



Proportion of adopters
Uptake rate
0
0.2
0.4
0.6
0.8
1
0
0.1
0.2
0.3
0.4
0.5
18
19
13
17
22
7
8
6
14
15
12
11
10
3
4
2
5
1